Social Finance in the Age of AI: A Tale of Two Platforms*

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Abstract

This paper studies how investors use generative AI in discussions across two major investing social media platforms with distinct governance and user bases: Seeking Alpha and Reddit's r/WallStreetBets. We document sharp cross-platform differences in adoption and market outcomes. On Seeking Alpha, AI adoption arises when information is scarce or contributors cover unfamiliar stocks; it is associated with more informative retail order flows, reduced user disagreement, and narrower bid-ask spreads. On WallStreetBets, AI adoption rises following surges in retail buying and is linked to sentiment contagion. Adoption is also followed by higher abnormal trading volume and volatility, wider spreads, and lottery-like return distributions. These results indicate that the adoption of AI and its relation to market outcomes are shaped by the institutional and behavioral context in which it is deployed.

JEL Codes: G12, G14, G15

Keywords: Generative AI, Large Language Models, Social Media, Financial Discourse, Retail Investors, Information Frictions, Market Microstructure

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1 Introduction

The cost of producing and processing information is a central determinant of the efficiency of capital markets.[1] The recent advent of powerful generative artificial intelligence (AI), particularly large language models (LLM) such as ChatGPT, has sharply reduced those costs, reshaping how investors produce, acquire, and process information (Blankespoor, Croom, and Grant 2024).[2]

On the other hand, New technology often generates multiple and even opposing effects on market outcomes. The same LLM that accelerates due diligence for analysts (Bertomeu et al. 2025) can also be deployed to incite speculative trading or craft pump-and-dump schemes. Financial regulators have expressed serious concerns about the use of AI. the Financial Stability Board warns that "GenAI could increase financial fraud and the ability of malicious actors to generate and spread disinformation in financial markets" (Financial Stability Board 2024). The emerging debate centers on three core issues: *when* content creators adopt GenAI, *how* users engage with and interpret AI-generated content, and *how* such content influences market prices and trading–and ultimately, whether AI adoption enhances efficiency or floods markets with noise and manipulation.

In this study we examine the adoption of AI in financial discourse and the association of AI use with market outcomes. A challenge for such research is that AI adoption is not observable in most disclosures, requiring specialized text analysis to detect, and that the association between AI adoption and outcomes are likely context-dependent. We address this challenge by exploiting variation across online platforms with markedly different governance regimes and user sophistication, combined with a state-of-the-art commercial AI detector. Specifically, we collect articles and messages on U.S. publicly listed firms from June 2022 to December 2024, spanning the November 30, 2022 introduction of ChatGPT, across two influential social media platforms: SeekingAlpha (SA) and Reddit's r/WallStreetBets (WSB).

[1] See Hayek (1945) (on information and markets in general), Fama (1970), Grossman and Stiglitz (1980), Diamond and Verrecchia (1981) and Kim and Verrecchia (1994).

[2] See Brynjolfsson, Li, and Raymond (2025), Noy and Zhang (2023), and Bertomeu et al. (2025) for evidence on AI lowering cost and improving output quality.

Seeking Alpha operates under strong editorial oversight: articles are reviewed prior to publication, and many authors are financially compensated for producing original investment analysis. Its user base consists largely of semi-professionals with investment expertise. In contrast, WallStreetBets is a decentralized Reddit community with no pre-publication review and looser content standards, where posts often highlight screenshots of high-stakes trades. Its users are generally less sophisticated and more prone to behavioral biases and peer effects. While moderators intervene to remove spam and egregious violations, overall oversight is far weaker than on Seeking Alpha. Together, these two platforms provide a natural testing ground for assessing how institutional and user contexts shape AI use and content generation in relation to market outcomes.

We use GPTZero, a state-of-the-art AI-content detector, to identify the likelihood of AI-generated text. The tool relies on linguistic complexity measures (perplexity, burstiness), sentence-level contextual classification, and internet text search to reduce misclassification of common or archived material. GPTZero has been employed in recent studies of financial markets such as Blankespoor, Croom, and Grant (2024) and Bradshaw et al. (2025). Jabarian and Imas (2025) show that, for general texts, GPTZero is among the leading commercial detectors, achieving high accuracy across models, genres, and even against "Humanizer" tools, while minimizing false positives. We further validate the effectiveness of GPTZero in detecting AI use in financial discourse using a test sample of human-written articles from SA and WSB randomly drawn from the pre-ChatGPT period and LLM-generated social media posts trained on pre-ChatGPT *Wall Street Journal* news mimicking SA and WSB styles. In these tests, GPTZero also outperforms alternative open-source detectors.

Applying GPTZero to our sample, We document that the average *AIProb*—the probability that an article or post is generated by AI (or at least with AI assistance)—rises from nearly zero in mid-2022 to roughly 10% on SA by late 2023, before declining slightly, and to about 7% on WSB by end-2024. These magnitudes are an order of magnitude larger than those documented in corporate filings (Blankespoor, Croom, and Grant 2024), suggesting that social-media commentators adopted AI earlier and more aggressively than did corporate filers.

We next examine how, when, and with what consequences market participants adopt AI across these platforms. We uncover three key findings. First, adoption motives differ across platforms. On SA, authors rely on AI when information is costly to gather; they are 22% more likely to use AI when covering a firm for the first time in six months, and usage is higher when analyst coverage or news availability is low. This evidence is consistent with authors turning to AI precisely when marginal research costs are high. In contrast, on WSB, adoption is unrelated to information availability. Instead, AI probability is 46-55% higher following periods of heavy retail buying. This suggests that WSB adoption is associated with noise trading rather than information production.

Second, AI-generated content can foster consensus (rational or otherwise) but can also amplify sentiment contagion. On SA, AI-generated articles attract 7% fewer comments over the next ten days, and comment sentiment is more uniform, with dispersion falling by 10% relative to the mean. In contrast, on WSB, AI content is not significantly associated with lower disagreement. Furthermore, it is associated with greater sentiment transmission: the sentiment of AI posts strongly predicts the sentiment of follow-up comments, a pattern absent on SA. These differences likely reflect platform-specific mechanisms: on SA, AI may enhance clarity and content quality, encouraging consensus; on WSB, AI may streamline punchy narratives that results in sentiment contagion.

Third, the market consequences of AI adoption appear to diverge sharply across platforms. On SA, AI presence is associated with improved market quality. Over the five days following publication, stocks with AI-generated content experience declines in abnormal trading volume and volatility, along with a tightening of bid-ask spreads. This evidence is consistent with AI helping traders reach accurate consensus, reducing the need for price discovery through trading. In contrast, on WSB, AI posts are on average followed by surges in abnormal trading volume, significantly higher volatility, and wider bid-ask spreads.

Moreover, WSB-based AI content strongly predicts destabilizing lottery-like outcomes. The odds of a MAX event (a 21-day high) increases by 26.9% on AI publication days and remains elevated by 17.2% over the next five days. The odds of a lottery event (MAX events also

in the top decile cross-sectionally) rises by 57.0% on the same day and 31.9% over the following week. In contrast, AI content on SA shows no link to either MAX or lottery events. Finally, SA-based AI content is associated with more informative retail order flows, measured by the ability of retail net buys to predict future returns, whereas WSB-based AI content does not exhibit any significant relationship with retail order flow informativeness.

Taken together, this evidence underscores the importance of platform governance and community characteristics in shaping the market implications of AI adoption. On SA, AI-assisted content is associated with indicators of greater informational efficiency, whereas on WSB, AI-assisted content is linked to noise trading and predicts lottery-like outcomes. These differences may derive from SA's editorial oversight in filtering and curating content. However, other contributors to these differences may include differences in user sophistication, incentives, or community norms. More broadly, the findings suggest that the uses of AI and its relationship with market outcomes depend on the institutional and behavioral environment in which it operates.

Our paper makes several contributions to the rapidly evolving literature on AI in financial markets. First, we broaden the scope of inquiry by shifting attention from formal disclosure channels to retail-facing online platforms. While existing research has begun to explore AI in formal corporate disclosures (Blankespoor, Croom, and Grant 2024) and professional analyst reports (Bertomeu et al. 2025), our study provides one of the first large-scale comparative analyses of AI's footprint in the more dynamic and loosely regulated domain of public equity commentary. We further show that this dimension of AI adoption is closely tied to trading activity, bid-ask spreads, and lottery-like return distributions.

Second, we are among the first to empirically quantify the moderating role of platform governance and user characteristics in shaping AI's market. While theory predicts that lower information costs should enhance market efficiency (e.g., Grossman and Stiglitz 1980; Diamond and Verrecchia 1981), and recent studies show evidence consistent with this prediction (Kim, Muhn, and Nikolaev 2025; Bertomeu et al. 2025), concerns about AI-induced noise, herding, and manipulation persist (Dou, Goldstein, and Ji 2025). Moreover, AI's rhetorical

capabilities can amplify behavioral biases such as attention-induced trading (Barber et al. 2022) and social transmission bias (Hirshleifer 2020; Han, Hirshleifer, and Walden 2022) and echo chambers (Cookson, Engelberg, and Mullins 2023).

Our cross-platform analysis addresses this tension: the association between AI and lottery-like events on WSB, but not SA, highlights how institutional context determines the association of AI with better price discovery versus speculative trading. In this respect, our analysis complements Bradshaw et al. (2025), who also study AI on SA platform, while our contrast with WSB yields allows us to draw broader comparative conclusions about AI adoption and its relationship with investor behavior and market outcomes.

Third, we provide evidence on the micro-foundations of AI adoption and its behavioral consequences. We document why and when content creators turn to AI across platforms, showing that platform-specific motivations shape both the production and reception of AI-generated content. These findings add nuance to existing research on productivity effects of AI (e.g., Brynjolfsson, Li, and Raymond 2025; Noy and Zhang 2023).

Finally, our evidence on the critical role of platform design has a bearing upon the theory of Acemoglu, Ozdaglar, and Siderius (2025) in which AI as a social media tool can cause belief polarization. Consistent with this view, we find that AI use is associated with sentiment amplification on the less regulated and more speculative WSB platform. This suggests that AI can foster echo chambers under weak governance.

2 Hypothesis Development

In a market with information frictions, any mechanism that lowers production costs or alters how readers process content—including AI assistance—can reshape both discussion patterns and market dynamics. However, the relationship between such technological adoption and outcomes likely depends on the institutional environment in which it occurs. Before developing our hypotheses about AI adoption in financial discourse, we first characterize the fundamental differences between our two platforms, as these structural features can deter-

mine both why content creators adopt AI and how this adoption is associated with market outcomes.

Seeking Alpha implements stringent editorial oversight where in-house editors manually review every article submission, providing iterative feedback to authors until the content meets the platform's standards. This review process, which typically takes 10-24 hours for weekday submissions, ensures quality control before publication. Authors are required to disclose any business relationships with and personal holdings in the companies they cover. Even the comments section undergoes active moderation to maintain substantive discussion. In contrast, Reddit's r/WallStreetBets operates as a decentralized platform with minimal oversight. Posts appear instantly without any pre-publication review, and there is only limited post-hoc moderation for spam and abuse.[3]

The platforms also differ in content guidelines for contributors. Seeking Alpha encourages "investment-oriented", "original", and "fundamental analysis", explicitly valuing whether an article "helps an investor in their decision making." WallStreetBets encourages users to share screenshots of high-stakes holdings and trades through designated "YOLO" and "Gains/Losses" flairs.

Users also have different incentives to post. Seeking Alpha writers are paid a fixed amount for each article and variable amount based on views by paid subscribers. So user following and reputation are important to maintain a steady flow of income. In contrast, there are no direct monetary compensations for posting on WSB. Instead, the reward is social capital, such as karma points, and collective recognition and identity as a community member. These divergent incentives are associated with contrasting patterns of AI deployment: on SA, authors use AI to maintain output quality to satisfy editorial standards and subscriber expectations; on WSB, users employ AI to craft narratives that maximize upvotes and community engagement.

These structural differences in governance, content guidelines, and user sophistication and incentives create distinct environments for AI deployment and its relationship with mar-

[3]The WSB content guidelines focus primarily on combating spam and abuse with rules like "no crypto," "no penny stocks," "no paper trading," "no pump-and-dumps," "no market manipulation," and "no social begging."

kets. Building on this institutional foundation, we structure our hypotheses around three core questions: (1) Why do content creators turn to AI? (2) How do users respond to AI-generated financial content? (3) How does the presence of AI-generated content on different platforms influence market outcomes? Throughout, we emphasize that AI adoption and its association with outcomes can manifest differently across platforms depending on governance and user characteristics.

2.1 Adoption of AI in content creation

We first consider the motivation of AI adoption in content creation. Recent studies show that AI significantly lowers the cost and time required to produce textual content for customer-support agents and professional writers, with this benefit being more pronounced when humans lack prior knowledge or experience (e.g., Brynjolfsson, Li, and Raymond 2025; Noy and Zhang 2023).

In the context of financial content creation, we posit that AI's ability to lower information production costs is most strongly associated with adoption when unassisted human research would be particularly expensive. This occurs when authors cover unfamiliar firms or industries, or when public news is scarce and producing novel insights independently is costly. In these scenarios, AI flattens the learning curve and enables publication that might otherwise be uneconomical. We therefore expect AI adoption to be more frequent in first-time coverage settings and during periods of low firm-specific news flow.

Beyond informational motives, AI adoption may also be driven by non-informational social motives. Users may turn to AI not to produce new information, but to generate content that emphasizes emotional connection, relatability, entertainment, or even manipulation. Rhetorical engineering–the ability of AI to craft stylistic and emotionally charged content–makes these motives especially effective (Matz et al. 2024; Cong et al. 2024). Importantly, such rhetorical use of AI should be more valuable on lightly moderated platforms with less sophisticated users who are more susceptible to emotions and social influence.

