AI Democratization and Trading Inequality*

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First Version: August 17, 2023
This Version: September 15, 2025

*We thank Valeri Nikolaev (editor) and an anonymous referee for their valuable comments and suggestions that have greatly improved this manuscript. We are grateful to Tania Babina, Elizabeth Blankespoor, Jeremy Bertomeu, Thierry Focault, Ahmed Guecioueur (discussant), Danling Jiang, Wei Jiang, Pete Kyle, Toomas Laarits (discussant), Christian Leuz, Miao Liu (discussant), Brandon Lock, Vitaly Meursault, Robert Novy-Marx, Jun Oh (discussant), Lin Peng, Steven Poser, Fabrice Riva (discussant), Rui Shen (discussant), Gregor Schubert, Qin Tan (discussant), Albert Di Wang (discussant), Dexin Zhou, and participants at 2025 Journal of Accounting Research (JAR) Conference, Midwest Finance Association Annual Meeting 2025, FARS Midyear Meeting 2025, 16th Annual Hedge Fund Research Conference, AI in Finance Conference 2025 at University of Maryland, China International Conference in Finance (CICF) 2025, CJAR Summer Workshop 2025, CUHK(SZ) Forum of Asian Accounting Scholars 2025, NTU Conference on AI for Finance 2025, AAA Annual Meeting 2025, Conference for Financial Economics and Accounting 2024, The Inaugural Future Scholars in Finance Forum, 1st Workshop on LLMs and Generative AI for Finance, "AI Era in Finance" Symposium 2024, Australian National University, Baruch College, Hong Kong University, McGill University, Monash University, Peking University, Renmin University of China, Southwestern University of Finance and Economics, Tsinghua University, and Washington University in Saint Louis for comments and suggestions.

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Abstract

We present the first analysis of how Generative AI (GenAI) shapes investors' trading activities. Using an AI-sentiment measure extracted from earnings-call transcripts to proxy for textual signals, we find notable shifts in trading behaviors around earnings calls. Before the wide deployment of ChatGPT, short selling was aligned with AI-sentiment, whereas retail trading was not. However, following ChatGPT's deployment, the alignment of retail traders with AI-sentiment significantly increases, while the alignment of short sellers weakens, albeit insignificantly. Stocks with higher information processing costs exhibit a more pronounced increase in retail trading alignment, scenarios where retail investors are likely to benefit more from AI. Further evidence shows that information asymmetry declines, and retail investors' trading profitability improves, whereas short sale profitability declines in stocks for which retail investors are more likely to trade based on AI signals. Retail investors also exhibit a modest increase in their trading intensity in these stocks, indicating greater participation. Exogenous outages reduce the alignment between retail trading and AI-sentiment, reinforcing our inferences. Collectively, this study suggests that AI is a promising technology for narrowing the information gap in trading on complex textual financial disclosures between investor classes with clear disparities in abilities to process public disclosures.

JEL: G10, G11, G14

Keywords: Artificial Intelligence, AI Access, ChatGPT, GenAI, Sentiment, Return Predictability, Machine Learning, Earnings Conference Calls, Retail Investors, Short Sellers, Households, Anomalies, Information Asymmetry, Trading Inequality

"I think AI very naturally, ..., will raise the floor in a big way. I hope AI can reduce inequality and more than that, I hope it can dramatically lift up the floor in the world."
—Sam Altman, OpenAI CEO

"Market forces won't naturally produce AI products and services that help the poorest."
—Bill Gates, Microsoft Cofounder

"The rich get richer..."
—Eric Schmidt, Former CEO of Google, when commenting on the role of AI

Introduction

Since the arrival of ChatGPT, the field of Generative AI (GenAI) has advanced at an unprecedented pace. Contemporary research in accounting and finance shows that GenAI models perform well in processing information (Kim et al., 2023a; Wong et al., 2024; Bai et al., 2023; Bernard et al., 2024; Jha et al., 2024; Lopez-Lira and Tang, 2023), implying that they could reduce information processing costs and enhance investors' financial decision-making. Relative to traditional machine learning models, openly accessible GenAI platforms offer two cost advantages to the general public. The first advantage is financial: models like ChatGPT are accessible at low monetary cost, sidestepping the capital expenditures typically associated with proprietary software and specialized hardware. The second is cognitive and technical: moving from code-based workflows to natural-language inputs and outputs lowers cognitive and technical entry barriers, compared to tools that require specialized programming and deep domain expertise in econometrics, statistics, accounting, or finance. Together, these financial, cognitive, and technical cost reductions lower barriers to entry for a much broader audience—including ordinary investors and the information intermediaries who help them access and comprehend financial disclosures (e.g., fintech builders, independent media, and other social-media commentators). As a result, GenAI has the potential to significantly benefit ordinary investors.

In this paper, we assess the impact of ChatGPT's introduction on the trading behaviors of two distinct investor classes surrounding major financial information disclosures (earnings conference calls): retail traders and short sellers. Retail traders represent the market's "floor" in terms of processing information disclosures, whereas short sellers sit at its "ceiling"—among the most informed investors, particularly capable of processing public information disclosures, across the entire trading spectrum.[1] [2] ChatGPT can aid retail traders in at least two significant ways. First, retail investors can directly use ChatGPT to perform textual analysis. Second, they can trade based on AI-generated signals produced by low-cost information intermediaries (e.g., Seeking Alpha and AlphaSense).[3] By contrasting the two classes of traders with significantly different levels of sophistication, we improve our test power to examine whether GenAI narrows the information gap between these two investor groups.

Although GenAI has the potential to reduce the information gap between retail investors and short sellers, existing research suggests that this gap could also widen. Short sellers, being among the most informed market participants, may be more adept than retail investors at capitalizing on information generated by ChatGPT in their trading activities, if the AI signals complement their own private signals (Kim and Verrecchia, 1994; Hellwig et al., 2012; Cheynel and Levine, 2020). This could reinforce the conventional "rich-get-richer" view. Consequently, it remains an open empirical question whether the adoption of ChatGPT will ultimately narrow or expand the informational divide between retail investors and short sellers.

We focus on the setting of earnings conference calls to examine whether access to AI-generated trading signals, extracted from these calls, narrows or enlarges the information gap between the two classes of traders. The setting of earnings calls are appealing for three reasons. First, earnings conference calls serve as a major voluntary disclosure channel for firms, revealing a significant amount of information to the public (Matsumoto et al., 2011). Second, managers often disclose complex and technical soft information during these calls, which may be challenging for retail investors to understand. Prior research demonstrates that short sellers trade profitably by interpreting earnings conference call tone differently than average investors (Blau et al., 2015). This

[1] Prior work (e.g., Engelberg et al., 2012; Wang et al., 2020) shows the primary source of short sellers' informational advantage is processing public disclosures. In addition, Blau et al. (2015) document consistent evidence in the earnings-call context—making short sellers a particularly suitable benchmark for our research setting.

[2] Empirically, Chen et al. (2019) show short selling predict returns stronger than 13F-reported hedge fund trades. It is also widely documented that hedge funds are more informed than mutual funds. Theoretically, short sellers face higher trading costs and risks than regular informed traders due to the embedded leverage and various short-sale constraints such as short-selling fees and recall risks. Thus, in equilibrium, the implied informativeness of short sellers is expected to be higher to justify the higher costs or risk they take.

[3] Our study does not pinpoint which channel contributes to the AI effect, but both are plausible and align with our argument that AI reduces retail investors' information processing costs. Anecdotally, AI-empowered trading ideas are increasingly shared by non-professional influencers on social media (see Internet Appendix Figure IA.1). Furthermore, some trading platforms now offer AI tools, such as Prolific's Alpha based on GPT-4, which can analyze earnings conference call transcripts and assist retail investors free of charge (Blankespoor et al., 2024). We leave the question of which channel is most impactful for future research.

complexity presents an opportunity for GenAI to reduce information processing costs for retail investors. Third, earnings conference calls have a well-defined event window, allowing us to employ an event-study approach.

We begin by exploring how the arrival of ChatGPT influences the trading behaviors of retail investors and short sellers around earnings conference calls. Specifically, we construct an AI signal extracted from the transcripts of these earnings calls and examine whether the introduction of ChatGPT impacts the trading behaviors of both investor classes based on the AI signal. If ChatGPT aids retail investors in comprehending conference call information, we anticipate that they will increasingly trade based on the AI signal following its introduction. Conversely, for short sellers who likely already possess sophisticated information processing capabilities similar to ChatGPT (e.g., using machine learning tools or obtaining private information), we expect no significant change in their trading behaviors. In fact, short sellers might reduce their reliance on the AI signal if the influx of retail investors trading on the same signal diminishes their profit opportunities.

To examine these conjectures, we employ the GPT-3.5-Turbo-16k API model to extract the AI signal (AI-sentiment) from earnings calls for the period spanning from 2021 to 2023 and the GPT-4o Mini model for the period beginning in 2024. This model choice offers three advantages discussed in Section 1.2. We examine AI-sentiment for at least two reasons. First, academic research suggests that sentiment is a critical, value-relevant piece of information that can be obtained from textual analysis (see, e.g., Tetlock, 2007; Loughran and McDonald, 2011). Additionally, Tetlock et al. (2008) demonstrate that textual sentiment captures hard-to-quantify aspects of firms' fundamentals. Second, top AI tools such as Needl.ai (Muceniece, 2024) have already used ChatGPT to produce such signal for market participants.[4] This underscores its importance and usefulness. However, our findings do not hinge on AI-sentiment being the sole AI-generated signal that retail investors trade on. We interpret retail investors aligning their trading with AI-sentiment as a proxy for the extent to which ordinary investors can trade based on a broad range of signals generated by GenAI.

A maintained assumption for our conjectures is that the AI signal is informative about firm fundamentals. We validate this assumption both before and after the wide deployment of AI. Specifically, AI-sentiment consistently predicts stock returns for up to 126 days, and no return

[4] See `https://www.needl.ai/help/sentiment-analysis`.

reversal is observed following the earnings call.

Next, we show short sellers align their trading with AI-sentiment immediately on the earnings call day and over the subsequent 21 days before the AI deployment. Conversely, retail investors display no reaction to AI-sentiment at all. This indicates a lack of alignment with AI-sentiment for retail investors before AI deployment. This pre-deployment pattern suggests that short sellers enjoyed an edge on processing complex financial information like earnings calls, plausibly reflecting technological advantages such as proprietary machine-learning models, whereas retail trading largely resembled noise on this dimension. Following deployment, the alignment of retail trading with AI-derived sentiment increases markedly—a full-decile increase in AI-sentiment corresponds to up to a 0.26 standard-deviation increase in retail trading on the earnings call day and over the subsequent month. By contrast, short sellers' alignment with AI-sentiment fails to rise and instead drifts slightly lower—albeit insignificantly. These findings are consistent with the prediction by Grossman and Stiglitz (1980) that, as more investors become informed, the incentive to acquire and trade on that information diminishes. As a result, the gap in AI alignment between retail trading and short selling significantly shrinks post-deployment. These results remain robust when using a difference-in-differences test that compares retail trading and short selling in the same firm-quarter, effectively controlling for many unobservable shocks that coincide with AI deployment.

To refine our analysis of trading on the AI signal, we narrow the focus to an intraday window that spans from the start of an earnings call to the market close on the same trading day. The rationale is that earnings conference calls likely dominate other information impacting asset prices within this brief period. Consequently, the AI-sentiment conveyed during the earnings call becomes a more crucial signal compared to longer daily or multi-day horizons. This short window setting allows us to more precisely isolate the impact of AI-generated information on retail trading behaviors. Our findings are consistent with those from the long-window analysis, further supporting the inference that access to AI tools such as ChatGPT significantly increases retail traders' reliance on AI-generated insights.

To mitigate the concern of confounding events that might drive our findings, we use ChatGPT outages as exogenous variation in its access for retail investors. If AI aids retail investors' trading, unexpected outages would weaken retail trading alignment with AI. We show that, when there are outages after the earnings conference call, retail trading alignment with AI declines relative to those periods without an outage.

In cross-sectional tests, we find the increase in AI-trading alignment is more pronounced for firms with higher operating uncertainty and poorer information environments. These patterns are consistent with AI playing a more prominent role in shaping retail trading in stocks characterized by high information processing costs. This might also explain why retail investors do not align their trading with AI signals for all stocks post-AI deployment.