Based on these considerations, we propose the following:

Hypothesis 1a *The adoption of AI for creating financial content is associated with efforts to overcome information production costs and information frictions, particularly when addressing unfamiliar topics or operating in information-scarce environments.*

Hypothesis 1b *The adoption of AI for creating financial content is associated with non-informational motives such as emotional connection, entertainment, or manipulation, with rhetorical engineering particularly valuable on lightly moderated platforms where less sophisticated users are more susceptible to emotional and social influence.*

On curated platforms such as Seeking Alpha, where editorial screening ensures baseline quality standards (Bradshaw et al. 2025) and users are relatively sophisticated and information-driven (Cookson et al. 2024), AI adoption is more likely to be associated with informational purposes. In contrast, on lightly moderated and speculative platforms such as WallStreetBets, AI adoption is more likely to be associated with non-informational purposes—emotional connection, entertainment, rhetorical persuasion, or even manipulation. In such settings, AI's ability to craft compelling narratives may be linked to retail trading unrelated to fundamentals. Thus, Hypothesis 1a is expected to be more applicable to SA, while Hypothesis 1b is expected to be more applicable to WSB.

2.2 User Responses to AI-Generated Content

If AI adoption is primarily for informational reasons, then the content it produces should help synthesize complex information into clearer and more accessible formats. This "convergence toward truth" mechanism aligns with findings that AI is associated with improved information processing (Kim, Muhn, and Nikolaev 2025; Siano 2025). In this case, AI-generated posts can guide users toward consensus, reduce disagreement, and potentially lower levels of subsequent comments, since less uncertainty remains to be debated. This relationship should be stronger on curated platforms with editorial oversight and relatively sophisticated users, such as SA.[4]

[4]An alternative explanation is that AI text tends to be more homogeneous and thus offers fewer novel or contentious points, naturally reducing discussion and disagreement. Users may also discount AI content as less authentic once recognizable. These effects likely depend on the context in which the technology is applied.

Alternatively, if AI adoption is primarily linked to non-informational motives (such as emotional connection, relatability, entertainment, or even manipulation), then AI's rhetorical and persuasive capabilities may dominate. By crafting stylistic and emotionally charged narratives, AI-generated content on lightly moderated platforms with less sophisticated users, such as WallStreetBets, is more likely to be associated with reinforcing user attention (Barber et al. 2022) and amplifying biased social transmission and echo chamber effects (Hirshleifer 2020; Han, Hirshleifer, and Walden 2022; Cookson, Engelberg, and Mullins 2023). These dynamics can be reflected in stronger engagement and greater sentiment contagion, with follower comments more likely to align with the initial post.[5]

Based on these considerations, we propose the following hypotheses:

Hypothesis 2a *If AI-generated content is associated with informational purposes, it will guide users toward consensus, reflected in lower sentiment dispersion in comments, and dampened subsequent engagement (e.g., fewer follow-up comments).*

Hypothesis 2b *If AI-generated content is associated with non-informational purposes, it will reinforce user attention and amplify biased social transmission, reflected in stronger engagement and greater sentiment contagion, with follower comments more likely to align with the sentiment of the initial post.*

2.3 Market Impact of AI-Generated Content

The relationship betwen AI-generated content and stock markets is unlikely to be uniform. Consistent with our earlier hypotheses, the association depend on whether AI is adopted for informational versus non-informational reasons, and these considerations interact with the institutional design of the platform.

On curated platforms such as SA, AI adoption is more likely to be associated with informational purposes. In this setting, AI deployment is linked to a greater supply of valuable signals and lower residual uncertainty in asset prices. Consistent with this view, AI adop-

[5]Recent experiments show LLMs consistently outperform humans in persuasion tasks (Schoenegger et al. 2025) and end-users can turn LLMs into persuasion tools just with simple prompting (Hackenburg et al. 2025).

tion on SA is expected to be associated with lower subsequent trading volume and volatility, as improved information reduces disagreement and the scope for speculation. We also expect narrower bid-ask spreads, as reduced uncertainty lowers adverse selection and inventory costs for market makers (see, e.g., Glosten and Milgrom 1985; Glosten 1989; Glosten and Harris 1988; Huang and Stoll 1997; Stoll 1989).

Hypothesis 3a *If AI-generated content is adopted for informational purposes, it will be associated with improve market efficiency, reflected in lower subsequent volatility, narrower subsequent bid-ask spreads, and stronger price-fundamental linkages, along with reduced trading volume.*

In contrast, on lightly moderated and speculative platforms such as WallStreetBets, AI adoption is more likely to be associated with non-informational purposes—emotional connection, entertainment, rhetorical persuasion, or even manipulation. In such settings, AI's ability to craft compelling narratives can be linked to amplified sentiment, reinforcing the biases emphasized in theories of noise trading and attention-driven speculation (Shleifer and Summers 1990; Barber et al. 2022) and biased social transmission (Hirshleifer 2020; Han, Hirshleifer, and Walden 2022; Cookson, Engelberg, and Mullins 2023; Bali et al. 2025). As a result, AI adoption on WSB is likely to be associated with stronger herding and speculative trading, higher volatility, and wider bid-ask spread, as unsophisticated retail flows impose inventory risk on intermediaries (Eaton et al. 2022). In this sense, AI functions less as an informational tool and more as a noise amplifier, reinforcing behavioral biases and reducing price efficiency.

Hypothesis 3b *If AI-generated content is adopted for non-informational purposes, it can amplify noise trading and speculative dynamics, reflected in higher volatility, greater trading volume, wider spread, and weaker price-fundamental linkages.*

3 Data

3.1 Social Media Financial Contents

Our primary data consist of the textual content collected from two distinct online platforms: Seeking Alpha (SA) and Reddit's r/WallStreetBets forum (WSB). The sample period spans from December 2022, immediately after the launch of ChatGPT in November 2022, to December 2024.

Seeking Alpha is recognized for its crowd-sourced equity research contributed largely by semi-professional analysts. We collect all articles published within the "Analysis" section, excluding earnings call transcripts and corporate presentations to focus on original analytical work. Following prior literature, we further restrict attention to (1) single-ticker articles (Chen et al. 2014), or (2) articles with a valid primary ticker identifying the central firm discussed (Campbell, DeAngelis, and Moon 2019). About 69% of the SA articles in our sample period meet this criterion.

WallStreetBets, in contrast, is a decentralized Reddit community known for meme-centric and shorter-form discussions by retail investors. We consider all submissions (original posts) and subsequent comments in our analysis (submissions comprise about 10% of total messages). We apply two filters. First, messages must reference a single valid stock symbol, excluding spurious ticker matches. Second, messages must exceed 50 words, which eliminates trivial remarks for reliable detection (about 250 characters, or 40-45 words).[6]

Our final sample consists of 57,581 SA articles and 64,848 WSB messages, each processed using GPTZero, a leading commercial AI-content detector that employs a seven-component model to analyze text at sentence, paragraph, and document levels. Trained on general textual data, GPTZero has demonstrated superior performance in detecting AI content (Jabarian and Imas 2025).

A natural question is whether it performs equally well on social-media financial texts

[6]Section 7 presents robustness checks with alternative samples that includes submissions only, or including all WSB messages regardless of length (assigning zero AI probability to those below 50 words).

that contain domain-specific jargon and analytical styles. To evaluate this, we conduct a validation study using 1,000 pre-ChatGPT human-written SA and WSB articles, along with AI-generated counterparts created from pre-ChatGPT Wall Street Journal news articles using multiple LLMs prompted to mimic SA and WSB styles. As shown in Appendix Table A2, GPTZero outperforms mainstream detectors (e.g., Wu et al. 2025) in distinguishing AI from human content in this setting.

Figure 1 plots the monthly fraction of AI contents on each platform. On SA, adoption rises sharply after ChatGPT's release, peaking at 10% by late 2023 before dropping to 3% by the end of 2024, coinciding with an editorial prohibition on AI use Bradshaw et al. (2025). On WSB, adoption is slower but steady: AI content remains under 2% until mid-2023 and then climbs gradually to around 7% by December 2024. The slower update is likely associated with WSB's short, slang-heavy, and meme-driven format, where human spontaneity is already low-cost, reducing the relative advantage of early AI tools.

3.2 Variables Construction

We collect financial market data from a number of sources. Daily stock returns, trading volume, and pricing information are from the Center for Research in Security Prices (CRSP), firm-level accounting data are from Compustat; quarterly institutional ownership is from Thomson Reuters Institutional Holdings (13F) database; and analysts coverage is from Institutional Brokers' Estimate System (IBES). To construct microstructure measures, we use the Trade and Quote (TAQ) database.

We construct variables at two levels: the individual article/message level and the aggregated stock-day level (summed over individual articles/messages for the same stock on the same day). Here, we focus on the key AI variables and defer the detailed definitions of all other commonly used variables to Appendix Table A.3.

For AI-content detection, GPTZero analyzes each article or message and outputs the probabilities that it belongs to one of three categories: AI-ONLY," "HUMAN-ONLY," or "MIXED" (human with AI assistance). These probabilities sum to one. For example, an article may

have probabilities of 0.58, 0.02, and 0.40 for being "AI-ONLY," "MIXED," and "HUMAN-ONLY," respectively. Based on these outputs, we define a continuous AI probability score, *AIProb*, as the sum of the "AI-ONLY" and "MIXED" probabilities, and use *AIProb* for our article-level analysis. In this example, the article's *AIProb* would be 0.60.[7]

The API also outputs a categorical label for each article, determined by the category with the highest probability. In the same example, the article would be classified as "AI-ONLY" because its probability is the highest among the three categories. At the stock-day level, we define *SA AIDAY*= 1 if at least one SA article about a given stock on day t is classified as "AI-ONLY" or "MIXED," and 0 otherwise. Similarly, we define *WSB AIDAY* for WSB posts. These platform-specific AI indicators serve as our key measures of AI presence in the stock-level analysis.

Other article-level variables include length (word count); sentiment, measured as the ratio $\frac{N_{\text{positive}}-N_{\text{negative}}}{N_{\text{positive}}+N_{\text{negative}}}$, where N_{positive} and N_{negative} are the counts of positive and negative words; textual complexity, measured by the proportion of complexity words (Loughran and McDonald 2024); the Fog Index, a readability measure defined as $0.4\times\frac{\text{Words}}{\text{Sentences}}+100\times\frac{\text{Complex Words}}{\text{Words}}$, where complex words are have three or more syllables); and indicators for quantitative content (count of numbers) and graphical content (count of images). Post-publication engagement is measured by the number of comments an article receives from publication through ten days after. User reactions are captured by disagreement, defined as the standard deviation of sentiment scores across comments in the same 10-day window, using platform-specific sentiment dictionaries.

We align publication times with market trading: articles posted before 4:00 p.m. are assigned to the same trading day, while those posted after 4:00 p.m. or on non-trading days are assigned to the next trading day. Outcome variables are measured after publication, typically over $t+1$ to $t+5$:cumulative abnormal returns (CAR, cumulative buy-and-hold returns adjusted by size, B/M, and momentum following Daniel et al. 1997); abnormal trading volume (AVOL, mean daily log dollar volume over $t+1$ to $t+5$ minus the mean over $t-41$ to $t-11$;

[7]The mean probability of a "MIXED" classification is very low-2.38% for SA and 0.10% for WSB. For robustness, Appendix A3 reports results where *AIProb* is constructed using only the "AI-ONLY" category.

effective bid-ask spreads (Spread, volume-weighted effective bid-ask spread); and realized volatility (Vol, standard deviation of the daily stock returns).

Table 1 present the summary statistics, with panel A for the article-level sample and panel B for the stock-day sample. The article-level sample comprises 57,729 SA articles and 65,148 WSB submissions over from December 2022 to December 2024. The last column in panel A presents differences, showing that all mean differences are significant at the 1% level.

The table indicates that SA tends to cover smaller firms ($146B vs. $344B), with higher book-to-market ratios (0.46 vs. 0.38) and greater institutional ownership (71% vs. 65%). WSB, in contrast, focuses on larger, more visible companies with greater analyst coverage (5.1 vs. 4.0). While statistically significant, these differences are economically modest. SA authors are also far more prolific (49.5 vs. 4.7 articles over six months).[8] SA articles attract more comments (11.3 vs. 0.3) and greater disagreement, whereas WSB posts draw much less engagement. SA articles have nearly three times the AI probability (10.6% vs. 3.6%), are much longer (1,454 vs. 114 words), more positive in tone, more complex, and contain more visual elements. These patterns align with SA's emphasis on in-depth analysis relative to WSB's shorter, meme-centric style.

Panel B reports stock-day statistics. SA covers more stocks (3,193 vs. 1,351), producing a larger stock-day sample. AI days occur in 0.24% of SA stock-days and 0.18% of WSB stock-days. On average, SA generates 3.59 articles per 100 stock-days compared to WSB's 9.43. Firm characteristics again show SA coverage tilting toward smaller firms with higher book-to-market ratios and less analyst coverage, while WSB emphasizes larger, more visible firms. A key market-level difference is bid-ask spreads: stocks discussed on SA exhibit wider spreads in the five days after publication (0.41% vs. 0.29%).

Taken together, Table 1 establish SA and WSB as distinct ecosystems with different informational, engagement, and liquidity environments, providing the context for examining how platform characteristics are associated with the role of AI in financial discourse.

[8]There are 1,998 authors on SA and 28,563 on WSB. Of these, 457 SA authors and 19,025 WSB authors publish only once in our sample, accounting for 0.79% and 22.8% of articles, respectively. On average, an SA author produces 28.78 articles over a tenure of 286 days, compared to 2.27 articles over 48 days for a WSB author.

4 AI Adoption

In this section, we empirically investigate the factors influencing AI adoption in financial content creation: whether AI deployment is consistent with assisting valuable information production or primarily associated with noise trading in the underlying stock, as outlined in Hypotheses 1a and 1b.

Before formally testing the hypotheses, we first examine the association between AI probability and the textual attributes of posts. The results are presented in Table 2, with columns 2, 4, and 6 including author fixed effect for SA and WSB posts, respectively; columns 5 and 6 also add an indicator for initial submissions to distinguish them from replies.

The results show several similarities in the textual characteristics of AI posts across the two platforms. AI content is generally more positive in sentiment, higher in complexity, and harder to read (as measured by the Fog Index). On SA, AI articles also contain fewer images and numbers, whereas on WSB they tend to include fewer images but more numbers—though these associations become insignificant once author fixed effects are included. Notably, WSB submissions exhibit a 193% higher AI probability than comments, indicating that users are more likely to rely on AI for creating original posts than for replies. Overall, the textual patterns of AI use appear broadly similar across the two platforms, motivating our shift to external factors such as information frictions and trading dynamics.