As retail investors increase their alignment with GenAI in trading, does their information gap with short sellers narrow? As discussed earlier, this may not occur if short sellers utilize ChatGPT to obtain superior, alternative signals, thereby maintaining or even widening the overall information gap. We perform two tests to explore this question. First, we examine bid–ask spread, a common measure of information asymmetry among market participants. Given that ChatGPT represents a market-wide shock, we follow Edmans et al. (2013) and focus on cross-sectional heterogeneity in retail traders' alignment with AI-sentiment for this analysis.[5] In other words, we aim to identify stocks whose retail investors are more (less) likely to trade on AI-generated signals after AI introduction and compare the changes in bid–ask spread between these two groups. Specifically, we classify stocks as high alignment group or low alignment group based on the stock-specific estimate of the change in retail investors' trading alignment with AI-sentiment following the introduction of AI. A treatment and control comparison using propensity score matching also helps alleviate the concerns of many other unobservable economic forces are evolving during the past few years. [6]

We find that before the AI introduction, there is no significant difference in bid–ask spread between the two groups. However, following the AI introduction, we observe a substantial decline in bid–ask spread for high alignment stocks relative to low alignment stocks, during the intraday short window after the call starts. This decline is sizable, representing 12% of the sample mean. The decline is also observed after the conference call day up to 21 days following the call. In

[5]Edmans et al. (2013) examine the effect of liquidity on corporate governance. They use the 2000-2001 minimum tick size reduction in the U.S. stock markets as exogenous variation for liquidity. They compare and contrast changes in corporate governance between stocks with high liquidity and those with low liquidity.

[6]Admittedly, our partitioning based on the outcome (alignment) which is itself affected by the AI deployment, raises concerns about conditioning on a consequence of treatment, potentially invalidating our causal interpretation. Additionally, our high alignment group may not represent a pre-existing characteristic but rather a mix of treatment and idiosyncratic shocks. To mitigate these concerns, we compare the three proxies of information processing costs measured in the pre-deployment period between the high and low alignment stocks. In untabulated results, we find that the high (low) alignment stocks have higher (lower) operating uncertainties and poorer (better) information environments. This result is consistent that high information processing costs, representing a pre-existing, persistent stock characteristic, might explain retail investors' trading alignment with AI signals.

summary, our evidence is consistent with the inference that the integration of AI has reduced the information gap between retail investors and short sellers.

Second, we investigate whether the increased alignment with GenAI insights translates into higher trading profit for retail investors and compare this change with the trading profit of short sellers. If GenAI reduces the information gap between retail investors and short sellers, we expect retail investors' trading profitability to rise among the stocks with high-AI alignment, and no such effect for stocks with low-AI alignment. We also predict a decline in short sale profitability for stocks with high-AI alignment attributed to increased competition from retail investors, while expecting no change for stocks with low-AI alignment. Consistent with these conjectures, we find that retail investors trading on high alignment stocks experience losses between the call day and up to 126 days after the call prior to the introduction of AI. In contrast, short-selling experiences significant gains in these set of stocks on call days. Combined with the evidence that short sellers trade with the AI signal, these results align with Blau et al. (2015), demonstrating that short sellers act as informed traders on call days. Their informativeness appears to be linked to their capacity to process textual information analogous to the AI signal. However, following the introduction of AI, retail trading profitability increases significantly while short sale profitability slightly declines in these stocks. For low-AI alignment stocks, neither retail investors' nor short sellers' trading profitability changes following AI introduction. Taken together, the gap in trading profitability between the two types of traders has narrowed following AI deployment for the stocks that retail investors are particularly likely to trade on AI-generated information.

Finally, to further corroborate our inference that AI narrows trading inequality for retail investors, we investigate whether retail investors become more inclined to participate in trading in the stock market. Due to data limitations, we measure investor participation by their trading intensity rather than stock holdings, although the latter would be preferable. The reduction in information asymmetry could plausibly lead to an increase in retail investors' trading intensity, as they become less concerned about adverse selection. Conversely, prior research indicates that retail investors frequently demonstrate overconfidence, overestimating the precision of their information, which results in excessive trading and significant losses (Odean, 1999). Additional research finds that feedback regarding information precision can reduce overconfidence-induced excessive trading and subsequently improve trading profit (Bregu, 2020). By offering a more accurate signal for firm fundamentals, AI deployment enables retail investors to reassess the precision of their information. Consequently, their trading intensity could potentially decline. Therefore, it is unclear ex ante which scenario will prevail. Our evidence shows a higher trading intensity on call days post-deployment for stocks with high-AI alignment compared to those with low-AI alignment, suggesting that adverse-selection effect dominates the overconfidence-reduction effect. In sum, we find evidence suggesting that AI deployment increases retail investors' participation in the stock market.

Overall, our findings imply that prior to AI's wide deployment, short sellers were able to exploit the informational advantages that AI could extract from complex financial information, while retail investors were not. However, with the introduction of AI tools such as ChatGPT, retail investors have gained investment insights generated by these advanced technologies. Consequently, their trades have increasingly aligned with the AI signals extracted by these tools. This development has effectively narrowed the information gap between short sellers and retail investors, leading to a smaller bid–ask spread, higher retail trading profitability, as well as greater retail participation among the high alignment stocks. These results highlight the transformative potential of modern technology to lower entry barriers and promote greater equality in financial markets. Additionally, our findings indicate that retail investors stand to gain more from the introduction of AI in stocks where their trading aligns with AI insights. Retail investors in these stocks typically face higher information processing costs compared to those in stocks where trades are less aligned with AI insights. Therefore, AI technology may provide benefits to those who need it.

As AI is still evolving, its full impact remains uncertain. Short sellers may take time to develop superior proprietary models internally that outcompete publicly available GPT-based tools. However, recent evidence (Challapally et al., 2025, MIT Project NANDA) suggests that broadly accessible tools such as ChatGPT are often more effective for improving productivity than internally developed enterprise models. Consequently, publicly accessible models such as ChatGPT may match or even surpass internal, proprietary models that short sellers may develop. Nevertheless, our proof of concept demonstrates that AI democratization can narrow trading inequality. We therefore call for sustained, cross-disciplinary inquiry to further study and track this evolving dynamic and its broader implications for financial markets, which is an issue of central interest to the public and policymakers.

Literature and Contribution

Our study contributes to the burgeoning literature on the impact of technology adoption on inequality in financial markets. Previous research on this issue, though less explored, presents mixed findings. For instance, Fuster et al. (2022) investigates the effects of machine learning (ML) technology on mortgage borrowers. They find that ML models are more accurate in predicting mortgage defaults and slightly enhance credit access; however, they also exacerbate interest rate disparities, particularly adversely affecting Black and Hispanic borrowers. On the other hand, Hong et al. (2020) finds that higher FinTech adoption leads to greater financial inclusion, as evidenced by greater individual participation and risk-taking in mutual fund investments. Their research also demonstrates that this positive effect is more pronounced for constrained individuals and those from underbanked areas.

Our paper also contributes to the nascent but rapidly growing literature on how AI influences information processing in financial markets. Several recent studies have begun to explore this intersection. For instance, Kim et al. (2023a) find that ChatGPT can accurately and succinctly summarize corporate disclosures, with these summaries being more value-relevant than the original disclosures. Bai et al. (2023) focus on the role of AI in obtaining information using large language models to generate responses to questions raised during earnings conference calls. They find that the divergence of AI-generated responses from the actual responses provided by management can predict market outcomes. In a similar vein, Jha et al. (2024) employ AI to extract corporate investment policies from conference calls, finding that this information has predictive power for future capital investments of firms. Furthermore, Chen et al. (2023), Kim et al. (2023b), and Lopez-Lira and Tang (2023) demonstrate that AI-derived sentiment can predict stock returns. Cheng et al. (2025) use ChatGPT outages to examine the impact of AI on investor trading. Their findings reveal that outages have a significantly negative effect on trading activities, particularly among non-retail investors. Our study builds on this body of research by examining whether the superior information processing abilities of AI translate into equality or contribute to disparities within financial markets. This investigation sets our work apart from Cheng et al. (2025) who focus on the average effect of AI on investor trading, and from Bertomeu et al. (2025), who concentrate on the impact of AI on financial analysts, a specific group within the class of sophisticated market participants. More specifically, we aim to understand the broader implications of AI adoption for two distinct classes of investors, each with different ability to process complex financial information.

Another closely related stream of research involves the use of technology by financial market regulators. Gomez (2024) examines the SEC's adoption of EDGAR, which electronically disseminates SEC filings. He finds that information asymmetry worsened around public information release dates following this adoption. His findings suggest that the deployment of EDGAR technology allows sophisticated investors to gain a greater information advantage, as less sophisticated investors face higher information processing costs for the SEC filings. Similarly, Blankespoor et al. (2014) investigate the effect of mandatory XBRL adoption on information asymmetry. They find evidence of higher abnormal bid–ask spread for XBRL-adopting firms around 10-K filings in the first year after adoption. In contrast, we find decreased information asymmetry following the adoption of AI. This discrepancy highlights the complex nature of how technology and data can affect market equality differently. It underscores that the plausible key driver behind these differing outcomes is whether the technology effectively lowers the financial, cognitive, and technical costs for the informationally disadvantaged group. In contrast, simply making data timely (EDGAR) and available in an machine-readable form (XBRL) may further benefit informed traders who already possess the technology to process information, thereby amplifying their informational advantage. [7]

As a rapidly evolving technology, the development of GenAI and investor attitudes toward its adoption can change significantly over time. Should GenAI capabilities continue to advance and become more widely accepted among disadvantaged investors, our findings could become even stronger. Conversely, if sophisticated investors have yet to fully capitalize on the potential of GenAI during our sample period, their benefits from AI insights might grow faster than those of retail investors. This accelerated advantage could potentially widen the information gap between sophisticated and retail investors, thus weakening our findings. In sum, the impact of AI on information processing and trading inequality is likely dependent on the specific time and context. Our findings are therefore dependent on the current stage of GenAI development, adoption rates, and investors' knowledge regarding AI. We encourage future research to explore these evolving dynamics further.

[7] Our findings are consistent with the widened bid–ask spread during the Italian ban on ChatGPT as documented in Bertomeu et al. (2025).

1 Sample, Variable Construction, and Descriptive Statistics

1.1 Earnings Calls

Given that the ChatGPT-3.5 model became publicly available in November 2022, our sample period spans from 2021 to 2024, covering two years before and two years after the release date. This time frame is chosen to strike a balance between providing a sufficiently long sample period and minimizing the impact of confounding events, such as the COVID-19 pandemic. We obtain 53,135 transcripts of earnings calls from S&P Capital IQ. Our sample is confined to common stocks on the NYSE, AMEX, and Nasdaq.[8] During our sample period, the average earnings call transcript comprises approximately 7,000 words, which is equivalent to 9,310 tokens, highlighting the extensive information typically conveyed through these calls.

1.2 AI-Sentiment

We use GPT-3.5-Turbo-16k to extract AI-sentiment from 2021 to 2023. Following its discontinuation in 2024, we adopt GPT-4o Mini to extract AI-sentiment only for the year of 2024, which is after the final knowledge date of GPT-4o Mini model (end of September 2023). However, our key findings hold when limiting the analysis to 2022–2023 (see Internet Appendix Table IA.2). We also verify that the signals generated by the two models are highly correlated (70%) in their overlapped post-final knowledge period. This choice has three key advantages. First, both models have a large processing capacity, enabling us to efficiently analyze a substantial volume of call transcripts. Second, both models have a well-defined knowledge cutoff date, enhancing our confidence that look-ahead bias is minimized in our analysis. Levy (2024) points out the possibility of a certain degree of look-ahead bias between a model's final knowledge date and its posting date. However, Lopez-Lira et al. (2025) demonstrate that LLMs cannot recall data after their knowledge cutoff date, indicating that human intervention between model posting date and knowledge cutoff date does not generate statistically significant look ahead bias. Notwithstanding, our central results are

[8] Considering that the knowledge base of the API version of GPT-3.5-Turbo-16k contains data available only up to September 2021, including data from 2021 in our sample may introduce look-ahead bias. A similar concern applies to the inclusion of data from 2024, given the release of the GPT-4o Mini in July 2024. To address these concerns, we conduct robustness tests by focusing our main analysis on the sample period from 2022 to 2023. This approach ensures a clear and untainted analysis, as it eliminates any potential influence from information that emerged after the model's training cutoff date.

stronger over the period after the posting date(s) of the model(s) we use (see Figure 1), further alleviating the posting date-based look-ahead bias concern. Third, the web-based version of this model is free to the general public, which is essential for access by retail investors and retail-facing information intermediaries.