4.1 Information Frictions

To test whether authors turn to AI when facing information frictions due to unfamiliarity (Hypothesis 1a), we examine the relationship between AI probability and proxies for an author's inexperience in covering a specific firm or industry. We estimate:

$$AIProb_{ijt} = \beta_1 Unfamiliarity_{ijt} + Controls + FE + \epsilon_{ijt}, \tag{1}$$

where $Unfamiliarity_{ijt}$ is an indicator variable that equals one if the author/user covers the stock i for the first time in the past six months.[9] *Controls* include stock size, book-to-market ratio and institutional ownership, as well as the author's past six-month activity (number of articles, number of AI articles, and average comments per article in the first 20 days after publication). In addition to stock and day fixed effects, we also add author fixed effects to control for time-invariant heterogeneity. Standard errors are two-way clustered by stock and day.

The results in Table 3 provide support for Hypothesis 1a. On Seeking Alpha (column 1), first-time firm coverage is associated with a 2.32 pp higher AI probability ($t = 9.42$). This effect is economically significant relative to an mean of 10.65 pp on SA: when venturing into new domains, authors are 22% more likely to use AI. Given that AI adoption exhibit strong author heterogeneity (e.g., Table 2), we include author fixed effects in column 2 and find that the effect of first-time firm coverage remains positive and robust, though smaller in magnitude.

We also find that firm size is negatively related to AI adoption: SA authors are more likely to use AI when writing about smaller firms, which typically suffer from limited information availability. For author characteristics, those with fewer articles in the past six months, those with prior experience using AI, and those whose articles generate more engagement (measured by comments per article) are all more likely to adopt AI. These associations persist even after controlling for author fixed effects.

In contrast, on WSB (columns 3–4), there is no statistically significant increase in AI adoption when contributors cover firm for the first time. This divergence indicates that, unlike on SA, WSB users' AI adoption is not primarily associated with efforts to overcome information frictions. Firm size is weakly and negatively correlated with AI adoption, and book-to-market ratio and institutional ownership show no systematic relationship. For WSB author characteristics, column 3 shows higher AI adoption among users with fewer past articles, prior AI use, and lower comment engagement, but these associations disappear once

[9] We re-estimate using first-time industry coverage and find similar results. See Appendix Table A4.

author fixed effects are introduced.

We further test Hypothesis 1a by examining whether AI adoption rises during periods of firm-specific information scarcity. We measure information availability using the daily count of high-relevance news items from RavenPack and proxy ex-ante information supply by the number of analysts following the stocks. We then estimate the following article-level regression:

$$AIProb_{ijt} = \beta_1 News_{it} + \beta_2 Analyst_{it} + Controls + FE + \epsilon_{ijt}, \tag{2}$$

where $News_{it}$ is the logarithm of one plus the number of highly relevant Dow Jones news articles (with a Ravenpack relevance score above 90 on firm i in the last three days), and $Analysts$ is the logarithm of one plus the number of analysts following the stock i in the most recent quarter.

Results in Table 4 provide additional support for Hypothesis 1a. On SA sample (columns 1-2), AI adoption is significantly less likely when news or analyst coverage is abundant. A one-standard-deviation increase in news coverage is associated with a 0.32 to 0.21 percentage point decrease in AI probability, while a one-standard-deviation increase in analyst following corresponds to a 0.73 to 0.33 percentage point decrease in AI probability. These findings suggest that SA contributors are more likely to use AI when traditional information sources are limited.

By contrast, no such relationship is observed on WSB (coumns 3-4), and in some specifications analyst coverage is even positively associated with AI adoption. This divergence highlights that information scarcity is not a primary driver of AI use on WSB.

Overall, these findings are consistent with the idea that AI flattens the learning curve in SA, lowing the marginal cost of research when authors lack deep prior knowledge. This interpretation is consistent with Brynjolfsson, Li, and Raymond (2025) and Noy and Zhang (2023), which find that AI's productivity benefits are often more pronounced for tasks where individuals have less experience. However, these patterns are absent on WSB, underscoring the platform differences in AI adoption.

4.2 Retail Trading

Beyond cost-saving, we test Hypothesis 1b, which posits that AI adoption on lightly moderated and speculative platforms like WSB is more likely to be assiciated with non-informational motives–such as emotional connection, entertainment, or even manipulation–rather than by the pursuit of better information. In this setting, users may turn to AI to craft persuasive or attention-grabbing narratives that resonate with peers and reinforce community dynamics. Consistent with this view, we expect AI adoption to be higher during periods of heightened retail interest, when intense retail buying creates fertile ground for sentiment amplification and speculative herding, rather than genuine information production.

To examine this, we study whether AI adoption is linked to intense retail investor buying. We estimate the following panel regression.

$$AIProb_{ijt} = \beta_1 Intense\ Retail\ Buy_{i[t-3,t-1]} + Controls + FE + \epsilon_{ijt}, \tag{3}$$

where $Intense\ Retail\ Buy_{i[t-3:t-1]}$ equals one if retail net order imbalance during days [t-3, t-1] falls in the top 10% of the cross-sectional distribution. Retail order net imbalance is calculated following Boehmer et al. (2021), defined as the number of shares bought minus the number of shares sold by retail investors, scaled by total retail trades. A spike in retail net order imbalance therefore serves as a proxy for strong retail buying pressure.

The results, presented in Table 5, are consistent with our hypothesis. For messages on WSB (columns 3–4), the coefficient on Intense Retail Buy is positive and highly significant, both statistically and economically. A surge in retail buying predicts a 1.67 to 1.97 percentage point increase in a content's AI probability, which correspond to a 46% to 55% rise relative to the platform's sample average. This indicates that WSB users are substantially more likely to adopt AI when a stock is experiencing intense retail buying.

In contrast, this relationship is not observed on Seeking Alpha. As shown in columns 1 and 2, the coefficient for Intense Retail Buy is statistically insignificant for SA articles. This divergence suggests that while AI adoption on SA is more closely associated with information

frictions and cost-saving, AI adoption on WSB is more strongly linked to retail-driven surges and speculative dynamics, consistent with non-information motives.

5 User Responses

We now turn to the association betweeen AI-generated content and user responses. This section proceeds in three steps. First, we examine whether AI is linked to the volume of user comments following a post. Second, we test whether AI is associated with lower disagreement among users, measured as the dispersion of comment sentiment. Finally, we analyze whether AI is related to sentiment contagion between original posts and subsequent user comments. Together, these analyses provide evidence on how AI corresponds not only to the quantity but also the quality and direction of user interaction.

5.1 AI Content and Subsequent Comments

To assess the relationship between AI-generated content on user engagement, we use the cumulative number of comments a content receives. We estimate the following panel regression model:

$$\log(1 + Comments_{ij[t,t+10]}) = \beta_1 AIProb_{ijt} + Controls + FE + \epsilon_{ijt}, \tag{4}$$

where $Comments_{ijt[t,t+10]}$ is the cumulative number of comments received for content j (on stock i by user u) between its publication on day t and day $t + 10$. We select $t + 10$ as the cutoff day because 85% of comments are received within 10 days after publication. *Controls* include the article characteristics used in Table 2, firm characteristics, and author past activities performance. Standard errors are two-way clustered by stock and day.

Table 6 presents the results. On Seeking Alpha (columns 1–2), an AI-generated article ($AIProb = 1$) is associated with 6–7% fewer comments compared to a human-generated article ($AIProb = 0$). These findings are consistent with Hypothesis 2a, which predicts that AI

contents linked to more valuable signals correspond to lower uncertainty about asset fundamentals and hence fewer discussions. On WSB, there is a similar negative relationship between AI content and follow-up comments without author fixed effect (column 3) but the association becomes insignificant after author fixed effect (column 4). The evidence suggests that AI is related to differences in user engagement across the two platforms.[10]

Beyond the volume of comments, however, AI may also be associated with changes in how users interact. On SA, fewer comments could reflect convergence of opinion, while on WSB, unchanged engagement may mask differences in how sentiment is distributed. We therefore next examine whether AI is linked to disagreement among users.

5.2 AI Content and Subsequent User Disagreement

We measure disagreement as the standard deviation of sentiment scores in the comments received within ten days of the initial post, standardized to zero mean and unit variance. The regression specification, as detailed in Table 7, is:

$$Disagreement_{ij[t,t+10]} = \beta_1 AIProb_{ijt} + Controls + FE + \epsilon_{ijt}, \tag{5}$$

where $\text{Disagreement}_{ij[t,t+10]}$ is the sentiment dispersion in comments for content j on stock i over the window $[t, t+10]$, standardized to zero mean and unit variance. As before, AI Prob_{ijt} is the AI probability of the initial article.

The results in Table 7 support the hypothesis that AI content is linked to lower user disagreement. On SA (column 1–2), the coefficient on AI-related probability is consistently negative and statistically significant. With day, stock, and author fixed effects, the coefficient

[10]For the control variables, longer articles, those with negative sentiment, and those easier to read (lower Fog Index) attract more comments across both platforms. On SA, complex and quantitative articles receive fewer comments, whereas on WSB quantitative articles attract more. Articles about large firms receive more comments, while those with higher institutional ownership receive fewer on SA (insignificant on WSB). Recent news releases also increase comments. Regarding author characteristics, SA articles from more prolific authors in the prior six months attract fewer comments, while on WSB they attract more (though insignificance emerges once author fixed effects are added). Articles by historically engaging authors draw more comments on SA but fewer on WSB. Finally, on WSB, initial submissions receive more comments than replies.

is −0.083, implying that AI-generated articles are associated with a 0.083 standard-deviation reduction in disagreement, which is a 10% decline relative to the mean. These findings are consistent with Hypothesis 2a, suggesting that AI-generated content corresponds to more homogeneous expressed opinions on SA. Another interpretation is that LLM-produced text is less nuanced and introduces fewer contentious points, thereby narrowing the scope for divergent interpretations (Bradshaw et al. 2025).

In contrast, on WSB (columns 3-4), we observe no significant association between AI and disagreement. This contrast is informative: on SA, AI is linked to user consensus, while on WSB, where discourse tends to be meme-driven, AI's influence may be associated with reinforcing prevailing sentiment and amplifying herding dynamics. This possibility motivates our next analysis of sentiment contagion.

5.3 Sentiment Contagion

Building on the contrast in disagreement effects, we next examine whether AI-generated content is associated with stronger sentiment contagion between articles and subsequent user comments (Hypothesis 2b). Given AI's demonstrated persuasive capabilities (Schoenegger et al. 2025; Hackenburg et al. 2025), we test whether AI articles are linked to stronger directional transmission of sentiment. We estimate the following specification:

$$\begin{aligned} CommentSentiment_{ij[t,t+10]} = &\beta_1 AIProb_{ijt} \times Sentiment_{ijt} + \beta_2 AIProb_{ijt} + \\ &\beta_3 Sentiment_{ijt} + Controls + FE + \epsilon_{ijt} \end{aligned} \tag{6}$$

where $\text{CommentSentiment}_{ij[t,t+10]}$ is the average sentiment of comments following article j about stock i over the window $[t, t+10]$, Sentiment_{ijt} is the sentiment of the article itself, and AIProb_{ijt} is the AI probability score. The interaction term β_1 captures whether AI content creates stronger sentiment transmission from articles to comments. Control variables and fixed effects follow our previous specifications.

Table 8 presents the results. For Seeking Alpha, we find no significant association between AI and sentiment contagion. The interaction coefficients are -0.022 and -0.046 and insignificant, indicating that AI-generated articles are not more likely to be linked to stronger sentiment contagion than human-written content. The baseline sensitivity of comment sentiment to article sentiment remains strong at 0.217, but AI does not appear to strengthen this relationship.

In contrast, Reddit's WallStreetBets shows significant associations consistent with sentiment contagion. The interaction coefficient is 0.090 and 0.135. Given the baseline sensitivity of 0.080 and 0.067, this represents a doubling of sentiment influence when content is AI-generated.

This result is consisent with Hypothesis 2b and resonates with the social transmission bias model of Hirshleifer (2020) and Han, Hirshleifer, and Walden (2022), which posits that investors share strategies within their social networks and convert others with a probability that increases in recent returns. Extending this logic to our setting, if past positive returns encourage submissions with positive sentiment and if they adopt AI to craft persuasive narratives, then naïve followers with representativeness heuristic (Tversky and Kahneman, 1974) are more likely to overextrapolate the signal and adopt similar beliefs about the stock, thereby amplifying sentiment contagion.

The social transmission bias model further predicts that such AI-assisted amplification of positive sentiment through social networks contributes to price bubbles and the emergence of "lottery-like" stocks. Motivated by this prediction, we next turn to the asset pricing patterns linked to AI-generated content.

6 Market Outcomes

In this section, we examine the impact of AI-generated content on market outcomes, focusing on trading volume, volatility, bid-ask spreads, episodes of extreme positive returns (i.e., "lottery" events), and the informativeness of retail order flows.

6.1 Volume, Volatility, and Bid-ask Spreads

We examine how the presence of AI-generated content is associated with trading behavior and stock liquidity. We estimate the following regression specification:

$$\text{Trading Metric}_{i[t+1,t+5]} = \beta_1 AIDay_{it} + \beta_2 Attention_{it} + \beta_3 Sentiment_{it} + Controls + FE + \epsilon_{it}, \tag{7}$$

We examine market quality over the subsequent five days: abnormal trading volume, return volatility, and the bid-ask spread. All dependent variables are standardized, so the coefficients represent changes in standard deviations.The key independent variable is $AIDay_{it}$, an indicator for firm-days with at least one AI-generated article for a given platform. We control for the total number of articles ($Attention_{it}$) as a proxy for social media attention and average sentiment of all content for that stock on that day (e.g., Cookson et al. 2024), and a vector of stock controls, *Controls*, including size, book-to-market ratio, institutional ownership, analyst coverage, an earnings announcement dummy, and past one-month abnormal return and volatility.

The findings indicate distinct patterns across platforms. On Seeking Alpha over the next five trading days, AI presence is associated with a 0.025 standard deviation decrease in abnormal volume, a 0.025 decrease in volatility, and a 0.017 decrease in effective bid-ask spreads. On WSB, we observe the opposite pattern. AI presence is associated with a 0.096 standard deviation increase in abnormal volume and a 0.110 increase in volatility. In the combined model (column 9), we also see evidence of wider spreads, by 0.021 standard deviations.

Overall, the across-platform comparison suggests that AI's relationships with market variables depend on institutional context. On SA, where editorial review ensures content quality and with relatively sophisticated user base, AI is associated with higher market efficiency (lower spreads, lower future volatility), consistent with Hypothesis 3a. On WSB, where anyone can instantly post AI-generated narratives, the same technology is linked to wider spreads, higher volatility and volume in subsequent periods, consistent with Hypothesis 3b.

While the combination of elevated trading volume and volatility following AI-generated content on WSB is consistent with speculative trading, one might argue that large fundamental information shocks could produce similar patterns. To further differentiate these possibilities, we next test whether AI content predicts extreme, lottery-like return events–sharp price run-ups followed by reversals–that prior studies identify as characteristic of overvaluation (e.g., Kumar, Page, and Spalt 2011; Bali, Cakici, and Whitelaw 2011).

6.2 Lottery-like Return Events

Following Bali, Cakici, and Whitelaw (2011) and Bali et al. (2025), we identify two types of events that capture lottery-like payoffs. A MAX event occurs when a stock's daily return is the highest over a trailing 21-trading-days window. A lottery event represents an even more extreme outcome: it is a MAX event and the MAXRET falls into the top decile of its daily cross-sectional distribution, where MAXRET is the 21-day highest return. These events reflect the lottery-like characteristics that attract sentiment-driven retail traders but are less likely to be associated with fundamental information arrival. We estimate logistic regressions predicting the probability of these events:

$$\text{MAX}_{i[t+1,t+5]}/\text{Lottery}_{i[t+1,t+5]} = \beta_1 AIDay_{it} + \beta_2 Attention_{it} + \beta_3 Sentiment_{it} + Controls + FE + \epsilon_{it}, \tag{8}$$

where the dependent variables are indicators for whether stock i experiences a MAX or lottery event either on day t or during the subsequent five-day window $[t+1, t+5]$.

Table 10 presents striking results. On WSB, AI content predicts the occurrences of both types of extreme events. For MAX events, AI presence is associated with an increase in odds by 26.9% in the same day ($e^{0.238} - 1$, column 3) and 17.2% ($e^{0.159} - 1$, column 4) in the next five days. The lottery event results are even more dramatic: AI content is associated with an increase in odds by 57.0% ($e^{0.451} - 1$) and 31.9% ($e^{0.277} - 1$) for the same day and the next five days using the combined sample.

On SA, we find no such statistically meaningful relationship. The AI day coefficients are statistically insignificant and economically negligible for both MAX and lottery events across all specifications. These patterns are consistent with Hypothesis 3b. Informed trading alone would be less likely to be associated with the extreme right-tail events we observe. That AI presence predicts lottery-like return episodes is consistent with sentiment-driven rather than information-driven trading.

In sum, the platform contrast indicates that on WSB, AI appears ahead of extreme positive returns. On SA, AI shows no detectable association with these speculative episodes. This evidence aligns with the view that platform governance is associated with whether AI is linked to market efficiency or with noise trading and price distortions.

6.3 Informativeness of Retail Orders

We have shown that AI deployment in content generation on WSB follows periods of intense retail buying and is associated with a higher likelihood of extreme daily price run-ups. These patterns are consistent with AI usage on WSB being associated with speculative trading. An alternative hypothesis is that the intense retail buying that precedes AI adoption on WSB could be linked to information, as shown in Boehmer et al. (2021) that retail net buying is associated with positive subsequent abnormal returns, a sign that retail buying may be informative.

In this subsection, we further investigate the relationship between AI deployment and the informativeness of retail order flows. If AI adoption on WSB is linked to information-related activity, we would expect a stronger positive relationship between retail net buying AI days and subsequent returns. To test this, we run the following panel regression:

$$\begin{aligned} \mathrm{CAR}_{i[t+1,t+5]} = {} & \beta_1 AIDay_{it} + \beta_2 AIDay_{it} \times OIB_{it} + \beta_3 AIDay_{it} \times Sentiment_{it} \\ & + \beta_4 Sentiment_{it} + \beta_5 Attention_{it} + \beta_6 OIB_{it} + Controls + FE + \epsilon_{it},, \end{aligned} \tag{9}$$

where $\mathrm{CAR}_{i[t+1,t+5]}$ is the DGTW-adjusted cumulative abnormal return from $t+1$ to $t+5$

(Daniel et al. 1997). The main variable of interest is the interaction between $AIDay_{it}$, an indicator for at least one AI article for stock i on day t, and OIB_{it}, the retail order imbalance calculated as the ratio between the net retail buys and total retail volume (in shares) following Boehmer et al. (2021).

The coefficient β_1 captures whether the relationship between retail order flow and subsequent returns is stronger on SA- or WSB-AI days. We also include the interaction between $AIDay_{it}$ and platform-specific sentiment as an additional control to account for the potential effect of sentiment in this relationship.

Table 11 presents the results. Across specifications, we find a positive and statistically significant coefficient on the $AIDay^{SA} \times OIB$ interaction in the SA sample. The coefficient of 0.433 in column 2 indicates that on days with AI content on Seeking Alpha, a one-standard-deviation increase in OIB predicts an additional 43.3 basis points in cumulative abnormal returns over the subsequent five trading days, compared to days without AI content. This association is economically meaningful and statistically significant at the 5% level.

In contrast, the interaction coefficient for the WSB sample ($AIDay^{WSB} \times OIB$) is positive but not statistically significant (columns 3–4), suggesting no detectable association between AI presence and the strength of the OIB-return relationship on WSB. This difference between platforms may reflect the distinct nature of their user bases and content types, with Seeking Alpha's more analytical focus being associated with greater benefits from AI-assisted information synthesis. The combined model (columns 5–6) shows the same pattern. The SA interaction remains significant while the WSB interaction remains insignificant, even when both are included simultaneously.

Overall, these results are consistent with the hypothesis that AI content is associated with more informative retail order flows on platforms focused on fundamental analysis, suggesting that the use of AI tools on SA may help retail investors better synthesize and act on complex information.

7 Robustness

This section provides additional robustness checks for our main. First, the results remain when we restrict the WSB sample to original posts (submissions). Second, our inferences are not sensitive to including or excluding very short WSB messages, for which AI-content detection is likely noisy. Third, we assess the sensitivity of our analysis to Seeking Alpha's AI ban around the end of 2023.

7.1 WSB Submissions Only

We address the concern that our WSB findings could be influenced by pooling high-effort original posts (submissions) with subsequent comments. Recognizing potential differences between posts and reactive comments, we restrict the WSB sample to submissions only and replicate Table 3 to 7. Results are presented in Appendix Table A5.

Despite the dramatically reduced sample size, our key findings remain consistent with those obtained from the full WSB sample. Columns 1-6 show that proxies for information cost, such as covering a firm for the first time (Unfamiliarity) or number of news articles (News), remain insignificant in explaining AI probability. Conversely, the noise-trading factor remains significantly positive. The probability of using AI in crafting WSB submissions increases by 13.41–17.53 percentage points after extreme retail buying, relative to an average AI probability of 12.54 percentage points for submissions on WSB. Columns 7-10 show that, after controlling for user fixed effects, AI content is not statistically associated with the number of follow-up comments or the level of disagreement.

7.2 Including Short Messages on WSB

Our main analysis excludes WSB messages shorter than 50 words to ensure sufficient text length for reliable AI detection by GPTZero. To verify that this filtering does not systematically bias our conclusions, we replicate the article-level analyses using all WSB messages, assigning a zero AI probability to those below the 50-word threshold and include an indica-

tor variable for messages exceeding 50 words in all specifications.

We replicate Table 3 to 7 using this sample and report the results in Appendix Table A6. The findings are largely consistent: AI presence *AIProb* is not significantly related to author unfamiliarity with the stock or to information scarcity, but is higher following periods of intense retail buying. Consistent with the main results, AI adoption is not significantly associated with disagreement. The main deviation is that the association between *AIProb* and subsequent comment volume becomes negative and statistically significant in this sample, whereas it was previously insignificant.

7.3 The Seeking Alpha AI Ban

Our analysis finds that the use of AI on Seeking Alpha declined substantially following an editorial ban on AI-generated content around the end of 2023 (see Figure 1). This policy change provides a quasi-natural experiment to validate our findings.

We examine whether the documented associations in Table 3 to Table 7 differ across periods. We extend our main analyses by including an interaction of the key variables with indicators for the Pre- and Post-Ban periods respectively (omitting intercept). The results are presented in Appendix Table A7. In the Pre-Ban period, proxies for information frictions are statistically significant correlates of AI adoption on Seeking Alpha. For instance, first-time firm coverage is associated with a 4.20 percentage point higher AI probability Pre-Ban but is statistically insignificant Post-Ban. Similarly, AI probability is higher when news or analyst coverage is scarce Pre-Ban, while the association is weaker or insignificant Post-Ban. Pre-Ban, AI-linked content is associated with fewer subsequent comments, with weaker or insignificant associations Post-Ban. For disagreement, in both periods *AIProb* is associated with lower disagreement, suggesting that other factors could contribute to the relationship between the estimated AI usage and disagreement.

Overall, the patterns are concentrated in the Pre-Ban sample, consistent with AI use being more closely associated with settings featuring higher information-production frictions. Post-Ban, these associations are attenuated, which is also consistent with reduced

on-platform AI usage following the platform policy.

8 Conclusion

This paper provides the first empirical analysis of how generative AI is reshaping financial discourse and market dynamics across distinct online platforms. By comparing the curated Seeking Alpha, whose contributors are largely semi-professional analysts, with the unmoderated Reddit's r/WallStreetBets, whose users are predominantly unsophisticated retail traders, we study how platform governance and user sophistication shape AI adoption and its relationship with market outcomes.

We find that AI adoption surged following ChatGPT's launch, but with starkly different motivations. On Seeking Alpha, authors use AI primarily to reduce information production costs, especially when covering unfamiliar firms or during information-scarce periods. On WallStreetBets, users deploy AI following retail trading surges, consistent with sentiment effects. Consistent with this interpretation, user responses also diverge: on Seeking Alpha, AI-generated posts attract fewer comments and lower disagreement, consistent with uncertainty reduction, whereas on WallStreetBets, AI posts trigger stronger sentiment contagion.

Market reactions mirror these contrasts. On Seeking Alpha, AI content is associated with higher market quality, as reflected in narrower bid-ask spreads, as well as lower subsequent volume and volatility. Furthermore, AI content is associated with more informative retail order flows. This evidence is consistent with AI being associated with better information processing. On WallStreetBets, in contrast, AI content predicts higher trading volume and volatility, wider bid-ask spreads, and elevated probabilities of "lottery-like" return events. These patterns are consistent with an association of AI content with sentiment-driven speculation.

These findings bear upon policy debates on whether AI deployment enhances or undermines market efficiency. They indicate that the market impact of AI is mediated by institutional context. Our findings suggest that the same tool that facilitates price discovery

on a curated platform may amplify exuberance on an unmoderated one. These findings also highlight a key tension in democratizing financial discourse: while AI lowers barriers to participation, absent appropriate governance and investor education there is a risk that AI degrades rather than improving market quality.

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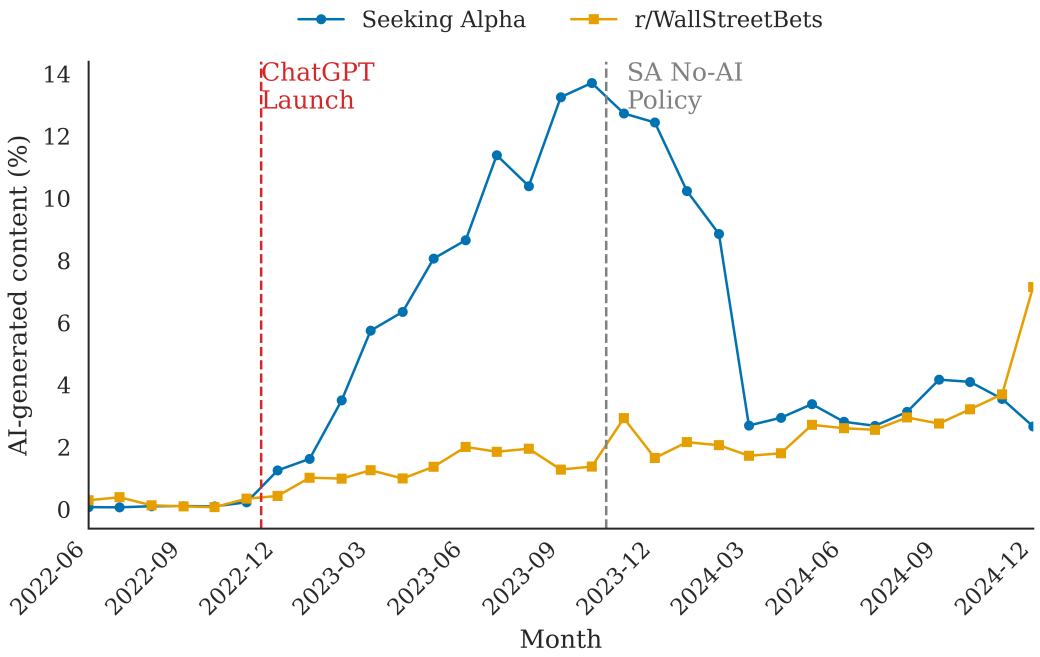


Figure 1: AI-generated Content Over Time

This figure plots the monthly share of AI-generated content on two platforms–Seeking Alpha and Reddit's r/WallStreetBets– from March 2022 through December 2024. The AI Proportion for each platform is computed from GPTZero's classification of all sampled articles/posts on that platform. The red vertical dashed line marks November 30, 2022, the launch date of ChatGPT. The grey vertical dashed line marks November 30, 2023, when Seeling Alpha started the no-AI policy.