To enhance the model's reasoning and problem-solving abilities, we follow the logic of "domain-specific prompting" to predefine the concept of conference call transcripts and configure the model to simulate the perspective of a financial expert. This approach ensures that the model's analysis is contextually grounded and aligned with the nuances of financial communication. First, the model is structured around distinct roles such as "system," "user," and "assistant" to facilitate the API model's comprehension of the definitions and institutional context surrounding earnings call transcripts. Additionally, the model is configured to simulate the perspective of a stock market trader, thereby enhancing the relevance and financial acumen of its responses. We also set the model temperature to zero to enhance accuracy and reduce the occurrence of model hallucinations. Next, we instruct the API model to evaluate the sentiment embedded in each earnings call transcript and generate a corresponding sentiment score on a scale of -10 to 10. This approach ensures that the model's analysis is grounded in context and aligned with financial market insights. We use the sentiment score provided by the model as our measure of AI-sentiment. AI-sentiment is demeaned and rescaled by the inter-decile range (the difference between the top and bottom deciles), so that a one-unit change corresponds to a shift from the bottom to the top decile—what we term a full-decile shift. This transformation facilitates interpretation of economic magnitudes in our regression analysis, aligning with conventions in the anomaly literature, which typically assesses the predictability of a full-decile change in an anomaly variable.

Prompt:

"role": "system", "content": *Forget all your previous instructions. You are a stock market trader with experience in both fundamental analysis and technical analysis. Knowledge cutoff: {date}.*

"role": "user", "content": *Can you define the concept of conference call transcript?*

"role": "assistant", "content": *A conference call transcript is a written document that accurately records the spoken dialogue from a multi-party telephone meeting. A conference call usually starts with managers' presentation. The starting point of presentation usually starts with one word 'Presentation' in one line with no other words in that line. The presentation is then followed by* *question-and-answer session where analysts and investors ask questions. The question-and-answer session usually starts with 'Question and Answer' in one line with no other words in that line.*

"role": "user", "content": *I will give you a text of conference call transcript. Describe the sentiment of the text on a scale of -10 to 10. Here, -10 means most negative and 10 means most positive and 0 means neutral.*

"role": "assistant", "content": *Sure. Please give me the text of conference call transcript you want me to analyze.*

"role": "user", "content": *{transcript text}*.

Our approach mimics the likely information-processing behavior of retail investors and the broad information intermediaries that help these investors access and comprehend complex financial disclosures, such as those provided by fintech builders, independent media, and other social-media commentators. These users are likely to have limited technological proficiency and financial or accounting knowledge. For such users, the most straightforward means of interpreting earnings conference calls is to input the transcript into a chat box powered by GPT-3.5 or later models. The model's output of sentiment-based information is easily comprehensible to anyone who understands natural human language. This significantly reduces the informational processing barrier for these general public users. In contrast, employing machine learning or large language models for sentiment generation or embedding typically requires significant investments in technology infrastructure. Furthermore, it necessitates specialized technical skills and overcoming cognitive barriers that are often beyond the capabilities of ordinary users. Consequently, we contend that the technical feasibility of this generative AI-based "distillation layer" sets it apart from other advanced technologies. It has the potential to democratize access to institutional-grade insights while significantly reducing financial, cognitive, or technical barriers.

1.3 Retail Trading

Retail trading data are obtained from the TAQ database for the period from 2020 through 2025Q1 to ensure a sufficient amount of data for computing the dependent variable of abnormal retail holding.[9] As outlined by Boehmer et al. (2021), the Regulation National Market System (Reg NMS) mandates

[9] 2020 data are used only to initialize the baseline for abnormal retail holding in 2021 and are not included in the regression. 2025Q1 data are required only to compute forward-moving retail measures for late-2024 observations. We use the same period for retrieving the short selling.

that a broker/dealer must provide a minimal price improvement over the National Best Bid or Offer (NBBO) for retail orders. We utilize this price improvement criterion to distinguish marketable orders placed by retail investors from those by institutional investors. Specifically, a transaction is classified as a retail purchase if its sub-penny price lies between 60 and 100 basis points, and as a retail sale if the sub-penny price is between 0 and 40 basis points. We employ a detrended, abnormal retail holding measure to proxy for the level of retail demand rather than the changes in demand, in line with the noise trader models that relate the level of demand to noise trader sentiment (e.g., De Long et al., 1990; Shleifer and Vishny, 1997). Specifically, following the spirit of Chen et al. (2019), the abnormal retail holding measure is defined as the holding detrended by its one-year (252 trading days) average, scaled by shares outstanding (see Appendix B). We standardize this abnormal retail holding measure (demeaned and with unit standard deviation) over the horizon it is measured for comparability across horizons and with short selling. Additionally, we winsorize the measure by year-quarter at the 1% and 99% percentiles in all the regressions to mitigate the impact of extreme values.

1.4 Short Selling

To develop a direct measure of short selling activity, we utilize short sale volume data from Financial Industry Regulatory Authority, Inc. (FINRA), a self-regulatory organization that provides security-level aggregate short-sale volume data on a daily basis.[10] The reliability of FINRA short volume data is supported by prior research (Blocher et al., 2021; Wang et al., 2020). Similar to retail trading, we construct a detrended abnormal short-seller holding measure, defined as the holding detrended by its one-year (252 trading days) average, scaled by shares outstanding (see Appendix B). We standardize this abnormal short-seller holding measure (demeaned and with unit standard deviation) over the horizon it is measured for comparability across horizons and with retail trading and winsorize by year-quarter at the 1% and 99% percentiles in all the regressions to mitigate the impact of extreme values.

[10] See https://www.finra.org/finra-data/browse-catalog/short-sale-volume-data and https://www.finra.org/finra-data/browse-catalog/short-sale-volume-data/monthly-short-sale-volume-files.

1.5 Bid–Ask Spread

We measure bid–ask spread using the following formula:

$$BidAskSpread_{i,d} = \frac{Ask_{i,d} - Bid_{i,d}}{(Ask_{i,d} + Bid_{i,d})/2}$$

The bid–ask spread, which is the difference between the ask price and the bid price, scaled by the midpoint of the bid and ask prices for stock i on day d. Bid and ask price data are obtained from CRSP. For intraday short-window analyses, we compute the bid–ask spread at each quote update and take the time-series average within the specified interval (e.g., *[EA, Call Start]* or *[Call Start, Close]*). We winsorize stock-level bid–ask spread within each year-quarter at the 1% and 99% percentiles to mitigate the impact of extreme values. In all the regressions, we multiply $BidAskSpread$ by 100 to ease interpretation.

1.6 Other Measures

We include the following control variables: $Beta$ represents the market beta relative to the CRSP equal-weighted return index, estimated over the past three years before the end of month t-1. BM is the ratio of book value of equity to market value of equity. MVE denotes the total market value of common equity. Momentum ($Mom12m$) is defined as the cumulative return from month t-12 to t-2. Standardized unexpected earnings (SUE) is derived based on a random walk model, specifically as the year-over-year difference in earnings per share (EPS), adjusted for the quarter-end price. We provide all variable definitions in Appendix A.

1.7 Summary Statistics

Table 1 presents summary statistics for the variables used in the empirical tests. We report summary statistics for 2021–2024. For years prior to 2024, AI-sentiment is computed using the GPT-3.5-Turbo-16k model. For 2024, we employ the GPT-4o Mini model, as GPT-3.5-Turbo-16k was discontinued by OpenAI in June 2024 and was no longer publicly accessible thereafter. AI-sentiment has a median of 0.060 and a standard deviation of 0.270 during 2021–2024. Bid–ask spread has a mean (median) of 34.5 (10.1) basis points and a standard deviation of 70.2 basis points, which are consistent with the values reported in Cheng et al. (2025).

2 Retail Trading, Short Selling, and AI

We contrast the daily trading behaviors between retail investors and short sellers around earnings calls to explore whether the information on the earnings call uncovered by AI-sentiment affects the trading dynamics of the two groups of investors. Specifically, we analyze the changes in the alignment of retail trading and short selling with the AI signal surrounding the wide deployment of ChatGPT. There are two interpretations of trading alignment with the AI signal. In a narrow sense, it gauges the extent to which investors base their trading on the specific AI signal. In a broader sense, it serves as a proxy for investors' overall reliance on AI. We do not take a definitive stance on either interpretation, as both are consistent with our predictions.

ChatGPT, released on 30 November 2022, experienced rapid growth, reaching 100 million active monthly users by January 2023.[11] This surge signals a greater public engagement with ChatGPT and its transition to widespread use. Thus, we designate January 1, 2023, as the date when ChatGPT's deployment became widespread. We define pre- (post-) democratization period as 2021–2022 (2023–2024). $After$ is a dummy variable that equals 1 for post-democratization period, and 0 for pre-democratization period.

Table 2 reports how retail trades (Panel A) and short sales (Panel B) align with the AI signal before and after the widespread deployment of ChatGPT. $RetailTrading$ ($ShortSelling$) is a detrended abnormal retail holding (short-seller holding) measure constructed in Section 1.3 (1.4). As discussed earlier, both $RetailTrading$ and $ShortSelling$ are standardized to have zero mean and a unit standard deviation.

In Table 2, Panel A (Panel B), we regress $RetailTrading$ ($ShortSelling$) on $AI\text{-}sentiment$ and $AI\text{-}sentiment \times After$. We examine retail trading (short selling) on the earnings call event-day and its average within 10 and 21 trading days after earnings calls.[12] Examining the relatively shorter windows within 21 trading days allows us to focus on investor responses that can leverage AI-driven investment insights. This approach helps minimize the influence of long-term factors. We control for other anomaly variables to rule out the possibility that traders simply trade on those public return-predictive signals. We include year-quarter fixed effects and cluster standard

[11]See https://www.reuters.com/technology/chatgpt-sets-record-fastest-growing-user-base-analyst-note-2023-02-01/.

[12]If an earnings call occurs after market closes (i.e., after 4 p.m.), we designate the next trading day as the event day (d) instead of the current calendar day.

errors by firm and year-quarter. Our variable of interest is *AI-sentiment* $\times$ $After$, which captures the changes in retail-AI alignment (short-seller-AI alignment) after AI deployment. A significantly positive (negative) coefficient for *AI-sentiment* $\times$ $After$ implies an increase in retail investors' (short sellers') alignment with *AI-sentiment* after AI deployment.

In Table 2, Panel A, we find negative coefficients for *AI-sentiment* in columns (1)–(3), but none is statistically significant. The evidence suggests that retail traders do not respond to AI-sentiment before AI deployment. This is consistent with retail investors having no access to sophisticated technologies that deliver AI-like insights before AI deployment. The positive and significant coefficients for *AI-sentiment* $\times$ $After$ suggest retail trading exhibits a significantly heightened reaction to AI-sentiment in the post-deployment period. In columns (1)–(3), the coefficients on *AI-sentiment* $\times$ $After$ range from 0.239 to 0.257. This indicates that a full-decile increase in *AI-sentiment* after AI deployment corresponds to up to a 25.7% standard deviation increase in retail trading on the earnings call day and over the subsequent month. This estimate is both highly statistically significant and economically substantial. Notably, these changes in retail response to AI-sentiment are not only large compared to their pre-deployment levels but also represent a directional shift. Retail traders transitioned from trading without alignment with AI-sentiment in 2021–2022 to trading in alignment with AI-sentiment in 2023–2024. Furthermore, the positive and significant total coefficients on *AI-sentiment* and *AI-sentiment* $\times$ $After$, ranging from 0.169 to 0.174, indicate that after AI deployment, retail trading experiences up to a 17.4% standard deviation increase with a full-decile shift in *AI-sentiment*. This paradigm shift suggests that AI deployment materially improves retail investors' trading accuracy.

In contrast, in Table 2, Panel B, the significantly negative coefficients for the *AI-sentiment* suggest that the short sellers' trading is strongly aligned with the AI signal in the pre-deployment period. This result is consistent with the findings of Blau et al. (2015), which indicate that short sellers possess superior information processing capacities for textual information from conference calls compared to average investors. A full-decile increase in AI-sentiment corresponds to up to 26.8% standard deviation decrease in short selling. The substantial short-seller-AI alignment suggests short sellers, as archetypal informed arbitrageurs with privileged access to technology and information, may already have proprietary AI/ML models or alternative information for earnings call analysis well before AI deployment. The positive but insignificant coefficients for *AI-sentiment* $\times$ $After$

indicate that short sellers do not significantly change their alignment with AI-sentiment after AI deployment. The sum of the coefficients on *AI-sentiment* and *AI-sentiment* $\times$ $After$ remains negative and significant, but with a smaller magnitude (ranging from -0.115 to -0.103) than the coefficients on *AI-sentiment* (ranging from -0.268 to -0.245), suggesting that short sellers' alignment with the AI signal does not increase and instead drifts slightly lower in a statistically insignificant manner. These findings align with Grossman and Stiglitz's (1980) prediction that, as a greater number of investors become informed, short sellers' motivation to seek out and trade on that information declines due to their high funding costs.[13]

To visually illustrate the dynamic evolution of AI alignment for retail investors and short sellers, we plot retail-AI alignment relative to short-seller-AI alignment over time, which is based on the difference-in-differences (DiD) framework discussed in Section 9.3 and detailed in Internet Appendix Table IA.3. In the DiD analysis, we stack the retail investor-stock and short seller-stock samples to more directly compare the retail-short gap pre- and post-deployment. Specifically, we repeat this DiD analysis for each half-year period between 2021 and 2024. In the regression model (3), we replace $After$ with a series of half-year dummy variables starting from 2021HY2 to 2024HY2, using the first half of 2021 (2021HY1) as the reference period. This approach allows us to benchmark the coefficients of each subsequent half-year against 2021HY1. In Figure 1, the AI alignment of retail investors relative to short sellers remains stable during 2021–2022, but shows a significant increase from 2023 onward, coinciding with the deployment of AI. These results help rule out the possibility of pre-existing trends before AI deployment and suggest a robust increase in retail-AI alignment caused by AI deployment shocks.

Overall, the findings suggest that the rollout of AI enables retail investors, who were unable to engage with AI strategies before AI deployment, to align their trading decisions correctly and more closely with the actionable insights extracted by AI from earnings calls. In effect, retail investors transition from noise to informed traders of AI-derived information. In contrast, short sellers' alignment with AI does not increase and instead drifts slightly lower, albeit insignificantly. Consequently, the gap in AI alignment between retail trading and short selling substantially shrinks post-deployment.

[13] Short volume remained relatively stable between 2021 and 2024, suggesting that lower shorting activity in 2023-2024 is unlikely to have influenced our findings.

3 AI and Short-Window Trading

To more precisely distinguish trading related to earnings calls from other intraday events, such as earnings releases, and to isolate the impact of AI-generated sentiment on trading, we refine the analysis in Section 2 by examining trading over shorter intraday intervals.

We partition each trading day into two intervals: *[EA, Call Start]*, from the earnings release to the start of the call, and *[Call Start, Close]*, from the start of the call to market close. We first calculate short-window detrended abnormal retail holding (short-seller holding) for the two intervals separately. Earnings calls likely dominate other information impacting asset prices within this brief *[Call Start, Close]* period. Since interval lengths vary across firms, particularly when earnings calls take place outside regular trading hours, we scale trading in each interval by its duration (in hours) to ensure comparability. This refinement enables more precise identification of trading responses to distinct informational events. Finally, we standardize short-window trading to have zero mean and a unit standard deviation.

Table 3 presents how retail trading (Panel A) and short selling (Panel B) align with AI-sentiment within short intraday windows on earnings call event day. In Table 3, Panel A, column (1) reports the results for the *[EA, Call Start]* window. The insignificant coefficient on *AI-sentiment* indicates that retail trading between the earnings release and the call start is not aligned with AI-sentiment. This suggests that the AI signal captures information unique to the call, beyond that conveyed in the earnings release. Column (2) reports results for the *[Call Start, Close]* window. Prior to AI deployment, retail trading is negatively aligned with AI-sentiment, consistent with retail investors' limited access to or misinterpretation of earnings calls. Post-deployment, AI alignment strengthens significantly. The coefficient on $AI\text{-}sentiment \times After$ is both statistically and economically significant, in a similar magnitude to that reported in Table 2, Panel A: a full-decile increase in the AI signal corresponds to a 27.6% standard deviation increase in retail trading during the post-call intraday window. Moreover, the sum of the coefficients on *AI-sentiment* and $AI\text{-}sentiment \times After$ is positive and significant, with a magnitude of 13.0%. This implies that retail trading is significantly aligned with AI-sentiment in the post-call intraday window in the post-deployment period.

In Table 3, Panel B, column (1), the trading of short sellers before the earnings call is not aligned with AI-sentiment before AI deployment. This evidence is consistent with the notion that short sellers are superior information processors, rather than merely anticipating news (Engelberg et al., 2012; Wang et al., 2020; Blau et al., 2015). In column (2), the negative and significant coefficient on *AI-sentiment* suggests strong short-seller-AI alignment within post-call intraday window before the deployment of AI (coefficient=-0.183). After AI deployment, short sellers show no significant increase in alignment with AI-sentiment. Instead, we observe a weaker and smaller short-seller-AI alignment during post-call intraday window in the post-deployment period (coefficient=-0.183+0.090=-0.093).

The short-window analysis provides compelling evidence that retail investors begin to incorporate AI-based sentiment information about the earnings call more effectively following AI deployment. The narrow window minimizes confounding from earnings release and other post-earnings developments, strengthening the interpretation that improved access to AI-generated information is the primary driver for our findings.

4 Heterogeneity in Retail Response to AI

Technological innovations typically do not impact users uniformly. We explore cross-sectional heterogeneity in the effect of AI on retail investors' trading. Prior research suggests that information processing costs hinder retail investors from trading profitably (Chau, 2025). If AI indeed excels at processing complex information, we expect the effect of AI on retail trading to vary with information processing costs. We employ two firm-level proxies for information processing costs—operating uncertainty and information environment quality.

We gauge operating uncertainty using earnings volatility and idiosyncratic return volatility, and capture information environment quality by analyst dispersion. We sort these characteristics into quartiles and define a binary variable, $HardToProcess$, equal to one for firms in the top quartile and zero for those in the bottom quartile.

Table 4 presents the results. Panel A shows that retail-AI alignment increases more following AI deployment for stocks with higher earnings volatility, idiosyncratic volatility, and analyst dispersion. The estimates are statistically significant and economically meaningful. For example, a full-decile increase in *AI-sentiment* post-deployment is associated with a 46.5% standard deviation increase in retail trading on earnings call day for firms in the top quartile of earnings volatility relative to those in the bottom quartile. Our evidence indicates that retail investors are more likely to trade in line with the AI signal when they are more likely to have higher information processing costs.

5 AI and Information Asymmetry

As retail investors increasingly align their trading decisions with AI insights, a natural question arises: does this reduce their information gap relative to informed market participants such as short sellers? On the one hand, a narrowing of this gap could alleviate adverse selection, thereby encouraging trading activity and enhancing liquidity (Glosten and Milgrom, 1985; Kyle, 1985). On the other hand, this may not occur if short sellers also adopt AI to extract superior or alternative signals, potentially maintaining or even widening the information gap and undermining liquidity. As AI introduction affects the entire capital market, we follow Edmans et al. (2013) and examine the question by exploiting cross-sectional heterogeneity in retail investors' trading based on AI signals. We compare liquidity changes between stocks where retail investors show a greater increase in retail-AI alignment (high alignment group) and those with lower alignment (low alignment group). The latter group serves as the benchmark for evaluating the change in liquidity for the former. This approach helps mitigate the concern of confounding events, as both high and low alignment stocks are exposed to the same external factors. Consequently, we can attribute our findings to AI deployment rather than to confounding events, unless those events differentially impact the two groups.

We define high and low alignment groups based on the change in retail-AI alignment following AI deployment. For each stock, we estimate the same regression model as that reported in Table 2, Panel A on earnings call day. We extract the coefficient estimate on the interaction term $\textit{AI-sentiment} \times After$, which captures the stock-specific change in retail investors' alignment with AI-sentiment. A higher coefficient reflects a greater increase in AI-informed retail trading after the introduction of AI. We classify stocks into high and low alignment groups based on the median value of the coefficient. Stocks with an above-median retail-AI alignment coefficient form the high alignment group, where $Treat^{AI}$ equals 1, while those below the median form the low alignment group, where $Treat^{AI}$ equals 0.[14] In addition, we apply propensity score matching (PSM) to balance observable characteristics between high and low alignment groups. This approach addresses the concerns regarding the functional form of control variables when testing the change in the information gap between retail investors and short sellers.[15]

We measure information asymmetry using the bid–ask spread. To assess the impact of AI deployment, we implement a difference-in-differences (DiD) framework by estimating the following regression:

$$BidAskSpread_{i,horizon} = \beta_0 + \beta_1 Treat_i^{AI} + \beta_2 Treat_i^{AI} \times After_d + \delta X_{i,d} + \alpha_d + \varepsilon_{i,d} \qquad (1)$$

The dependent variable, $BidAskSpread_{i,horizon}$, is the average bid–ask spread of stock i measured across both short- and long-horizon windows. For the short-window analysis, we follow the intraday design used in Section 3 and compute bid–ask spreads for two intervals: *[EA, Call Start]*, from the earnings release to the start of the call, and *[Call Start, Close]*, from the start of the call to market close.[16] For the long-window analysis, we calculate average daily bid–ask spreads over the 10-day and 21-day windows following the earnings call.

The variable $After$ is a post-treatment indicator that equals one for the period following AI deployment and zero otherwise. The coefficient on $Treat^{AI} \times After$ captures the differential change in bid–ask spread for high versus low alignment stocks following the introduction of AI. X represents control variables, which include $Beta$, book-to-market ratio (BM), firm size, and momentum. We also control for the absolute value of SUE so that any changes in bid–ask spreads are not simply driven by the magnitude of the earnings surprise.

Table 5 presents the results. In column (1), we find a slight, statistically insignificant increase in bid–ask spreads during the *[EA, Call Start]* interval. In contrast, column (2) shows a significant

[14] In untabulated results, we find that stocks in the high alignment group exhibit higher earnings volatility, idiosyncratic volatility, and analyst earnings forecast dispersion (both before the AI deployment and over the full sample) compared to stocks in the low alignment group. This evidence suggests that retail investors, who have higher information processing costs, tend to align their trading with AI insights.

[15] High and low alignment groups are matched based on the estimated propensity scores using 1-to-1 nearest-neighbor matching without replacement and a caliper of 0.10 on the propensity-score distance. High alignment observations without a suitable low alignment match within the caliper are excluded. Balance tests reported in Internet Appendix Table IA.4 confirm that observable characteristics are well matched between high and low alignment groups.

[16] We obtain qualitatively similar results when we calculate spreads using share-weighted, market-cap-weighted, or time-weighted schemes.

decrease in spreads during the *[Call Start, Close]* interval, suggesting that the liquidity improvement is driven by information conveyed during the earnings call rather than by the initial earnings announcement. The reductions are also statistically significant at longer horizons. Columns (3) and (4) document a decline in spreads over the 10- and 21-day windows following the call, consistent with a persistent decrease in information asymmetry for high alignment stocks.

The economic magnitudes are also meaningful: for instance, bid–ask spreads for high alignment stocks during the *[Call Start, Close]* interval declines by 6.5 basis points post-AI deployment, representing 12% of the sample mean. In addition, the coefficients on $Treat^{AI}$ are statistically insignificant across specifications, indicating no systematic differences in information asymmetry between high and low alignment groups prior to AI deployment.

Taken together, the intraday short-window and long-window analyses consistently show that stocks with high-AI alignment exhibit improved liquidity. The intraday results help isolate the timing and source of this improvement, pointing to the earnings call as the key informational event. These findings suggest that AI deployment narrows the information gap between retail investors and short sellers, and that short sellers do not appear to leverage AI more efficiently than retail investors.

6 AI and Trading Profitability

This section addresses whether reduced information asymmetry between retail investors and short sellers due to AI deployment is reflected in trading profitability. If AI deployment enhances retail investors' trading decisions, we expect an improvement in their trading profitability, particularly for stocks that experience a significant increase in retail-AI alignment, following the implementation of AI. At the same time, we expect a decline in trading profitability for short sellers, as their informational advantage diminishes. We measure trading profitability by the predictability of investor trading for future returns for three horizons, extending up to 126 days following earnings calls, as detailed in Appendix C, which shows that AI-sentiment predicts future returns over this period. Higher predictability implies greater profitability.