Table 1. Summary Statistics

This table shows the textual attributes of articles on Seeking Alpha and posts on Reddit's r/WallStreetBets, together with the characteristics of the firms they discuss, over the sample period (December 2022–December 2024). Panel A reports summary statistics for each platform, covering AI probability, article characteristics, firm-level fundamentals, and author past activities. Panel B provides summary statistics of variables used in the stock-day sample. The detailed definitions of all variables are in Appendix Table A1.

Panel A: Article-level sample

	SA						WSB						Diff
	N	Mean	SD	p25	p50	p75	N	Mean	SD	p25	p50	p75	SA-WSB
AIProb (%)	57,581	10.65	21.65	0.91	2.75	6.28	64,848	3.60	14.36	0.52	0.68	1.57	7.05***
Length	57,581	1453.67	675.77	1022	1309	1705	64,848	114.18	124.75	61	79	119	1339.49***
Sentiment	57,581	0.03	0.01	0.02	0.02	0.03	64,848	0.02	0.03	0.00	0.02	0.04	0.01***
Complexity (%)	57,581	0.22	0.27	0.05	0.14	0.31	64,848	0.09	0.37	0.00	0.00	0.00	0.13***
Fog Index	57,581	14.57	2.38	12.96	14.39	15.88	64,848	10.66	6.93	7.59	9.48	12.00	3.91***
Quantitative (%)	57,581	3.80	2.24	2.38	3.41	4.73	64,848	2.67	3.52	0.00	1.69	3.85	1.13***
Graphical (%)	57,581	0.46	0.31	0.24	0.41	0.62	64,848	0.02	0.25	0.00	0.00	0.00	0.44***
Comments	57,581	11.32	20.00	1	4	13	64,848	3.85	36.67	0	1	2	7.47***
Disagreement	57,581	0.04	0.05	0.00	0.04	0.07	64,848	0.02	0.04	0.00	0.00	0.02	0.05***
Size ($B)	54,429	146.29	416.43	2.04	12.21	73.54	63,400	343.38	565.22	3.08	46.31	637.67	-197.09***
BM	54,429	0.46	0.55	0.12	0.30	0.62	63,400	0.38	0.45	0.05	0.20	0.54	0.08***
IO	54,429	0.71	0.25	0.60	0.75	0.86	63,400	0.65	0.29	0.58	0.66	0.79	0.06***
News	57581	16.29	41.81	0	3	14	64848	33.05	57.26	2	10	42	-16.76***
Analysts	54,429	3.97	3.00	1.47	3.31	5.89	63,400	5.11	3.42	2.21	4.78	7.36	-1.14***

Panel B: Stock-level sample

	SA						WSB					
	N	Mean	SD	p25	p50	p75	N	Mean	SD	p25	p50	p75
AIDay (×100)	1,607,466	0.24	4.85	0	0	0	687,418	0.18	4.28	0	0	0
Articles (×100)	1,607,466	3.59	22.37	0	0	0	687,418	9.43	136.15	0	0	0
Sentiment (×100)	1,607,466	0.08	0.50	0	0	0	687,418	0.06	0.60	0	0	0
AR_t (%)	1,459,930	0.02	5.18	-1.25	-0.04	1.15	648,718	0.03	4.31	-1.17	-0.04	1.08
$CAR_{[t+1,t+5]}$ (%)	1,594,720	0.11	11.68	-3.46	-0.18	3.07	682,020	0.13	12.65	-3.31	-0.18	2.92
$AVOL_{[t+1,t+5]}$ (%)	1,591,465	2.87	60.09	-29.55	-2.29	28.54	680,946	3.02	56.58	-27.32	-2.10	26.51
$Volatility_{[t+1,t+5]}$ (%)	1,594,720	2.85	4.64	1.31	2.09	3.42	682,020	2.78	3.94	1.24	1.98	3.28
$Spread_{[t+1,t+5]}$ (%)	1,520,352	0.41	1.21	0.07	0.14	0.41	653,059	0.29	0.60	0.05	0.09	0.21
Size ($B)	1,484,486	14.11	91.72	0.30	1.35	5.32	653,497	26.67	135.58	0.76	3.01	13.88
BM	1,484,486	0.62	0.96	0.22	0.45	0.80	653,497	0.56	0.65	0.19	0.40	0.73
IO	1,484,486	0.68	0.35	0.50	0.77	0.90	653,497	0.71	0.35	0.60	0.80	0.90
News	1607466	4.45	21.60	0	1	4	687418	6.80	31.75	0	2	5
Analysts	1,484,486	1.91	1.86	0.37	1.10	2.58	653,497	2.46	2.19	0.74	1.84	3.68
Earnings Day	1,484,486	0.01	0.12	0	0	0	653,497	0.02	0.12	0	0	0
$CAR_{[t-21,t-1]}$ (%)	1,462,355	1.60	23.58	-6.78	0.27	7.73	649,907	1.66	20.29	-6.49	0.41	7.54
$Volatility_{[t-21,t-1]}$ (%)	1,605,333	3.19	4.32	1.68	2.47	3.83	686,727	3.12	3.52	1.59	2.33	3.69

Table 2. Textual Attributes of AI-Generated Articles

This table examines the association between GPTZero's AI probability score and textual attributes of articles/posts at the article level using the following regression:

$$AIProb_{ijt} = \gamma' \boldsymbol{X}_{ijt} + \epsilon_{ijt}$$

where AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. $\boldsymbol{X}_{ijt}$ is content j's characteristics (standardized to zero mean and unit variance). Columns 1–2 report results for articles published on Seeking Alpha; Columns 3–4 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day, with t-statistics in parentheses. $^{*}p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

	SA		WSB			
	(1)	(2)	(3)	(4)	(5)	(6)
Length	0.345***	-0.043	2.737***	1.479***	2.106***	1.286***
	(3.44)	(-0.32)	(16.88)	(10.13)	(13.70)	(8.49)
Sentiment	2.943***	0.774***	0.858***	0.220***	0.804***	0.216***
	(22.31)	(8.02)	(8.82)	(3.15)	(8.83)	(3.07)
Complexity	1.866***	0.410***	0.577***	0.260***	0.550***	0.255***
	(14.94)	(5.04)	(6.51)	(2.88)	(6.55)	(2.83)
Fog Index	1.771***	3.839***	0.397***	0.171**	0.424***	0.178**
	(13.29)	(20.35)	(6.97)	(2.35)	(7.66)	(2.44)
Graphical	-0.402***	-0.962***	0.054	-0.030	-0.382***	-0.164
	(-3.27)	(-7.35)	(0.63)	(-0.24)	(-4.10)	(-1.37)
Quantitative	-1.332***	-0.313***	0.278***	0.200*	0.139*	0.170
	(-9.78)	(-2.87)	(3.17)	(1.81)	(1.75)	(1.58)
Submissions					6.964***	2.834***
					(9.00)	(4.09)
Day FE	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X
Author FE		X		X		X
Obs.	57,581	57,581	64,848	64,848	64,848	64,848
Adj. R^2 (%)	9.9	59.5	10.3	56.9	12.0	57.1

Table 3. Author Unfamiliarity and AI Adoption

This table examines the association between author unfamiliarity and the likelihood of AI use at the article level using the following panel regression specification:

$$AIProb_{ijt} = \beta_1 Unfamiliarity_{ijt} + Controls + FE + \epsilon_{ijt},$$

where AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. $\text{Unfamiliarity}_{ijt]}$ is an indicator equal to one if the author has not covered firm i in the prior six months. *Controls* include firm characteristics and measures of the author's prior activity/performance (each standardized to zero mean and unit variance). Columns 1–3 report results for articles published on Seeking Alpha; Columns 4–6 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^*p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

	SA		WSB	
	(1)	(2)	(3)	(4)
Unfamiliarity	2.322***	0.555***	0.007	-0.012
	(9.42)	(3.26)	(0.04)	(-0.08)
Size	-0.573	-1.781**	-1.398*	-0.527
	(-0.54)	(-2.20)	(-1.86)	(-0.54)
BM	0.919***	0.291	0.162	-0.320
	(2.84)	(0.86)	(1.00)	(-1.40)
IO	0.943*	0.452	0.363	-0.480
	(1.69)	(1.21)	(0.95)	(-1.19)
Author Article	-3.418***	-1.109***	-0.808***	-0.055
	(-20.60)	(-8.10)	(-8.50)	(-0.58)
Author AI Article	8.358***	2.497***	2.356***	-0.431***
	(36.41)	(19.15)	(6.99)	(-2.68)
Author Comments	0.490***	0.468***	-0.168*	0.061
	(3.32)	(3.74)	(-1.78)	(0.56)
Submissions			9.089***	4.364***
			(10.95)	(5.88)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	18.7	59.5	11.5	56.6

Table 4. Information Scarcity and AI Adoption

This table examines the association between information scarcity–proxied by recent news flow and analyst coverage-and article-level AI usage using the following regression specification:

$$AIProb_{ijt} = \beta_1 News_{it} + \beta_2 Analyst_{it} + Controls + FE + \epsilon_{ijt},$$

where AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. News_{it} is the log of one plus the number firm-specific news items in the prior three days and $Analysts_{it}$ is the log of one plus the number of analysts covering the firm in the most recent quarter. *Controls* include firm characteristics and measures of the author's prior activity/performance (each standardized to zero mean and unit variance). Columns 1–3 report results for articles published on Seeking Alpha; Columns 4–6 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	SA		WSB	
	(1)	(2)	(3)	(4)
News	-0.319**	-0.206**	-0.050	-0.215
	(-2.15)	(-2.11)	(-0.37)	(-1.41)
Analysts	-0.729***	-0.332**	0.527**	0.162
	(-3.42)	(-1.98)	(2.42)	(0.79)
Size	-0.389	-1.673**	-1.727**	-0.520
	(-0.37)	(-2.06)	(-2.06)	(-0.50)
BM	0.920***	0.288	0.221	-0.326
	(2.81)	(0.84)	(1.34)	(-1.39)
IO	0.960*	0.454	0.429	-0.463
	(1.73)	(1.22)	(1.14)	(-1.18)
Author Article	-3.678***	-1.131***	-0.809***	-0.053
	(-22.16)	(-8.26)	(-9.29)	(-0.59)
Author AI Article	8.383***	2.497***	2.356***	-0.430***
	(36.57)	(19.16)	(6.99)	(-2.67)
Author Comments	0.479***	0.472***	-0.169*	0.061
	(3.22)	(3.76)	(-1.78)	(0.56)
Submissions			9.088***	4.363***
			(10.93)	(5.88)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	18.5	59.5	11.5	56.6

Table 5. Intense Retail Buying and AI Adoption

This table examines the association between recent intense retail buying and article-level AI usage using the following panel regression specification:

$$AIProb_{ijt} = \beta_1 Intense\ Retail\ Buy_{i[t-3,t-1]} + Controls + FE + \epsilon_{ijt},$$

where AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. *Intense Retail Buy* is an indicator equal to one if retail order imbalance over [t-3:t-1] ranks in cross-sectional top 10%. *Controls* include firm characteristics and measures of the author's prior activity/performance (each standardized to zero mean and unit variance). Columns 1–2 report results for articles published on Seeking Alpha; Columns 3–4 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; *t*-statistics are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	SA		WSB	
	(1)	(2)	(3)	(4)
Intense Retail Buy	-0.186	-0.460	1.588**	1.992***
	(-0.31)	(-1.10)	(2.53)	(3.19)
Size	-0.775	-1.844**	-1.548**	-0.713
	(-0.72)	(-2.23)	(-2.00)	(-0.68)
BM	0.949***	0.347	0.227	-0.226
	(2.85)	(1.00)	(1.47)	(-1.12)
IO	1.095**	0.440	0.427	-0.565
	(1.99)	(1.13)	(1.07)	(-1.37)
Author Article	-3.719***	-1.135***	-0.606***	-0.043
	(-21.86)	(-8.04)	(-9.01)	(-0.49)
Author AI Article	8.499***	2.510***	0.757***	-0.362**
	(36.76)	(18.87)	(5.97)	(-2.52)
Author Comments	0.428***	0.493***	0.031	0.071
	(2.80)	(3.83)	(0.39)	(0.61)
Submissions			8.812***	4.320***
			(10.62)	(5.50)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	52,695	52,695	60,473	60,473
Adj. R^2 (%)	18.8	60.0	9.6	57.9

Table 6. AI-Generated Content and Follow-Up Comment Volume

This table examines the association between AI probability score and the volume of follow-up comments over the subsequent ten days, using the following regression:

$$\log(1 + Comments_{ij[t,t+10]}) = \beta_1 AIProb_{ijt} + Controls + FE + \epsilon_{ijt},$$

where $Comments_{ij[t,t+10]}$) is the number of comments received on content j about firm i between day t and $t + 10$. AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. *Controls* include article characteristics, firm characteristics, and measures of the author's prior activity/performance (standardized to zero mean and unit variance). Columns 1–3 report results for articles published on Seeking Alpha; Columns 4–6 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^{*}p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

	SA		WSB	
	(1)	(2)	(3)	(4)
AIProb	-0.073***	-0.065**	-0.142***	-0.014
	(-3.13)	(-2.48)	(-5.13)	(-0.26)
Length	0.115***	0.114***	0.069***	0.088***
	(13.88)	(11.71)	(19.23)	(12.20)
Sentiment	-0.046***	-0.080***	-0.023***	-0.020***
	(-7.16)	(-11.74)	(-10.93)	(-5.16)
Complexity	-0.057***	-0.032***	-0.001	-0.004
	(-7.07)	(-5.15)	(-0.31)	(-0.75)
Fog Index	-0.067***	-0.033***	-0.013***	-0.014**
	(-13.89)	(-3.91)	(-6.30)	(-2.54)
Graphical	0.048***	-0.012	0.005	0.005
	(8.41)	(-1.65)	(0.91)	(0.80)
Quantitative	-0.011**	-0.042***	0.027***	0.032***
	(-2.01)	(-6.33)	(7.54)	(7.90)
Size	0.184*	0.199**	0.022	0.041
	(1.66)	(2.44)	(0.44)	(0.50)
BM	-0.012	-0.001	0.012	-0.006
	(-0.47)	(-0.06)	(1.00)	(-0.28)
IO	-0.026	-0.056**	-0.005	0.008
	(-0.82)	(-2.01)	(-0.47)	(0.33)
News	0.089***	0.072***	0.011**	0.013
	(9.53)	(9.52)	(2.10)	(1.26)
Analysts	0.010	0.007	0.009	0.025*
	(0.88)	(0.67)	(1.14)	(1.80)
Author Article	-0.106***	-0.015**	0.017***	0.014**
	(-15.41)	(-2.06)	(4.45)	(2.00)
Author AI Article	0.026***	0.006	0.014***	0.006
	(4.87)	(1.25)	(3.41)	(0.99)
Author Comments	0.195***	0.012*	0.004	-0.026***
	(20.25)	(1.84)	(0.76)	(-4.89)
Submissions			1.787***	1.930***
			(54.31)	(53.81)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	51.6	64.2	38.5	43.1

Table 7. AI-Generated Content and Comment Disagreement

This table examines the association between an article's AI probability score and the dispersion of follow-up comment sentiment over the subsequent ten days using the following regression:

$$Disagreement_{ij[t,t+10]} = \beta_1 AIProb_{ijt} + Controls + FE + \epsilon_{ijt},$$

where $\text{Disagreement}_{ij[t,t+10]}$ is the standard deviation of comment sentiment following content j about firm i over $[t, t+10]$ (standardized to zero mean and unit variance). AIProb_{ijt} is the AI probability score for content j about firm i, posted on day t. *Controls* include article characteristics, firm characteristics, and measures of the author's prior activity/performance (standardized to zero mean and unit variance). Columns 1–2 report results for articles published on Seeking Alpha; Columns 3–4 report results for contents on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	SA		WSB	
	(1)	(2)	(3)	(4)
AIProb	-0.083***	-0.082***	-0.002	0.001
	(-4.05)	(-3.18)	(-0.07)	(0.17)
Length	0.072***	0.063***	0.037***	0.056***
	(13.48)	(8.34)	(7.68)	(6.64)
Sentiment	0.005	-0.014**	-0.019***	-0.022***
	(1.05)	(-2.45)	(-5.83)	(-3.94)
Complexity	-0.027***	-0.012**	-0.002	0.001
	(-4.96)	(-2.45)	(-0.46)	(0.14)
Fog Index	-0.026***	0.014*	-0.007**	-0.001
	(-6.46)	(1.81)	(-1.97)	(-0.17)
Graphical	0.051***	0.018**	0.012***	0.023**
	(10.77)	(2.54)	(2.78)	(2.44)
Quantitative	0.003	0.003	0.043***	0.043***
	(0.52)	(0.44)	(11.57)	(7.67)
Size	0.132*	0.157***	0.039	-0.020
	(1.92)	(2.78)	(0.78)	(-0.22)
BM	-0.012	-0.008	-0.001	-0.013
	(-0.61)	(-0.45)	(-0.07)	(-0.55)
IO	0.002	-0.017	-0.023*	-0.052
	(0.10)	(-0.71)	(-1.82)	(-1.57)
News	0.044***	0.034***	0.022***	0.020
	(6.58)	(5.15)	(3.45)	(1.62)
Analysts	-0.005	-0.008	0.007	0.009
	(-0.47)	(-0.78)	(0.65)	(0.46)
Author Article	-0.055***	-0.014*	0.020***	0.015
	(-8.79)	(-1.83)	(4.67)	(1.45)
Author AI Article	0.025***	0.013**	0.008	0.007
	(4.86)	(2.39)	(1.41)	(0.63)
Author Comments	0.091***	0.005	-0.005	-0.024***
	(14.56)	(0.73)	(-0.95)	(-3.21)
Submissions			1.536***	1.539***
			(73.97)	(42.06)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	23.8	29.2	24.1	24.9

Table 8. AI-Generated Content and Sentiment Alignmment

This table examines the association between an article's AI probability score and the alignment between article sentiment and subsequent comment sentiment using the following regression:

$$Comment\ Sentiment_{ij[t,t+10]} = \beta_1 AIProb_{ijt} + \beta_2 AIProb_{ijt} \times Sentiment_{ijt} + Controls + FE + \epsilon_{ijt},$$

where Comment Sentiment$_{ij[t,t+10]}$ is the mean sentiment of comments following content j about firm i over $[t, t+10]$. AIProb$_{ijt}$ is the AI probability score for content j about firm i, posted on day t. Sentimentijt is the main text sentiment score. *Controls* includes the article characteristics, firm characteristics, and author history performance (standardized to zero mean and unit variance). Columns 1–3 report results for articles published on Seeking Alpha; Columns 4–6 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	SA		WSB	
	(1)	(2)	(3)	(4)
AIProb	-0.001	-0.001	-0.004**	-0.008**
	(-0.80)	(-0.50)	(-2.49)	(-2.43)
AIProb × Sentiment	-0.022	-0.046	0.090**	0.135**
	(-0.40)	(-0.83)	(2.38)	(2.22)
Length	0.003***	0.002***	0.000	0.000
	(14.10)	(7.17)	(-1.61)	(0.66)
Sentiment	0.227***	0.217***	0.080***	0.067***
	(13.49)	(11.85)	(12.93)	(7.27)
Complexity	0.000*	0.000	0.000	0.000
	(-1.95)	(-0.06)	(-0.06)	(-0.17)
Fog Index	0.000	0.001***	0.000	0.000
	(-1.41)	(3.46)	(-1.58)	(0.29)
Graphical	0.002***	0.001***	0.000	0.000
	(8.79)	(4.32)	(0.63)	(0.03)
Quantitative	0.001***	0.000	0.001***	0.001**
	(2.81)	(0.69)	(3.98)	(2.20)
Size	0.002	0.003	-0.001	0.000
	(0.85)	(1.25)	(-0.16)	(-0.03)
BM	-0.001	0.000	-0.001	0.000
	(-0.93)	(-0.66)	(-1.59)	(-0.11)
IO	0.001	0.001	0.000	0.001
	(0.94)	(0.57)	(0.06)	(0.37)
News	0.000	0.000	0.000	0.000
	(0.38)	(-0.11)	(-0.62)	(-0.49)
Analysts	0.000	0.000	0.000	0.002
	(0.20)	(0.00)	(0.93)	(1.57)
Author Article	-0.001***	0.000	0.000	0.000
	(-3.46)	(-1.32)	(0.24)	(-0.24)
Author AI Article	0.000	0.000	0.000	0.000
	(1.14)	(0.01)	(-0.20)	(0.18)
Author Comments	0.001***	0.000	0.000	0.000
	(5.11)	(1.01)	(1.32)	(-0.61)
Submissions			0.021***	0.019***
			(33.19)	(11.23)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	8.3	10.1	3.4	0.1

Table 9. AI Day and Subsequent Volume, Volatility, and Bid-Ask Spreads

This table examines the association between platform-level "AI Day" and subsequent trading metrics over $[t+1, t+5]$, using the following panel regression specification:

$$\text{Trading Metric}_{i[t+1,t+5]} = \beta_1 AIDay_{it} + \beta_2 Attention_{it} + \beta_3 Sentiment_{it} + Controls + FE + \epsilon_{it},$$

where $\text{Trading Metric}_{i[t+1,t+5]}$ measures trading activity for stock i, standardized to zero mean and unit variance. Columns (1), (4), and (7) report abnormal daily volume; columns (2), (5), and (8) report return volatility; and columns (3), (6), and (9) report the effective bid-ask spread. $AIDay_{it}^{SA}$ is an indicator equal to one if at least one AI-generated article/post about stock i appears on day t on SA. $Sentiment_{it}$ is the average platform-level sentiment across all content about stock i on day t. $Attention_{it}$ is the logarithm of one plus the number of articles about stock i on day t. $AIDay_{it}^{WSB}$, $Sentiment_{it}^{WSB}$, and $Sentiment_{it}^{WSB}$ are defined similarly for WSB. All regressions include firm-characteristic controls and stock and day fixed effects. Standard errors are two-way clustered by stock and day. t-statistics are reported in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	SA			WSB			Combined		
	AVOL (1)	Vol. (2)	Spread (3)	AVOL (4)	Vol. (5)	Spread (6)	AVOL (7)	Vol. (8)	Spread (9)
AIDay^{SA}	-0.025**	-0.025*	-0.017***				-0.021*	-0.021*	-0.017***
	(-2.13)	(-1.92)	(-4.84)				(-1.87)	(-1.74)	(-5.13)
Sentiment^{SA}	-0.004***	-0.011***	0.000				-0.002	-0.009***	0.000
	(-2.62)	(-8.17)	(-0.54)				(-1.51)	(-7.39)	(-0.35)
Attention^{SA}	0.018***	0.014***	-0.001***				0.015***	0.011***	-0.001***
	(10.61)	(8.19)	(-2.68)				(8.89)	(7.27)	(-2.91)
AIDay^{WSB}				0.096***	0.110**	0.011	0.093***	0.104**	0.021***
				(2.88)	(2.37)	(1.31)	(2.75)	(2.28)	(2.70)
Sentiment^{WSB}				0.006***	0.001	-0.001	0.004***	0.001	0.000
				(4.53)	(1.05)	(-1.57)	(4.43)	(1.09)	(-0.78)
Attention^{WSB}				0.032***	0.031***	0.002***	0.020***	0.019***	0.002***
				(9.57)	(8.27)	(3.05)	(8.36)	(7.75)	(2.75)
Size	-0.196***	-0.196***	-0.373***	-0.171***	-0.212***	-0.271***	-0.202***	-0.198***	-0.361***
	(-6.26)	(-7.25)	(-10.82)	(-4.66)	(-5.89)	(-4.90)	(-6.68)	(-7.53)	(-10.76)
BM	-0.008	-0.043***	0.021*	-0.029**	-0.027**	0.023	-0.011	-0.039***	0.027**
	(-0.84)	(-4.12)	(1.76)	(-1.99)	(-2.00)	(1.44)	(-1.14)	(-3.94)	(2.33)
IO	-0.020**	-0.010	-0.017**	-0.008***	-0.003	-0.014	-0.018**	-0.007	-0.019*
	(-2.38)	(-1.38)	(-1.97)	(-3.04)	(-0.72)	(-1.15)	(-2.31)	(-0.91)	(-1.96)
News	0.094***	-0.006**	-0.009***	0.096***	-0.009**	-0.005***	0.093***	-0.005*	-0.009***
	(26.83)	(-2.01)	(-8.10)	(18.64)	(-2.43)	(-3.27)	(26.11)	(-1.77)	(-8.22)
Analysts	-0.037***	0.002	-0.009***	-0.035***	0.001	-0.011**	-0.036***	0.002	-0.009***
	(-7.31)	(0.30)	(-2.62)	(-4.81)	(0.13)	(-2.46)	(-7.28)	(0.37)	(-2.62)
Earnings Day	0.375***	0.131***	0.008***	0.412***	0.113***	0.005	0.359***	0.126***	0.007**
	(26.17)	(9.08)	(2.66)	(26.20)	(8.00)	(1.54)	(25.96)	(9.20)	(2.16)
Abn. Ret. [t-21,t-1]	0.241***	0.024***	-0.027***	0.272***	0.017**	-0.034***	0.238***	0.024***	-0.028***
	(4.04)	(4.09)	(-3.02)	(25.06)	(2.27)	(-4.83)	(4.19)	(3.94)	(-3.05)
Volatility [t-21,t-1]	0.028	0.038	-0.006	0.110***	0.085***	-0.030***	0.036	0.042	-0.009
	(0.77)	(1.47)	(-1.47)	(3.78)	(4.79)	(-3.53)	(0.90)	(1.55)	(-1.44)
Day FE	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X
Obs.	1,424,099	1,424,099	1,358,845	635,343	635,343	608,811	1,446,761	1,446,761	1,379,841
Adj. R^2 (%)	18.1	34.8	78.1	21.1	39.0	80.1	17.8	34.7	78.3

Table 10. Large-Return Events Following AI Days

This table examines the association between "AI Day" and the incidence of large-return events (MAX and Lottery) using the following the following logistic regression specification:

$$\text{MAX}_{i[t+1,t+5]}/\text{Lottery}_{i[t+1,t+5]} = \beta_1 AIDay_{it} + \beta_2 Attention_{it} + \beta_3 Sentiment_{it} + Controls + FE + \epsilon_{it},$$

where the dependent variables, $MAX_{i[t+1,t+5]}$ and $Lottery_{i[t+1,t+5]}$, are indicators equal to one if stock i experiences a MAX or Lottery event in the $[t+1, t+5]$ window, and zero otherwise. A MAX event occurs when the daily return is the highest over the prior 20 trading days. A lottery event is a MAX event for which the corresponding maximum return also ranks in the top decile across all stocks on that day. $AIDay_{it}^{SA}$ is an indicator equal to one if at least one AI-generated article/post about stock i appears on day t on SA. $AIDay_{it}^{WSB}$ is defined similarly for WSB. Sentiment and Attention measures are define as in Table 9. All regressions include firm-characteristic controls and stock and day fixed effects. Standard errors are two-way clustered by stock and day. t-statistics are reported in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	SA		WSB		Combined	
	$\text{MAX}_{[t+1,t+5]}$	$\text{Lottery}_{[t+1,t+5]}$	$\text{MAX}_{[t+1,t+5]}$	$\text{Lottery}_{[t+1,t+5]}$	$\text{MAX}_{[t+1,t+5]}$	$\text{Lottery}_{[t+1,t+5]}$
	(1)	(2)	(3)	(4)	(5)	(6)
AIDay^{SA}	0.023	-0.041			0.027	-0.030
	(0.49)	(-0.29)			(0.57)	(-0.21)
Sentiment^{SA}	-0.018***	-0.019			-0.015***	-0.008
	(-4.56)	(-1.36)			(-4.04)	(-0.57)
Attention^{SA}	0.029***	0.086***			0.025***	0.067***
	(6.94)	(6.36)			(6.22)	(4.94)
AIDay^{WSB}			0.160**	0.269	0.158**	0.282*
			(2.11)	(1.58)	(2.05)	(1.66)
Sentiment^{WSB}			0.010***	0.015	0.007***	0.013*
			(2.73)	(1.37)	(2.82)	(1.70)
Attention^{WSB}			0.046***	0.142***	0.028***	0.088***
			(6.56)	(6.49)	(6.21)	(6.34)
Size	-0.480***	-0.781***	-0.536***	-0.760***	-0.476***	-0.800***
	(-9.65)	(-9.43)	(-8.25)	(-6.69)	(-9.57)	(-9.79)
BM	-0.098***	-0.138***	-0.100***	-0.089*	-0.094***	-0.126***
	(-4.46)	(-3.45)	(-3.81)	(-1.66)	(-4.41)	(-3.31)
IO	-0.006	-0.103	0.001	-0.090	-0.004	-0.085*
	(-0.53)	(-1.56)	(0.23)	(-1.44)	(-0.40)	(-1.74)
News	0.001	0.083***	-0.016*	0.095***	0.000	0.083***
	(0.21)	(5.07)	(-1.83)	(3.90)	(0.05)	(5.22)
Analysts	-0.006	-0.038	-0.004	-0.057	-0.006	-0.043
	(-0.57)	(-1.23)	(-0.35)	(-1.15)	(-0.55)	(-1.39)
Earnings Day	1.062***	1.494***	1.126***	1.590***	1.051***	1.456***
	(38.77)	(28.79)	(35.66)	(24.18)	(38.89)	(28.34)
Abn. Ret. [t-21,t-1]	-0.925***	-0.130***	-0.802***	-0.123***	-0.928***	-0.146***
	(-37.39)	(-7.04)	(-26.26)	(-4.90)	(-37.58)	(-8.05)
Volatility [t-21,t-1]	-1.744***	-0.041*	-1.439***	-0.021	-1.769***	-0.039*
	(-39.28)	(-1.80)	(-23.90)	(-0.82)	(-37.90)	(-1.71)
Day FE	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X
Obs.	1,424,072	680,696	635,342	274,574	1,446,735	700,185