Table 6 reports the return prediction of retail trading (Panel A) and short selling (Panel B) surrounding AI deployment. $RetailTrading$ ($ShortSelling$) is a detrended abnormal retail holding (short-seller holding) measure as defined in Section 1.3 (1.4). Both $RetailTrading$ and $ShortSelling$ are standardized to have zero mean and a unit standard deviation. We use $RetailTrading$ ($ShortSelling$) to predict future returns, similar to Gomez et al. (2024). CAR is the cumulative abnormal returns calculated following the DGTW method (Daniel et al., 1997), which adjusts for size, book-to-market ratio, and momentum characteristics. We examine $RetailTrading$ ($ShortSelling$) on earnings call day d and CAR over 10-, 21-, and 126-day windows following earnings calls. We time CAR by 100 to ease interpretation. We analyze the high-AI alignment and low-AI alignment subsamples separately to avoid the complexity of a four-way interaction that would arise from including a $Treat^{AI}$ interaction.

Table 6, Panel A, columns (1)–(3) report results for the high-AI alignment subsample. The coefficients on $RetailTrading$ are negative and statistically significant, indicating that prior to AI deployment, retail investors' trading on the earnings call day is uninformative and leads to significant subsequent losses. Conversely, the coefficients on $RetailTrading \times After$ turn positive and statistically significant across all three horizons. For example, in column (3), a one-standard-deviation increase in retail trading on the earnings call day after AI deployment is associated with a 6.056% higher return over the 126-day horizon, compared to the period before AI deployment. These findings suggest that AI has substantially improved retail investors' trading profitability.

In Panel B, columns (1)–(3), we turn to short sellers in the high-AI alignment subsample. The coefficients on $ShortSelling$ are negative and significant, suggesting that short selling on earnings call day generates significant trading gains before AI deployment, consistent with the strong short-seller-AI alignment in the pre-deployment period documented in Table 2, Panel B. These results suggest that short sellers are informed traders on call days, which is consistent with the findings of Blau et al. (2015), and their informativeness is related to the AI signal. However, the coefficients on $ShortSelling \times After$ are positive and particularly significant over the 126-day window. This decline in short sellers' profitability implies that the informational edge of short sellers may have weakened once retail investors begin to trade more effectively on AI signals.

For the low-AI alignment subsample, neither retail investors nor short sellers exhibit meaningful changes in trading performance. Retail trading remains uninformative both before and after AI deployment, and short selling yields gains in the pre-deployment period. Notably, short-sale gains in the low-AI alignment group seem to be smaller than that in the high-AI alignment group.

These findings suggest that in low alignment stocks, typically easier to value due to lower information processing costs, AI signals play a limited impact. Consequently, there is little information advantage for both retail investors and short sellers in these stocks.

Overall, these findings show that retail investors' trading performance improves, while short sellers' performance weakens, in high alignment stocks following AI deployment. This pattern is consistent with retail investors adopting AI-generated signals to enhance their decisions. In contrast, the trading results remain largely unchanged in low alignment stocks, where AI signals appear less valuable. Taken together, our evidence suggests that AI may help reduce the trading inequality between retail investors and short sellers, once retail investors start trading on AI-generated information.

7 AI and Market Participation of Retail Investors

Next, we examine whether retail investors increase or decrease their participation in the stock market after the implementation of AI. We measure stock market participation based on retail investors' trading intensity. As discussed in the Introduction, on the one hand, retail investors might increase their trading intensity due to reduced adverse selection. On the other hand, they might decrease their trading intensity if AI signals reduce overconfidence-induced excessive trading.

To assess the changes in retail stock market participation post-AI deployment, we estimate the following regression:

$$RetailTradingIntensity_{i,d+T} = \beta_0 + \beta_1 Treat_i^{AI} + \beta_2 Treat_i^{AI} \times After_d + \delta X_{i,d} + \alpha_d + \varepsilon_{i,d} \quad (2)$$

where $RetailTradingIntensity_{i,d+T}$ is a non-directional trading intensity measure calculated using the sum of the number of retail buy trades and retail sell trades, scaled by its one-year average (demeaned and with unit standard deviation). $Treat^{AI}$ is defined as in Section 5. We control for the absolute value of SUE to capture the magnitude rather than the direction of earnings surprises. Since trading intensity captures unsigned trading rather than trading direction, this ensures that the regression accounts for the intensity of information shocks, regardless of whether they are positive or negative, as these plausibly drive retail trading activity. Other controls include beta, book-to-market ratio, firm size, and momentum.

Table 7 presents the results. The insignificant coefficients on $Treat^{AI}$ suggest no significant difference in the pre-deployment period in retail participation between high and low alignment stocks. By contrast, the coefficients on $Treat^{AI} \times After$ are positive, although marginally significant, suggesting retail investors slightly increase their trading intensity in stocks with high retail-AI alignment post-AI deployment relative to low alignment stocks.

Taken together, our evidence suggests retail investors are more inclined to participate in the stock market after AI deployment, particularly in high-AI alignment stocks. This evidence is consistent with the reduced information asymmetry between retail investors and short sellers.

8 Additional Analysis: Return Prediction of AI-Sentiment

Despite the fact that sentiment has been shown to be a first-order textual information that captures hard-to-quantify fundamental information (e.g.,Tetlock, 2007; Loughran and McDonald, 2011; Tetlock et al., 2008, one might still wonder whether AI-generated sentiment itself contains fundamental information relevant for asset prices. To address this, we examine its return predictability before and after the deployment of AI. Appendix C presents the results for the 2021–2022 sample period (before AI introduction) and for the 2023–2024 sample period (after AI introduction). In both subsample periods, AI-sentiment significantly predicts future returns. A one-standard-deviation increase in *AI-sentiment* is associated with a 1.290% increase in 10-day returns in the pre-AI period, and a 1.622% increase in the post-AI period. Furthermore, AI-sentiment consistently predicts stock returns up to 21 days post-call with statistical significance at the 1% level in both periods, and there is no return reversal observed up to 126 days post-call in post-AI period.

These findings support that AI-sentiment carries information about future stock performance, rather than merely noise or bias, both before and after AI deployment.

9 Robustness Checks

To further assess the validity of our findings, we conduct a series of robustness checks that address alternative measurement choices, potential model inconsistencies, and other confounding factors. Specifically, we first replicate our findings using the alternative retail trading measure proposed by Barber et al. (2024). Second, we restrict the sample to 2022–2023 to alleviate concerns related to model inconsistency and potential look-ahead biases. Third, we employ difference-in-differences (DiD) frameworks to more directly examine the gap between retail trading and short selling, focusing on both trading activity and trading profitability. Fourth, we examine whether our findings could be confounded by contemporaneous market events by exploiting unexpected ChatGPT outages as exogenous shocks to AI access. Finally, we assess whether our AI-sentiment measure inadvertently captures firm fundamentals by explicitly controlling for accounting profitability (ROA and ROE).

9.1 Alternative Retail Measure (Barber et al., 2024)

A recent study by Barber et al. (2024) introduces an alternative measure of retail trading using the quoted spread midpoints to sign the trades. While our main analyses rely on the measure of Boehmer et al. (2021), recent evidence by Battalio et al. (2023) suggests that the incremental benefits of Barber et al. (2024)'s measure may depend on sample representativeness. In particular, Battalio et al. (2023) find that the trade classification approach proposed by Barber et al. (2024) does not yield clear advantages when applied to more representative retail samples, which is also the case in our setting. Nonetheless, to ensure robustness, we replicate all main analyses using Barber et al. (2024)'s measure.

First, we revisit the retail trading alignment tests (see Internet Appendix Table IA.1, Panel A and B). Our main results show that retail investors increase their trading alignment with AI-sentiment after AI deployment, both in short intraday windows and across longer horizons. Using Barber et al. (2024)'s measure, we obtain qualitatively identical results: retail trading exhibits a stronger response to AI-sentiment in the post-deployment period, indicating that retail investors increasingly trade on AI-generated signals.

Second, we replicate the analysis on heterogeneity in retail response to AI (see Internet Appendix Table IA.1, Panel C and D) and the results still hold.

Third, we replicate the bid–ask spread analysis (see Internet Appendix Table IA.1, Panel E). In the main results, we find that high alignment stocks experience a relative decline in spreads following AI deployment, consistent with reduced information asymmetry. These findings remain robust when high and low alignment stocks are defined using Barber et al. (2024)'s measure.

Last, we revisit the trading profitability test (see Internet Appendix Table IA.1, Panel F). Using Barber et al. (2024)'s measure, we continue to find that the predictive power of retail trading increases post-deployment for high alignment stocks, corroborating the main results that AI improves retail trading outcomes.

Taken together, our conclusions are insensitive to the choice of retail trading measure.

9.2 Restricted Sample: 2022–2023

A potential concern with our main analysis is that the construction of AI-sentiment relies on two different large language models across the sample period. Specifically, GPT-3.5-Turbo-16k was available from January 2021 through June 2024; thereafter, OpenAI discontinued it and replaced it with GPT-4o Mini. While we have shown that sentiment measures from the two models are highly correlated, readers may still be concerned that model heterogeneity introduces measurement inconsistency. Moreover, including data from 2021 raises the possibility of look-ahead bias, since GPT-3.5-Turbo-16k incorporates knowledge up to September 2021. To address these concerns, we re-estimate our main analyses using the 2022–2023 subsample, which is entirely covered by GPT-3.5-Turbo-16k and therefore avoids both look-ahead bias and mixed-model usage. Detailed results are reported in Internet Appendix Table IA.2.

Our main results on trading alignment with AI-sentiment remain unchanged. In both the long-window and the short-window analyses, retail investors' trading becomes more strongly aligned with AI-sentiment following the arrival of AI, whereas short sellers' alignment remains largely unchanged across most horizons. The statistical significance and economic magnitudes are very similar to those using 2021–2024 sample period.

In sum, the 2022–2023 subsample yields results that are both directionally and statistically consistent with our main analyses of trading-AI alignment. These robustness checks confirm that our conclusions are not driven by the use of different models in constructing AI-sentiment, and reinforce the validity of our main inferences.

9.3 AI and Trading: Difference-in-Differences

In Section 2, we examine retail trading and short selling separately. One potential concern is whether the AI deployment effect impacts these two groups of traders differently across various stocks. To mitigate firm- and trader-related endogeneity concerns and more directly compare the retail-short gap pre- and post-deployment, we develop a difference-in-differences (DiD) framework. Specifically, we employ the following regression:

$$\begin{aligned} &StandardizedTrading_{i,g,d+T} \\ &\quad = \beta_0 + \beta_1\, AI\text{-}sentiment_{i,d} + \beta_2\,(AI\text{-}sentiment_{i,d} \times Treat_g^{IsRetail}) + \beta_3\,(AI\text{-}sentiment_{i,d} \times After_d) \\ &\quad + \beta_4\,(Treat_g^{IsRetail} \times After_d) + \beta_5\,(AI\text{-}sentiment_{i,d} \times Treat_g^{IsRetail} \times After_d) + \delta\, X_{i,d} + \alpha_{i,d} + \gamma_g + \epsilon_{i,g,d} \end{aligned} \tag{3}$$

where the dependent variable is the standardized trading of trader g on stock i in the T trading days following earnings call day d. We categorize retail investors as the treatment group. We stack the retail investor-stock and short seller-stock samples to form a unified dataset. Since each firm holds earnings calls on a quarterly basis, our unit of observation is at the stock-trader-quarter level. This includes both retail trading (treatment group) and short selling (control group) for each stock in each quarter.

To ensure comparability between retail trading and short selling, we first invert the sign of $ShortSelling$ so that a positive correlation between $ShortSelling$ and AI-sentiment reflects that short selling is aligned with AI-sentiment. We then separately standardize $ShortSelling$ and $RetailTrading$ with zero mean and a unit standard deviation, and stack them into a unified dependent variable $StandardizedTrading$. $Treat^{IsRetail}$ is a dummy variable that equals 1 if the trading variable for a stock in a given quarter is retail trading and 0 if it is short selling. $X_{i,d}$ is the vector of control variables including $Beta$, BM, MVE, $Mom12m$, and SUE.