Table 11. AI Day and Retail Order Flow Informativeness

This table examines the association between "AI Day" and the relationship between retail order flow and subsequent returns, using the following panel regression specification:

$$\begin{aligned}\text{CAR}_{i[t+1,t+5]} = {} & \beta_1 AIDay_{it} + \beta_2 AIDay_{it} \times OIB_{it} + \beta_3 AIDay_{it} \times Sentiment_{it} \\ & + \beta_4 Sentiment_{it} + \beta_5 Attention_{it} + \beta_6 OIB_{it} + Controls + FE + \epsilon_{it},\end{aligned}$$

where $\text{CAR}_{[t+1,t+5]}$ is the DGTW-adjusted cumulative abnormal return over $[t+1, t+5]$. $OIB_{i,t}$ is the net retail order imbalance (net retail buys divided by total retail share volume) for stock i on day t. $AIDay_{it}^{SA}$ is an indicator equal to one if at least one AI-generated article/post about stock i appears on day t on SA. $AIDay_{it}^{WSB}$ is defined similarly for WSB. Sentiment and Attention measures are define as in Table 9. All regressions include firm-characteristic controls and stock and day fixed effects. Standard errors are two-way clustered by stock and day. t-statistics are reported in parentheses. Significance levels are denoted as: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	SA		WSB		Combined	
	(1)	(2)	(3)	(4)	(5)	(6)
AIDay^{SA}	-0.362***	-0.530			-0.365***	-0.521
	(-3.24)	(-1.60)			(-3.26)	(-1.58)
$\text{AIDay}^{SA} \times \text{OIB}$	0.425**	0.433**			0.433**	0.440**
	(2.11)	(2.16)			(2.11)	(2.16)
$\text{AIDay}^{SA} \times \text{Sentiment}^{SA}$		0.029				0.027
		(0.60)				(0.56)
Sentiment^{SA}	-0.024**	-0.026**			-0.023**	-0.025**
	(-2.08)	(-2.22)			(-2.00)	(-2.13)
Attention^{SA}	0.023*	0.025*			0.022*	0.024*
	(1.69)	(1.80)			(1.65)	(1.76)
AIDay^{WSB}			-0.062	0.018	-0.047	0.076
			(-0.19)	(0.05)	(-0.14)	(0.20)
$\text{AIDay}^{WSB} \times \text{OIB}$			0.345	0.342	0.467	0.463
			(0.97)	(0.96)	(1.09)	(1.07)
$\text{AIDay}^{WSB} \times \text{Sentiment}^{WSB}$				-0.019		-0.019
				(-0.36)		(-0.50)
Sentiment^{WSB}			-0.003	-0.002	-0.001	0.000
			(-0.30)	(-0.23)	(-0.12)	(-0.01)
Attention^{WSB}			0.002	0.002	0.002	0.001
			(0.11)	(0.09)	(0.13)	(0.09)
OIB	0.011	0.011	0.035*	0.035*	0.004	0.004
	(0.44)	(0.44)	(1.68)	(1.68)	(0.15)	(0.15)
Size	-3.343***	-3.343***	-3.282***	-3.282***	-3.393***	-3.393***
	(-13.25)	(-13.25)	(-10.94)	(-10.94)	(-13.34)	(-13.34)
BM	-0.219**	-0.219**	-0.207*	-0.207*	-0.215**	-0.215**
	(-2.22)	(-2.22)	(-1.75)	(-1.75)	(-2.20)	(-2.20)
IO	-0.036	-0.036	-0.069	-0.069	-0.004	-0.004
	(-0.82)	(-0.82)	(-0.93)	(-0.93)	(-0.07)	(-0.07)
News	0.007	0.007	-0.008	-0.008	0.000	0.000
	(0.28)	(0.28)	(-0.28)	(-0.28)	(-0.00)	(-0.00)
Analysts	-0.122**	-0.122**	-0.061	-0.061	-0.128**	-0.128**
	(-2.29)	(-2.29)	(-1.20)	(-1.20)	(-2.39)	(-2.39)
Earnings Day	0.052	0.052	0.085	0.085	0.039	0.039
	(0.50)	(0.50)	(0.76)	(0.77)	(0.38)	(0.38)
Abn. Ret. [t-21,t-1]	-0.388***	-0.388***	-0.336***	-0.336***	-0.427***	-0.427***
	(-9.52)	(-9.52)	(-5.29)	(-5.29)	(-9.74)	(-9.74)
Volatility [t-21,t-1]	0.043	0.043	0.039	0.039	0.041	0.041
	(0.60)	(0.60)	(0.40)	(0.40)	(0.62)	(0.62)
Day FE	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X
Obs.	1,370,204	1,370,204	611,887	611,887	1,391,872	1,391,872
Adj. R^2 (%)	3.6	3.6	5.3	5.3	3.5	3.5

Appendix

A AI Detection Method Comparison

A.1 Simulated Sample Construction

To evaluate the detectors, we require a corpus in which the true source of every document is known. We therefore build a test set that pairs real finance commentary with machine-generated text written to the same brief. We randomly select 1,000 long-form equity articles from Seeking Alpha and 1,000 discussion messages from r/WallStreetBets, all dated between December 2020 and November 2021. The window lies well before public LLM deployment.

We then generate AI text based on Wall Street Journal news. We start from collecting 2,854 articles that appeared in the Wall Street Journal “Markets," “Stocks," “U.S. Markets," and “Heard on the Street" section between December 2020 and November 2021. Each article is fed to three frontier models-Llama 3.3, GPT-4o, and Claude 3.5-under two fixed instructions. Prompt 1 asks the model to recast the story in Seeking Alpha’s house style, while Prompt 2 requests a Reddit r/WallStreetBets “DD" post. The exact instructions are reproduced below. The exercise yields 17,124 synthetic documents (2,854 articles times 3 models times 2 styles), bringing the evaluation set to 19,124 observations, roughly 10 percent human and 90 percent AI.

Prompt 1 - Seeking Alpha style:

Your task is to write a short-form Seeking Alpha analysis.
Here is the article I want you to write based on:

`{article}`

Important Instructions – Carefully craft a single analysis that:
Use Seeking Alpha’s voice: write as a seasoned, opinionated investor, offering a clear perspective.
Paraphrase, never copy sentences from the article provided.
Total length 1,000-1,500 characters, including spaces.
Output your analysis directly, without any preamble.

Prompt 2 - Reddit style:

Your task is to write a short-form r/wallstreetbets Due Diligence (DD).
Here is the article I want you to write based on:

`{article}`

Important Instructions – Carefully craft a single analysis that:
Use r/wallstreetbets DD tone, potentially using slang and emphasizing high-risk/high-reward scenarios.
Paraphrase, never copy sentences from the article provided.
Total length 1,000-1,500 characters, including spaces.

Output your analysis directly, without any preamble.

A.2 Detectors

We compare four families of detectors that capture the main strands of the literature (See, e.g., Wu et al. (2025)).

GPTZero is a proprietary ensemble of multiple lexical and probabilistic features calibrated to minimize false positives. It returns probabilities for "Human", "AI", and "MIXED", as documented in detail above. Perturbation curvature is represented by DetectGPT (Mitchell et al. 2023). The algorithm measures how log-likelihood falls when the text is lightly masked, exploiting the idea that AI prose sits at a local optimum of its own model. We implement the authors' public code and methodologies. Statistical signatures follow Su et al. (2023). We report the Normalised Perplexity Ratio (NPR) and five auxiliary scores-Log-Likelihood Ratio, entropy, token rank, raw log-likelihood, and log-rank-computed under a Llama 3.3 reference. Cut-offs are set at the 28.6-percentile of each score's distribution in the human subset, a value that equates type-I and type-II costs in a validation grid.

A.3 Detection Results

Appendix Table A2 summarises accuracy and F1 statistics averaged across the full benchmark. GPTZero identifies provenance with 98 percent accuracy and an F1 of 0.99. DetectGPT attains 81 percent accuracy ($F1 = 0.89$); NPR matches that level, and the remaining statistics hover between 76 and 80 percent. The Log-Likelihood Ratio is the strongest of the auxiliary scores, yet still trails GPTZero by roughly twenty percentage points. Because following empirical discussions rely on the accurate classification of each document, we adopt GPTZero as the detector for all subsequent analysis and treat its output as the measure of AI involvement in platform content.

Table A1. Description of Variables

Variable	Definition
Article level	
AIProb_{ijt}	The sum of probability scores of content j for the AI-ONLY and MIXED categories, assigned by GPTZero.
$\text{AI-Only Prob}_{ijt}$	The probability scores of content j for the AI-ONLY categories, assigned by GPTZero.
Class_{ijt}	The classification (i.e., AI-ONLY, MIXED, HUMAN) of content j, assigned by GPTZero.
Length_{ijt}	Natural logarithm of word count of content j. For clarity, the descriptive statistics in Table 1 are based on the original, untransformed word count.
Sentiment_{ijt}	Sentiment scores of content j derived from platform-specific dictionaries (Loughran and McDonald (2011) for Seeking Alpha; Hu et al. (2025), modified for Reddit slang and emojis, for r/WallStreetBets). The sentiment score is calculated as follows: $$\text{Sentiment}_{ijt} = \frac{N_{\text{positive}} - N_{\text{negative}}}{N_{\text{positive}} + N_{\text{negative}}}$$ Where N_{positive} and N_{negative} are respectively the count of positive/negative words in the platform-specific content j. To reduce the impact of extreme values, the resulting ratio is winsorized at the 1st and 99th percentiles.
Complexity_{ijt}	Complexity scores derived from Loughran and McDonald (2024)'s dictionaries, calculated as follows: $$\text{Complexity}_{ijt} = \frac{\text{Words in Dictionary}}{textTotalWords}$$ Where #Words in Dictionary are the count of the specific complexity words identified in Loughran and McDonald (2024).
$\text{Quantitative}_{ijt}$	Total count of numbers mentioned divided by word count of a article, winsorized at the 1st and 99th percentiles.
Graphical_{ijt}	Total count of images divided by word count, winsorized at the 1st and 99th percentiles.
Fog Index_{ijt}	Fog Index is a readability test for English writing, calculated as follows: $$\text{Fog Index}_{ijt} = 0.4 \times \left(\frac{\text{Words}}{\text{Sentences}} + 100 \times \frac{\text{Complex Words}}{\text{Words}} \right),$$ where Words represents the total number of words in content j; Sentences represents the total number of sentences in content j; Complex Words represents the count of words with three or more syllables (excluding common suffixes like -es, -ed, -ing, proper nouns, and familiar jargon). To reduce the impact of extreme values, the resulting ratio is winsorized at the 1st and 99th percentiles.
Submissions_{ijt}	An indicator that identifies whether content j in Reddit r/WallStreetBets is a submission (top-level post).
$\text{Unfamiliarity}_{ijt}$	An indicator that identifies whether an author or user is addressing a specific firm i in their published content j for the first time within a recent six-month period.