As shown in Internet Appendix Table IA.3, Panel A, retail trading increases by 35.1%-37.0% standard deviations more than short selling in alignment with a full-decile increase in AI-sentiment after AI deployment. Furthermore, despite much less retail-AI alignment compared to that of short sellers in the pre-deployment period (negative and significant coefficients on $AI\text{-}sentiment \times Treat^{IsRetail}$), retail-AI alignment is not significantly different from short-seller-AI alignment in the post-deployment period (insignificant coefficients on $AI\text{-}sentiment \times Treat^{IsRetail} + AI\text{-}sentiment \times Treat^{IsRetail} \times After$).

Similarly, we stack the short-window retail trading and short selling and estimate a DiD regression as in Equation (3). In Table IA.3, Panel B, retail-AI alignment within post-call intraday window significantly increases relative to that of short sellers after AI deployment. Consequently, the post-deployment gap in AI alignment between retail investors and short sellers narrows.

These findings confirm a robust shift in retail trading behaviors towards greater alignment with AI insights than short selling post-deployment, suggesting that AI deployment bridges the information gap between privileged short sellers and general retail investors.

9.4 AI and Trading Profitability: Difference-in-Differences

In Section 6, we examine the trading profitability of retail investors and short sellers in stocks exhibiting a significant increase in retail-AI alignment following AI implementation. To quantify the gap in trading profitability between retail investors and short sellers, we further estimate the following regression on high alignment subsample:

$$\begin{aligned} CAR_{i,d+T} = {} & \beta_0 + \beta_1\, StandardizedTrading_{i,g,d} + \beta_2\, Treat_g^{IsRetail} \\ & + \beta_3\,(StandardizedTrading_{i,g,d} \times Treat_g^{IsRetail}) + \beta_4\,(StandardizedTrading_{i,g,d} \times After_d) \\ & + \beta_5\,(Treat_g^{IsRetail} \times After_d) + \beta_6\,(StandardizedTrading_{i,g,d} \times Treat_g^{IsRetail} \times After_d) \\ & + \delta\, X_{i,d} + \alpha_d + \epsilon_{i,g,d} \end{aligned} \tag{4}$$

where $StandardizedTrading_{i,g,d}$ is a unified trading variable constructed by stacking retail trading and short selling, where short selling is sign-inverted and both components are separately standardized to have zero mean and unit variance, as defined in Section 9.3 and Equation (3). $Treat_g^{IsRetail}$ is a dummy variable that equals 1 if the trading variable for a stock in a given quarter is retail trading and 0 if it is short selling. $X_{i,d}$ is the vector of control variables including $Beta$, BM, MVE, $Mom12m$, and SUE. A positive and significant β_6 indicates that retail investors generate greater trading gains relative to short sellers following AI deployment.

In Internet Appendix Table IA.5, column (1)–(3), the coefficients on $StandardizedTrading_{i,g,d}$ are positive and significant, suggesting that short sellers generate significant gains on high alignment stocks pre-AI period, consistent with the results in Table 6, Panel B. The coefficients on $StandardizedTrading \times Treat^{IsRetail}$ capture the pre-deployment profitability gap between retail investors and short sellers. The negative and significant coefficients on $StandardizedTrading \times$

$Treat^{IsRetail}$ suggest that retail investors underperformed short sellers in the pre-AI period. In contrast, the coefficients on $StandardizedTrading \times Treat^{IsRetail} \times After$ are positive and significant, indicating that retail trading on earnings call day after AI deployment is associated with greater post-call returns relative to short sellers.

9.5 AI Access Shocks: Evidence from ChatGPT Outages

To rule out the possibility that confounding events drive our findings, we exploit unexpected ChatGPT outages as exogenous shocks to retail investors' access to AI tools. If confounding events drive our findings, then unexpected outages that temporarily prevented retail investors from accessing AI signals, should not affect the findings. If, instead, retail investors indeed benefit from the timely generated AI information from various sources, then we would expect outage to undo some of the effect of our AI signal on trading and bid–ask spread.

We obtain outage events from OpenAI's Status page, which documents the date, start and end time, and severity (major or partial).[17] We focus on major outages that caused widespread service failures on ChatGPT, with an average (median) downtime of approximately 66 (32) minutes. To ensure that outages are relevant for the trading window of interest, we restrict attention to outages that occur on the same day as the earnings call, with a start or end time after the call. When multiple outages occur on the same day, we sum their durations. We measure outages in two ways: a dummy variable equal to one if an outage occurs and zero otherwise, and the total outage duration in hours. Finally, we define the variable $After\&Outage$ to indicate outage periods in the post-deployment context, since ChatGPT—and thus relevant outage data for retail users—only became available after AI deployment.

Internet Appendix IA.6 presents the results. We focus on short-window retail trading and bid–ask spread from the start of the call to market close on earning call day, as defined in Section 3 and Section 5. Panel A reports the effect of ChatGPT outages on retail-AI alignment in the short post-call window. Consistent with earlier findings (Table 3, Panel A), the coefficients on $AI\text{-}sentiment \times After$ are positive, indicating that retail trading aligns more closely with AI-sentiment following AI deployment. However, the interaction term $AI\text{-}sentiment \times After\&Outage$ is negative and statistically significant when measured by duration. This result implies that outages

[17] See https://status.openai.com/history.

attenuate the AI effect on retail investors' trading, which rule out the possibility that confounding events explain our findings.

Panel B shows that bid–ask spread declines for high alignment stocks following AI deployment, as indicated by the negative and significant coefficients on $Treat^{AI} \times After$. During outage periods, spread widens: the coefficients on $Treat^{AI} \times After\&Outage$ are positive and marginally significant when outages are measured by a dummy, and remain positive though statistically insignificant when measured by duration. We urge readers to interpret this analysis with caution, as there are only 34 major outages that meet our selection criteria. Consequently, the reliability and power of the tests should be interpreted with caution.

Overall, the outage analyses provide some evidence that confounding events are unlikely to fully drive our findings.

9.6 Additional Controls: Firm Profitability

A potential concern is that our AI-sentiment measure may capture firm fundamentals, such as accounting profitability. To address this, we re-estimate the specifications from Table 2, which examine retail- and short-seller-AI alignment before and after AI deployment, adding controls for return on assets (ROA) and return on equity (ROE), alongside the baseline firm characteristics ($Beta$, BM, MVE, $Mom12m$, and SUE). As shown in Internet Appendix Table IA.7, the results remain robust. Retail trading becomes more aligned with AI-sentiment after the arrival of AI, whereas short sellers' alignment does not significantly change.

10 Conclusion

The past decades have been marked by significant advancements, such as the development of machine-processable information reporting formats and the proliferation of big data. These changes have provided considerable advantages to sophisticated investors who already have the financial knowledge to process and use this information effectively. Consequently, this technological progress has the potential to further exacerbate the already extreme wealth gap in society. The advent of AI deployment, while holding the promise of making advanced analytical tools more accessible to the general public, also has the potential to exponentially exacerbate inequality among traders in the financial market. If the benefits of AI tools are predominantly leveraged by those already well-positioned, this could accelerate the process wherein "the rich get richer" at an unprecedented rate. This study conducts the first analysis of how democratized AI impacts human traders' use of democratized information, particularly contrasting highly informed investors with ordinary retail investors. By employing ChatGPT, one of the most widespread and advanced AI technologies, we analyze earnings calls and develop an easy-to-construct and value-relevant AI-sentiment measure. In the years before the existence of ChatGPT, we find that short selling is notably aligned with AI-sentiment in the three weeks following earnings calls, whereas retail trading showed little alignment. Following the widespread deployment of ChatGPT, retail investors' alignment with AI signals has increased substantially relative to the pre-ChatGPT era, even though the alignment of short selling with AI appears to have weakened somewhat. Supporting the causal role of AI, periods of ChatGPT outages, which reduce the ability of retail investors to use AI insights, correspond to a reduction in retail-AI alignment. Additional analysis suggests that when retail investors face higher information processing costs, they tend to show greater alignment. We further examine the implications of AI deployment for information asymmetry, trading profitability, and market participation. Our evidence suggests information asymmetry declines for stocks for which retail investors significantly increased alignment with AI-sentiment, compared to stocks with limited change in alignment following AI deployment. We also observe a significant improvement in trading profitability and greater market participation among retail investors in stocks with a high increase in alignment. In contrast, short sale profitability in these stocks declines. Taken together, our study demonstrates that the information gap between retail investors and short sellers has narrowed, and retail investors have benefited significantly from AI deployment. Therefore, democratizing AI holds promise for promoting equality in financial markets.

We acknowledge that our study centers on the role of AI in processing information, specifically focusing on key informational events such as earnings conference calls, which occur up to four times a year for a given firm. However, AI, as a versatile and general-purpose technology, has the potential to process various other types of information as well. For instance, AI can be utilized to analyze frequently released media articles (Lopez-Lira and Tang, 2023), discussion boards on regulatory websites (Wong et al., 2024), and SEC filings (Kim et al., 2023b). Determining whether our findings can be extended to these additional contexts is an intriguing avenue for future research.

Expanding the scope of AI's application beyond earnings calls could further illuminate its impact on information processing and trading behaviors across diverse sources of financial data. Furthermore, as AI technology continues to evolve, its potential impact on overall financial market efficiency remains an important area to explore.

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Appendix A Variable Definition

Category	Variable	Definition
Time	*After*	*After* is a dummy variable equals one for periods subsequent to January 1, 2023.
Return	*CAR (%)*	Cumulative abnormal returns (*CAR*) are calculated following the DGTW method (Daniel et al., 1997).
Sentiment	*AI-sentiment*	*AI-sentiment* is the sentiment score of earnings call transcripts computed by GPT-3.5-Turbo-16k model for 2021–2023 and GPT-4o Mini model for 2024, demeaned and rescaled by the inter-decile range (the difference between the top and bottom deciles).
Controls	*Beta*	*Beta* is the market beta with respect to the CRSP return index.
	BM	*BM* is the book value of equity over the market value of equity.
	MVE	*MVE* is the natural logarithm of total market value of common equity.
	Mom12m	*Mom12m* is 12-month momentum computed as the cumulative return from month t-12 to t-2.
	SUE	*SUE* is the difference between reported earnings and expected earnings, assuming earnings follow a seasonal random walk trend.
	abs(SUE)	*abs(SUE)* is the absolute value of *SUE*
Trading	*RetailTrading*	*RetailTrading* is the deviation of a stock's retail holding (scaled by shares outstanding) from its one-year average (demeaned and with unit standard deviation).
	RetailTradingIntensity	*RetailTradingIntensity* is the sum of number of retail buy trades and retail sell trades, scaled by its one-year average (demeaned and with unit standard deviation).
	ShortSelling	*ShortSelling* is the deviation of a stock's short-seller holding (scaled by shares outstanding) from its one-year average (demeaned and with unit standard deviation).
	StandardizedTrading	*StandardizedTrading* includes both retail trading and short selling. We invert the sign of *ShortSelling* and separately standardize both *ShortSelling* and *RetailTrading* (demeaned and with unit standard deviation).
BidAskSpread	*BidAskSpread*	*BidAskSpread* is the difference between the daily bid and ask price scaled by the average of bid and ask price. For intraday analyses, we compute the quoted bid–ask spread at each quote update and take the time-series average within the specified interval (e.g., [EA, Call Start] or [Call Start, Close]). In all regressions, we multiply it by 100 to ease interpretation.
Outage	*After&Outage (dummy)*	*After&Outage (dummy)* is a dummy variable that equals one if major ChatGPT outages occur on the same day as an earnings call.
	After&Outage (duration)	*After&Outage (duration)* is a continuous variable representing the duration of major ChatGPT outages (in hours) occurring on the same day as an earnings call. For multiple outages occurred within the day, we sum the total duration.
Treatment	$Treat^{IsRetail}$	$Treat^{IsRetail}$ is a dummy variable that equals one if the trading variable for a stock in a given quarter is retail trading and zero if it is short selling.
	$Treat^{AI}$	$Treat^{AI}$ is a dummy variable that equals one if the stock's retail-AI alignment is above the median (high alignment) and zero otherwise (low alignment). Retail-AI alignment is the coefficients of *AI-sentiment*After*, obtained by running regressions in Table 2 Panel A on a stock-by-stock basis on the earnings call day. The high and low alignment groups are balanced using propensity score matching.