Variable	Definition
First Time Industry$_{ijt}$	This variable is an dummy indicator that identifies whether an author or user is addressing the specific industry of the firm i in their published content for the first time within a recent six-month period.
News$_{ijt}$	Natural logarithm of one plus the number of news articles concerning firm i mentioned in content j in the past three days, sourced from RavenPack.
Analysts$_{ijt}$	Natural logarithm of one plus the number of analysts covering firm i mentioned in content j, sourced from Institutional Brokers' Estimate System (IBES).
Strong Retail Buy$_{ijt}$	A dummy variable that equals 1 if firm i's retail order imbalance ranks in the preceeding three days ranks in the top 10% across-sectionally. Order imbalance is calculated as in Boehmer et al. (2021).
Comments$_{ij[t,t+10]}$	Natural logarithm of number of user comments received on an article from its publication day (t) through 10 days post-publication ($t+10$).
Disagreement$_{ij[t,t+10]}$	Standard deviation of sentiment scores from user comments posted in response to content j during the period $[t, t+10]$. The sentiment scores for these comments are calculated using the dictionary from Loughran and McDonald (2011) for Seeking Alpha content, and a dictionary from Hu et al. (2025), modified for Reddit slang and emojis, for r/WallStreetBets content.
Comment Sentiment$_{ij[t,t+10]}$	Mean sentiment of comments following content j from its publication day (t) through 10 days post-publication ($t+10$).
Size$_{ijt}$	Natural logarithm of the market capitalization for firm i mentioned in content j.
BM$_{ijt}$	Natural logarithm of book-to-market ratio for firm i mentioned in content j.
IO$_{ijt}$	Institutional ownership, calculated as the percentage of common shares outstanding of firm i mentioned in content j, held by institutional investors as of the last quarter ending before day t.
Author Articles$_{ijt}$	Natural logarithm of one plus the number of articles published by a given author in the past six months.
Author AI Articles$_{ijt}$	Natural logarithm of one plus the number of AI-ONLY or MIXED articles by a given author in the past six months.
Author Comments$_{ijt}$	Natural logarithm of one plus the average number of comments per article within 21 days, where the average is taken across all articles that a given author publishes in the past six months.
Stock-day level	
AIDay$_{i,t}$	An indicator that equals one if at least one article about firm i published on day t is classified as AI-ONLY or MIXED by GPTZero.
Sentiment$_{it}$	The average sentiment score of articles about firm i on day t. Value set to a neutral score of zero for days without any content of firm i.
Attention$_{it}$	Natural logarithm of one plus the number of articles on SA (or posts on WSB) of firm i on day t.
Size$_{it}$	Natural logarithm of the market capitalization for firm i.
BM$_{it}$	Natural logarithm of book-to-market ratio for firm i.
IO$_{it}$	Institutional ownership, calculated as the percentage of common shares outstanding of firm i held by institutional investors as of the last quarter ending before day t.
News$_{it}$	Natural logarithm of one plus the number of news articles concerning firm i in the past three days, sourced from RavenPack.

Variable	Definition
Analysts_{it}	Natural logarithm of one plus the number of analysts covering firm i, sourced from Institutional Brokers' Estimate System (IBES).
AR_{it}	Abnormal return adjusted for size, book-to-market, and momentum following Daniel et al. (1997) on day t.
$\text{CAR}_{i[t+1,t+5]}$	Cumulative buy-and-hold returns adjusted for size, book-to-market, and momentum following Daniel et al. (1997) over the 5 trading days from $t+1$ to $t+5$.
$\text{AVOL}_{i[t+1,t+5]}$	Average abnormal volume for firm i over the 5 trading days from $t+1$ to $t+5$: $$\text{AVOL}_{i[t+1,t+5]} = \frac{1}{5}\sum_{s=1}^{5}\log(1+Volume_{i,t+s}) - \frac{1}{31}\sum_{s=-41}^{-11}\log(1+Volume_{i,t+s}),$$ where $Volume$ is the dollar volume, calculated as the numbers of shares traded multiplied by the price per share.
$\text{Volatility}_{i[t+1,t+5]}$	Standard deviation of the daily stock returns for firm i over the 5 trading days from $t+1$ to $t+5$.
$\text{Spread}_{i[t+1,t+5]}$	Average daily volume-weighted effective bid-ask spread for firm i over the 5 trading days from $t+1$ to $t+5$.
OIB_{it}	Retail order imbalance for stock i on day t, computed as $$OIB_{i,t} = \frac{\text{retail buy volume}_{i,t} - \text{retail sell volume}_{i,t}}{\text{retail buy volume}_{i,t} + \text{retail sell volume}_{i,t}}$$ (volume in shares) using marketable retail trades identified following Boehmer et al. (2021).
$\text{MAX}_{i[t+1,t+5]}$	A MAX event is when the daily return is the highest over the prior 20 trading days.
$\text{Lottery}_{i[t+1,t+5]}$	A lottery event is a MAX event where the corresponding 20-day maximum return also ranks in the top decile compared to all other stocks on that same day.
$\text{CAR}_{i[t-21,t-1]}$	Cumulative abnormal returns adjusted for size, book, and momentum following Daniel et al. (1997) over the preceding 21 trading days from $t-21$ to $t-1$.
$\text{Volatility}_{i[t-21,t-1]}$	Standard deviation of the daily stock returns for firm i over the preceding 21 trading days from $t-21$ to $t-1$.

Table A2. AI Detection Method Comparison

This table compares AI text detection methods on our benchmark dataset, reporting overall accuracy and F1 scores. Accuracy is the proportion of documents whose provenance (AI-generated or human-written) is correctly identified, and the F1 score is the harmonic mean of precision and recall, providing a balanced assessment of classification performance. Higher values indicate better performance on both metrics. The comparison includes GPTZero, DetectGPT, NPR, Log-Likelihood Ratio (LLR), Entropy, Rank, Log Likelihood, and Log Rank.

Detection Method	**Accuracy**	**F1 Score**
GPTZero	98%	99%
DetectGPT	81%	89%
NPR	80%	89%
LLR	78%	87%
Entropy	76%	86%
Rank	76%	86%
Log Likelihood	76%	86%
Log Rank	76%	86%

Table A3. Robustness: AI Content Measure Based on an "AI-Only" Probability

This table replicates Tables 3 to 7 using an alternative AI measure that relies only on the "AI-only" category from GPTZero. Panels A and B report results for Seeking Alpha and r/WallStreetBets, respectively. Columns 1—6 examine article-level AI use. Columns 7—8 and 9—10 examine the association between AI content and subsequent comment volume and disagreement, respectively. Standard errors are two-way clustered by stock and day, and *t*-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

Panel A: SA Sample

	AI-Only Prob						Comments		Disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unfamiliarity	2.352***	0.511***								
	(11.69)	(3.69)								
News			-0.381***	-0.129*			0.088***	0.072***	0.044***	0.034***
			(-3.18)	(-1.74)			(9.49)	(9.52)	(6.56)	(5.16)
Analysts			-0.591***	-0.265*			0.010	0.007	-0.005	-0.008
			(-3.28)	(-1.91)			(0.85)	(0.67)	(-0.49)	(-0.77)
Strong Retail Buy					-0.080	-0.249				
					(-0.17)	(-0.73)				
AI-Only Prob							-0.154***	-0.081**	-0.127***	-0.076**
							(-5.56)	(-2.58)	(-4.82)	(-2.21)
Day FE	X	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X	X
Author FE		X		X		X		X		X
Obs.	54,429	54,429	54,429	54,429	52,695	52,695	54,429	54,429	54,429	54,429
Adj. R^2 (%)	17.0	61.8	16.6	61.7	16.9	62.2	51.6	64.2	23.8	29.2

Panel B: WSB Sample

	AI-Only Prob						Comments		Disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unfamiliarity	0.073	-0.032								
	(0.42)	(-0.22)								
News			-0.085	-0.208			0.007	0.010	0.016**	0.019
			(-0.62)	(-1.43)			(1.29)	(0.90)	(2.17)	(1.48)
Analysts			0.513**	0.163			0.011	0.024	0.008	0.009
			(2.32)	(0.82)			(1.02)	(1.64)	(0.73)	(0.42)
Strong Retail Buy					1.597***	1.889***				
					(2.59)	(3.08)				
AI-Only Prob							0.357***	0.226***	0.424***	0.199**
							(6.46)	(2.73)	(8.28)	(2.51)
Day FE	X	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X	X
Author FE		X		X		X		X		X
Obs.	63,400	63,400	63,400	63,400	60,473	60,473	63,400	63,400	63,400	63,400
Adj. R^2 (%)	8.1	56.6	8.1	56.6	5.9	58.1	10.5	25.6	7.4	15.9

Table A4. Author Industry Unfamiliarity and AI Adoption

This table examines the association between author unfamiliarity with a firm's industry and article-level AI use, using the following panel regression specification:

$$AIProb_{ijt} = \beta_1 First\ Time\ Industry_{ijt} + Controls + FE + \epsilon_{ijt},$$

where AIProb_{ijt} is AI probability score of content j about firm i posted on day t. $\text{First Time Industry}_{ijt]}$ is an indicator equal to one if the author has not covered firm i's industry in the prior six months. $\mathbf{X}_{ijt}$ includes firm characteristics and measures of the author's prior activity/performance (each standardized to zero mean and unit variance). Columns 1–3 report results for articles published on Seeking Alpha; Columns 4–6 report results for posts on Reddit's r/WallStreetBets. Standard errors are two-way clustered by stock and day; t-statistics are shown in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	SA		WSB	
	(1)	(2)	(3)	(4)
First Time Industry	2.034***	0.294	0.019	-0.079
	(7.04)	(1.39)	(0.11)	(-0.52)
Size	-0.644	-1.808**	-1.397*	-0.536
	(-0.61)	(-2.24)	(-1.86)	(-0.55)
BM	0.933***	0.293	0.161	-0.319
	(2.87)	(0.87)	(0.99)	(-1.40)
IO	0.933*	0.453	0.363	-0.480
	(1.69)	(1.22)	(0.95)	(-1.19)
Author Article	-3.449***	-1.120***	-0.806***	-0.060
	(-20.85)	(-8.15)	(-8.56)	(-0.63)
Author AI Article	8.371***	2.497***	2.356***	-0.431***
	(36.57)	(19.15)	(6.99)	(-2.68)
Author Comments	0.495***	0.472***	-0.168*	0.061
	(3.34)	(3.77)	(-1.78)	(0.55)
Submissions			9.088***	4.364***
			(10.95)	(5.88)
Day FE	X	X	X	X
Stock FE	X	X	X	X
Author FE		X		X
Obs.	54,429	54,429	63,400	63,400
Adj. R^2 (%)	18.6	59.5	11.5	56.6

Table A5. Robustness: WSB submissions-only sample

This table presents replication results of Tables 3–7 for the r/WallStreetBets (WSB) submissions-only sample. Columns 1-6 examine article-level AI use; Columns 7-8 and 9-10 examine the association between AI content and user responses on the platform. Standard errors are two-way clustered by stock and day; *t*-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

	AI-Only Prob						Comments		Disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unfamiliarity	0.532	-1.112								
	(0.69)	(-0.73)								
News							0.021	-0.085	0.075***	0.024
							(0.84)	(-1.24)	(2.78)	(0.18)
Analysts							-0.019	0.204	0.087*	0.515**
							(-0.41)	(1.11)	(1.67)	(2.33)
Strong Retail Buy					13.408***	17.534*				
					(2.73)	(1.87)				
AIProb							-0.315***	-0.031	-0.040	-0.160
							(-5.38)	(-0.10)	(-0.64)	(-0.46)
Day FE	X	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X	X
Author FE		X		X		X		X		X
Obs.	6,487	6,487	6,487	6,487	6,127	6,127	6,487	6,487	6,487	6,487
Adj. R^2 (%)	10.4	23.1	10.5	23.8	11.5	25.9	8.1	-57.5	4.7	-76.4

Table A6. Robustness: Including Messages below 50 Words on WSB

This table presents replication results of Tables 3–7 for the full Reddit r/WallStreetBets message sample (including submissions and comments below 50 words). Columns 1-6 examine article-level AI use; Columns 7-8 and 9-10 examine the association between AI content and user responses on the platform. Standard errors are two-way clustered by stock and day; t-statistics are in parentheses. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	AI-Only Prob						Comments		Disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unfamiliarity	-0.008	0.017								
	(-0.56)	(1.53)								
News			-0.006	-0.005			0.015***	0.013***	0.025***	0.020***
			(-0.56)	(-0.61)			(6.88)	(6.37)	(9.27)	(7.68)
Analysts			0.039**	0.032***			0.002	0.001	0.000	0.000
			(2.53)	(3.33)			(0.65)	(0.35)	(0.07)	(0.08)
Strong Retail Buy					0.159*	0.112*				
					(1.85)	(1.95)				
AIProb							-0.373***	-0.262***	0.130***	0.000
							(-5.38)	(-10.13)	(3.44)	(-0.00)
Word Count > 50	2.925***	2.675***	2.924***	2.677***	2.761***	2.572***	-0.488***	-0.510***	-0.056***	-0.024***
	(26.15)	(28.10)	(26.19)	(27.99)	(27.01)	(27.49)	(-45.88)	(-63.88)	(-8.65)	(-4.23)
Day FE	X	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X	X
Author FE		X		X		X		X		X
Obs.	949,674	949,674	949,674	949,674	901,387	901,387	949,674	949,674	949,674	949,674
Adj. R^2 (%)	9.7	46.6	9.7	46.6	9.0	46.0	11.5	17.9	1.4	1.0

Table A7. Robustness: Pre- and Post-Ban Interaction Effects

This table presents replication results of Tables 3–7 for the Seeking Alpha sample, interacting key variables with indicators for the Pre-Ban and Post-Ban periods (Post-Ban defined as dates after 2023-10-31). Columns 1-6 examine article-level AI use; Columns 7-8 and 9-10 examine the association between AI content and user responses on the platform. Standard errors are two-way clustered by stock and day; *t*-statistics are shown in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

	AIProb						Comments		Disagreement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unfamiliarity × Pre-Ban	4.197***	1.107***								
	(11.87)	(4.77)								
Unfamiliarity × Post-Ban	0.450	0.024								
	(1.52)	(0.10)								
News × Pre-Ban			-0.696***	-0.262*						
			(-3.40)	(-1.94)						
News × Post-Ban			0.040	-0.157						
			(0.21)	(-1.24)						
Analysts × Pre-Ban			-0.912***	-0.313*						
			(-3.83)	(-1.66)						
Analysts × Post-Ban			-0.454*	-0.346*						
			(-1.89)	(-1.82)						
Strong Rtl. Buy × Pre-Ban					-0.012	0.600				
					(-0.01)	(0.97)				
Strong Rtl. Buy × Post-Ban					0.382	0.321				
					(0.51)	(0.54)				
AIProb × Pre-Ban							-0.150***	-0.090***	-0.005***	-0.003**
							(-4.97)	(-2.69)	(-4.19)	(-2.14)
AIProb × Post-Ban							0.027	-0.037	-0.002*	-0.005***
							(0.87)	(-1.15)	(-1.96)	(-3.54)
Day FE	X	X	X	X	X	X	X	X	X	X
Stock FE	X	X	X	X	X	X	X	X	X	X
Author FE		X		X		X		X		X
Obs.	54,429	54,429	54,429	54,429	52,695	52,695	54,429	54,429	54,429	54,429
Adj. R^2 (%)	18.9	59.6	18.6	59.5	18.8	60.0	51.6	64.2	22.1	27.1