Appendix B Constructing Retail Trading and Short Selling Measures

To construct the abnormal retail holding measure, we first calculate net buying activity by retail investors, denoted as $NB_{i,d}$, by subtracting the volume of sales from the volume of purchases of stock i on day d (scaled by share outstanding). We then employ a detrended, abnormal retail holding measure to proxy for the level of retail demand rather than the changes of demand, in line with the noise trader models that relate the level of demand to noise trader sentiment (e.g., De Long et al., 1990; Shleifer and Vishny, 1997). Specifically, let $RH_{i,d}$ denote the retail holding (scaled by share outstanding) of a stock i on day d, and the abnormal retail holding measure, defined as the holding detrended by its one-year (252 trading days) average can be expressed as follows:

$$
\begin{aligned}
RetailTrading_d &= RH_d - \frac{(RH_{d-1}+RH_{d-2}+\cdots+RH_{d-252})}{252} \\
&= RH_d - RH_{d-1} + \left(\frac{251}{252}RH_{d-1} - \frac{251}{252}RH_{d-2}\right) + \left(\frac{250}{252}RH_{d-2} - \frac{250}{252}RH_{d-3}\right) + \cdots \\
&\quad + \left(\frac{1}{252}RH_{d-251} - \frac{1}{252}RH_{d-252}\right) \\
&= NB_d + \tfrac{251}{252}NB_{d-1} + \tfrac{250}{252}NB_{d-2} + \cdots + \tfrac{1}{252}NB_{d-251} \qquad \text{(A1)}
\end{aligned}
$$

where the last row of the formula provides a method to compute retail holding using retail net buy.

To construct the abnormal short-seller holding measure, we first calculate a short volume measure, denoted as $SV_{i,d}$, which represents the aggregate number of shares of stock i that were reported to be sold short during regular trading hours on day d (scaled by share outstanding). The validity of this measure is supported by prior research (Blocher et al., 2021; Wang et al., 2020). We then construct a detrended abnormal short-seller holding measure, which can be derived from the short volume measure. Specifically, let SH_d denote the short-seller holding (scaled by share outstanding) of a stock i on day d. The abnormal short-seller holding measure, defined as the holding detrended by its one-year (252 trading days) average can be expressed as follows:

$$
\begin{aligned}
ShortSelling_d &= SH_d - \frac{(SH_{d-1}+SH_{d-2}+\cdots+SH_{d-252})}{252} \\
&= SH_d - SH_{d-1} + \left(\frac{251}{252}SH_{d-1} - \frac{251}{252}SH_{d-2}\right) + \left(\frac{250}{252}SH_{d-2} - \frac{250}{252}SH_{d-3}\right) + \cdots \\
&\quad + \left(\frac{1}{252}SH_{d-251} - \frac{1}{252}SH_{d-252}\right) \\
&= SV_d + \tfrac{251}{252}SV_{d-1} + \tfrac{250}{252}SV_{d-2} + \cdots + \tfrac{1}{252}SV_{d-251} \qquad \text{(A2)}
\end{aligned}
$$

where the last row of the formula provides a method to compute short-seller holding using short volume data.

Appendix C AI and Return Prediction

This table presents the return predictability of AI-sentiment before and after AI deployment. Pre-deployment (post-deployment) period is 2021–2022 (2023–2024). *CAR* is cumulative abnormal returns calculated following the DGTW method (Daniel et al., 1997). *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	$CAR_{i,[horizon]}$					
	Pre-Deployment Period			Post-Deployment Period		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d+1 d+10]	[d+1 d+21]	[d+1 d+126]	[d+1 d+10]	[d+1 d+21]	[d+1 d+126]
$AI\text{-}sentiment_{i,d}$	1.290***	2.017***	2.649	1.622***	2.282***	6.720*
	(0.307)	(0.381)	(1.674)	(0.369)	(0.589)	(3.022)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-22	21-22	21-22	23-24	23-24	23-24
N	15374	15373	15354	18753	18751	16247
r2	0.007	0.006	0.010	0.007	0.007	0.011

Figure 1 Time Trend of Retail-AI Alignment

This figure presents retail-AI alignment relative to short sellers based on half-year frequency between 2021 and 2024 where the first half of 2021 is the reference. In regression model (3), we replace *After* with a series of half-year dummy variables starting from 2021HY2 to 2024HY2 and plot the coefficients of each half-year dummy variable.

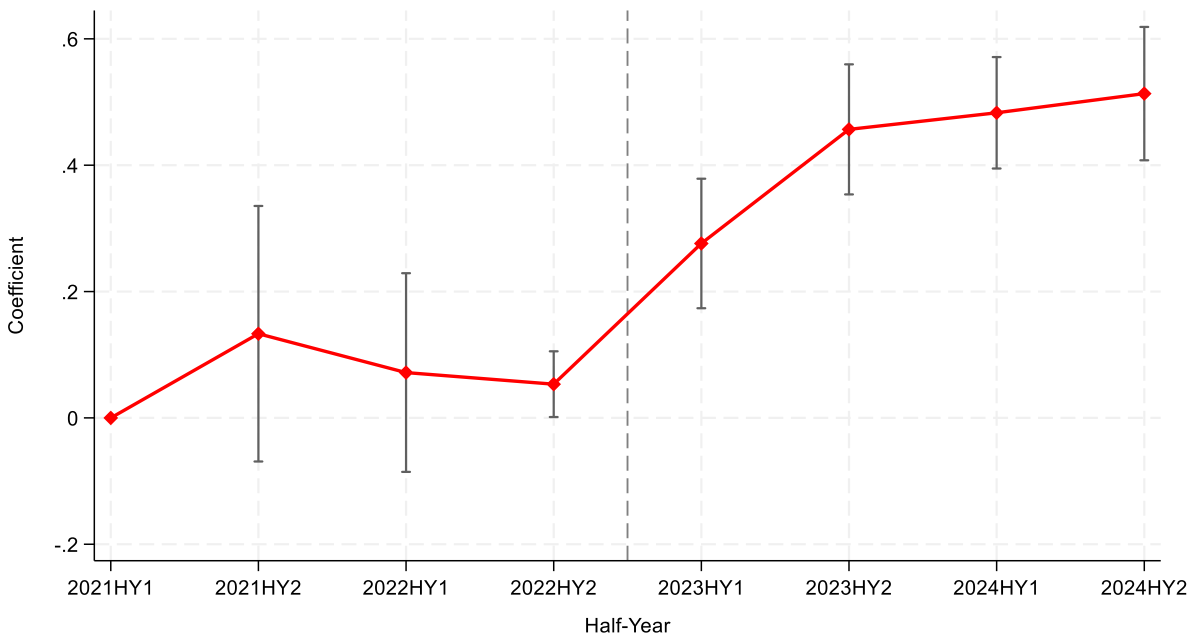


Table 1 Summary Statistics

This table presents summary statistics of variables using 2021–2024. All variables are defined in Appendix A.

Variable	N	Mean	P1	P50	P99	Std Dev
AI-sentiment (demeaned and rescaled)	34130	0.000	-0.910	0.060	0.300	0.270
Return (%)	34130	-0.204	-27.531	-0.176	28.562	10.254
Beta	34130	1.270	0.150	1.190	3.100	0.600
BM	34130	0.500	-0.670	0.390	2.840	0.810
MVE	34130	14.320	9.150	14.420	19.290	2.210
Mom12m	34130	0.200	-0.850	0.060	3.320	1.080
SUE	34130	0.090	-0.400	0.000	0.940	3.770
RetailTrading	34130	0.0001	-0.0322	-0.0005	0.0450	0.0155
RetailTradingIntensity	34130	2.579	0.174	1.904	10.600	2.183
ShortSelling	33130	0.300	0.020	0.140	3.920	0.650
BidAskSpread (time by 100)	29462	0.345	0.003	0.101	3.814	0.702

Table 2 AI and Trading

This table presents how retail-AI alignment and short-seller-AI alignment change around AI deployment. Panel A (B) reports the alignment of retail trading (short selling) with AI-sentiment. The sample period is 2021–2024. *RetailTrading* is abnormal retail holding calculated in Section 1.3. *ShortSelling* is abnormal short-seller holding calculated in Section 1.4. *RetailTrading* and *ShortSelling* are both standardized (demeaned and with unit standard deviation). *After* is a dummy variable equals one for periods subsequent to January 1, 2023. *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Retail Trading

	$RetailTrading_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.085	-0.074	-0.070
	(0.058)	(0.055)	(0.053)
$AI\text{-}sentiment_{i,d}*After_{d}$	0.257***	0.248***	0.239***
	(0.064)	(0.063)	(0.060)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	34130	34129	34128
r2	0.014	0.013	0.013
$AI\text{-}sentiment_{i,d} + AI\text{-}sentiment_{i,d}*After_{d}$	0.172***	0.174***	0.169***
	(0.041)	(0.042)	(0.040)
p-value	0.001	0.001	0.001

Panel B: Short Selling

	$ShortSelling_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.245***	-0.267***	-0.268***
	(0.075)	(0.085)	(0.084)
$AI\text{-}sentiment_{i,d}*After_d$	0.142	0.153	0.153
	(0.081)	(0.092)	(0.091)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	33130	33124	33034
r2	0.216	0.214	0.215
$AI\text{-}sentiment_{i,d} + AI\text{-}sentiment_{i,d}*After_d$	-0.103**	-0.114***	-0.115***
	(0.037)	(0.037)	(0.037)
p-value	0.014	0.008	0.007

Table 3 AI and Short-Window Trading

This table presents how short-window retail-AI alignment and short-seller-AI alignment change around AI deployment. The sample period is 2021–2024. Panel A (B) reports the alignment of short-window retail trading (short selling) with AI-sentiment before and after AI deployment. We compute *RetailTrading* (*ShortSelling*), the abnormal retail (short-seller) holdings as defined in Sections 1.3 (1.4), over two intervals on earnings call day d: from the earnings announcement to call start [d EA, d Call Start], and from call start to market close [d Call Start, d Close]. We scale trading in each interval by its duration (in hours) to ensure comparability and then standardize short-window trading to have zero mean and unit standard deviation. *After* is a dummy variable equals one for periods subsequent to January 1, 2023. *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Short-Window Retail Trading

	Retail Trading$_{i,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
AI-sentiment$_{i,d}$	0.004	-0.146*
	(0.035)	(0.071)
*AI-sentiment$_{i,d}$*After$_d$*	0.083	0.276***
	(0.070)	(0.075)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	17983	33682
r2	0.009	0.010
*AI-sentiment$_{i,d}$ + AI-sentiment$_{i,d}$*After$_d$*	0.087	0.130***
	(0.059)	(0.030)
p-value	0.165	0.001

Panel B: Short-Window Short Selling

	$ShortSelling_{i,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
$AI\text{-}sentiment_{i,d}$	-0.022	-0.183***
	(0.043)	(0.047)
$AI\text{-}sentiment_{i,d}*After_d$	-0.010	0.090
	(0.059)	(0.057)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	22169	30557
r2	0.042	0.101
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	-0.032	-0.093**
	(0.035)	(0.034)
p-value	0.379	0.015

Table 4 Cross-Sectional Heterogeneity in Retail-AI Alignment

This table presents cross-sectional variation in the alignment of retail trading with AI-sentiment around AI deployment across dimensions of information frictions. The sample period is 2021–2024. Panel A focuses on operating uncertainty, proxied by earnings volatility and idiosyncratic volatility. Panel B examines information environment quality, proxied by analyst dispersion. *HardToProcess* equals one for firms in the top quartile of the respective proxy and zero for those in the bottom quartile. *RetailTrading* is the abnormal retail holding, calculated in Section 1.3 and standardized to have zero mean and unit variance. *After* is a dummy variable equals one for periods subsequent to January 1, 2023. *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Operating Uncertainty

	Retail Trading$_{i,[horizon]}$					
	Earnings Vol			Idiosyncratic Vol		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d]	[d+1:d+10]	[d+1:d+21]	[d]	[d+1:d+10]	[d+1:d+21]
*AI-sentiment$_{i,d}$*After$_d$*	0.109	0.102	0.099	0.186**	0.178**	0.178**
	(0.078)	(0.071)	(0.069)	(0.076)	(0.072)	(0.074)
*AI-sentiment$_{i,d}$*After$_d$ *HardToProcess$_{i,d}$*	0.465**	0.498**	0.466**	0.352	0.406*	0.373*
	(0.188)	(0.183)	(0.177)	(0.205)	(0.201)	(0.208)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	15330	15327	15327	16921	16920	16919
r2	0.026	0.023	0.022	0.028	0.027	0.027

Panel B: Information Environment Quality

	Retail Trading$_{i,[horizon]}$		
	Analyst Dispersion		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
*AI-sentiment$_{i,d}$*After$_d$*	0.077	0.067	0.074
	(0.054)	(0.048)	(0.048)
*AI-sentiment$_{i,d}$*After$_d$*HardToProcess$_{i,d}$*	0.186*	0.207**	0.161*
	(0.095)	(0.089)	(0.090)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	16554	16558	16558
r2	0.022	0.021	0.021

Table 5 AI and Information Asymmetry

This table presents the effect of AI deployment on information asymmetry for high retail-AI alignment stocks. The sample period is 2021–2024. *BidAskSpread* is the difference between the daily bid and ask price scaled by the average of bid and ask price, multiplied by 100 to ease interpretation. We include both short-window and long-window bid–ask spread. Short window includes two intervals: from the earnings announcement to call start [d EA, d Call Start], and from call start to market close [d Call Start, d Close]. $Treat^{AI}$ is a dummy variable equal to one for stocks with high retail-AI alignment (above the median) and zero for those with low alignment (below the median). We measure retail-AI alignment as the coefficient of *AI-sentiment*After*, obtained by running regressions in Table 2, Panel A, on a stock-by-stock basis on the earnings call day. The high and low alignment groups are balanced using propensity score matching. *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *abs(SUE)* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	$BidAskSpread_{i,[horizon]}$			
	(1)	(2)	(3)	(4)
	[d EA, d Call Start]	[d Call Start, d Close]	[d+1:d+10]	[d+1:d+21]
$Treat_i^{AI}$	-0.243	-0.029	-0.007	-0.006
	(0.187)	(0.022)	(0.013)	(0.013)
$Treat_i^{AI}*After_d$	0.209	-0.065***	-0.037***	-0.039***
	(0.159)	(0.020)	(0.011)	(0.011)
Control	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24	21-24
N	24268	27409	28664	28584
r2	0.220	0.410	0.453	0.466

Table 6 AI and Trading Profitability

This table presents the effect of AI deployment on trading profitability in two subsamples: stocks with high and low retail-AI alignment. The sample period is 2021–2024. We measure retail-AI alignment as the coefficient of *AI-sentiment*After*, obtained by running regressions in Table 2, Panel A, on a stock-by-stock basis on the earnings call day. Stocks are classified as high (low) alignment if their alignment measure is above (below) the median. The high and low alignment groups are balanced using propensity score matching. *CAR* is cumulative abnormal returns calculated following the DGTW method (Daniel et al., 1997). *RetailTrading* is abnormal retail holding calculated in Section 1.3. *ShortSelling* is abnormal short-seller holding calculated in Section 1.4. *RetailTrading* and *ShortSelling* are both standardized (demeaned and with unit standard deviation). *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Retail Trading Profitability

	$CAR_{i,[horizon]}$					
	High Alignment			Low Alignment		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]
$RetailTrading_{i,d}$	-0.377*	-0.971***	-2.541***	-0.193	0.081	-0.797
	(0.183)	(0.228)	(0.705)	(0.303)	(0.433)	(0.835)
$RetailTrading_{i,d}*After_d$	0.715*	1.678***	6.056**	-0.266	-0.956*	-0.984
	(0.362)	(0.539)	(2.264)	(0.359)	(0.536)	(1.182)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	15180	15179	14394	15179	15178	14164
r2	0.011	0.012	0.019	0.007	0.006	0.005

Panel B: Short Selling Profitability

	$CAR_{i,[horizon]}$					
	High Alignment			Low Alignment		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]
$ShortSelling_{i,d}$	-0.688**	-1.304**	-5.819***	-0.434	-0.812*	-4.118***
	(0.255)	(0.563)	(0.956)	(0.327)	(0.415)	(1.200)
$ShortSelling_{i,d}*After_d$	0.431	0.755	4.195**	0.131	0.295	2.702
	(0.504)	(0.828)	(1.529)	(0.362)	(0.549)	(1.767)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	15011	15011	14242	15010	15009	14005
r2	0.012	0.012	0.027	0.007	0.006	0.009

Table 7 AI and Retail Market Participation

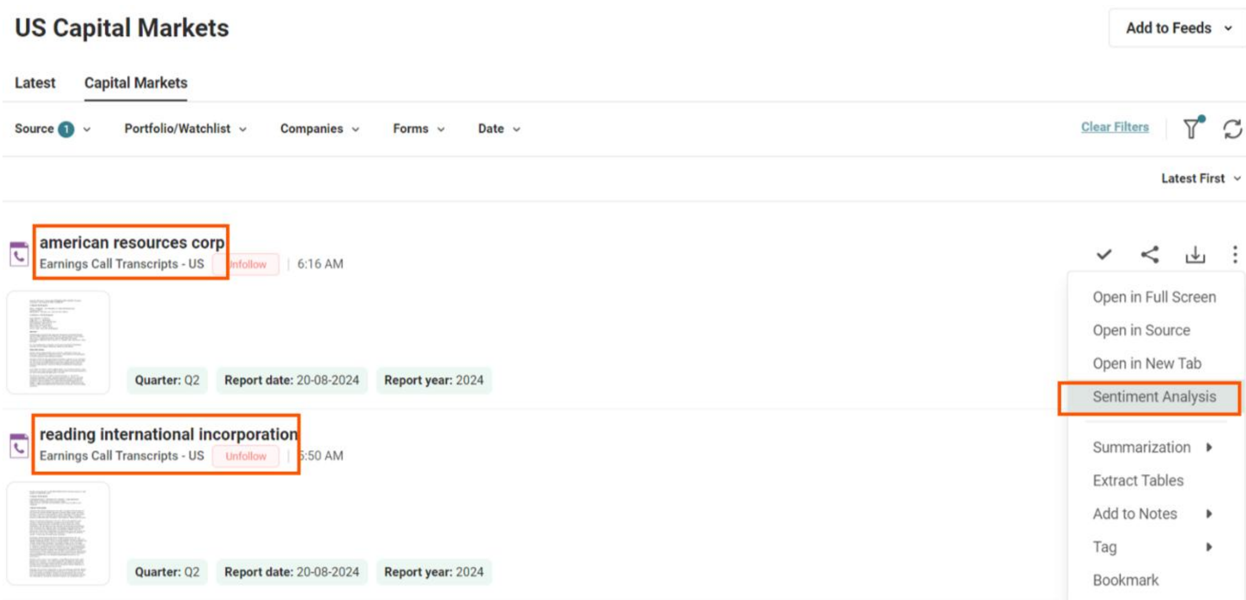
This table presents the effect of AI deployment on market participation of retail investors for high retail-AI alignment stocks. The sample period is 2021–2024. *RetailTradingIntensity* is the sum of number of retail buy trades and retail sell trades, scaled by its one-year average (demeaned and with unit standard deviation). $Treat^{AI}$ is a dummy variable that equals one if the stock's retail-AI alignment is above the median and zero otherwise. Retail-AI alignment is the coefficient of *AI-sentiment*After*, obtained by running regressions in Table 2, Panel A, on a stock-by-stock basis on the earnings call day. The high and low alignment groups are balanced using propensity score matching. *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *abs(SUE)* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	$RetailTradingIntensity_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$Treat^{AI}_i$	0.003	0.002	-0.013
	(0.020)	(0.014)	(0.016)
$Treat^{AI}_i*After_d$	0.020	0.034	0.058*
	(0.021)	(0.020)	(0.028)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	30364	30476	30476
r2	0.055	0.229	0.278

Figure IA.1 Anecdotal Evidence: AI-Empowered Trading in Intermediary Platforms and Social Media

This figure presents how AI tools empower retail trading across different channels. Panel A shows an intermediary platform (Needl.ai) that applies sentiment analysis to earnings call transcripts and provides investors with ready-made signals. Panel B shows AI-driven trading strategies circulated on Reddit.

Panel A: Needl.ai's Sentiment Signal on Earnings Call Transcript



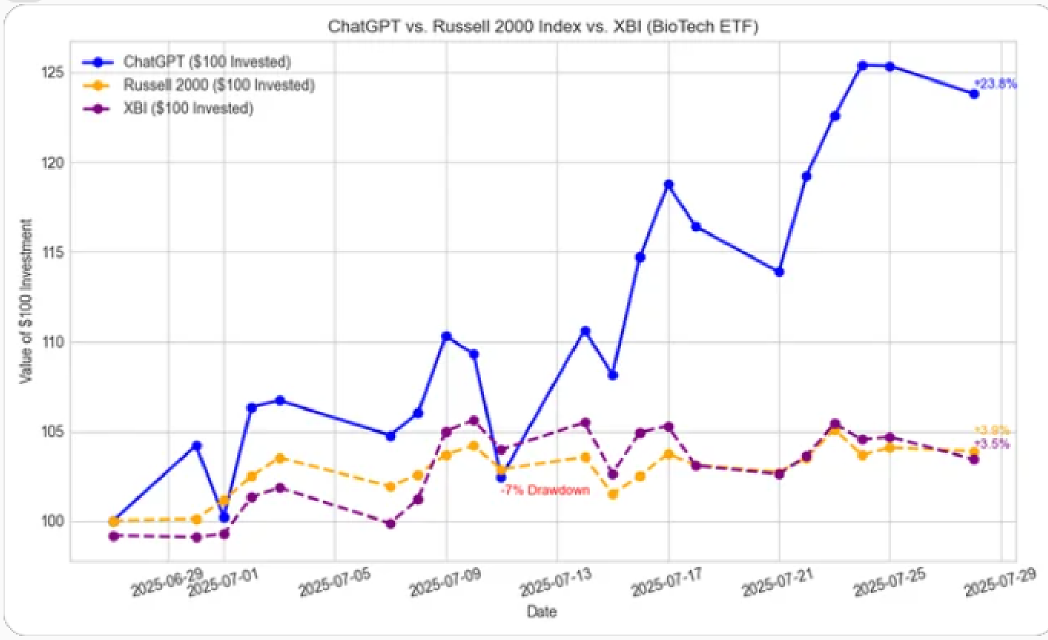
24	Ronen Tsimerman	And we're happy that so many KOLs are choosing our systems in order to do the independent studies	Positive
25	Ronen Tsimerman	We can't really provide more data than this because, again, it's an independent study we are not the sponsors	Negative
26	Ronen Tsimerman	We do not decide when to submit a paper or when to submit an abstract to one of the conferences	Positive
27	Ronen Tsimerman	But as soon as we have the data as soon as we see it, we, of course, release it to everyone	Positive
28	Ronen Tsimerman	We have achieved our goals through the first half of 2024, and for the remainder of 2024 and into early '25, we expect more data from independent studies on breast cancer and other indication	Positive
29	Kemp Dolliver	First, with regard to the first half, China was zero in the first half	Negative
30	Kemp Dolliver	The next question relates to the ICESECRET data and your plans and ability to leverage that data in the US in particular. Okay, great	Positive
31	Ben Haynor	First one for me, just looking at some of these independent breast cancer studies, they are for slightly different patient populations and actually, it seems like in several cases, patients that are less well off than the ICE3 cohort was	Negative
32	Ben Haynor	And what should investors take away from the potential for a broader applicability of ProSense. Makes sense	Positive
33	Ben Haynor	But I think you mentioned in the press release there is something like 15 ongoing independent studies being performed out there	Positive

Panel B: AI-Generated Trading Ideas on Reddit

r/dataisbeautiful • 2 mo. ago
OpenArcher7341

[OC] 4 Weeks of ChatGPT Controlling a Live Stock Portfolio

OC



This is part of a 6-month experiment to see how a language model performs in picking small, undercovered stocks with only a $100 budget.

If your curious, the GitHub for everything is: https://github.com/LuckyOne7777/ChatGPT-Micro-Cap-Experiment

I also post about it weekly on my blog: https://nathanbsmith729.substack.com/publish/home?utm_source=menu

Disclaimer: None of this is financial advice or me trying to sell something, just a cool little experiment I wanted to show off.

Thanks for reading!

r/ChatGPT • 2 mo. ago
Plastic-Edge-1654

Watching ChatGPT Make Me Money While I Chill and Crack a Cold One!

Educational Purpose Only

ChatGPT o3 vs GROK 3		AI BOT		
Trade Count	Instrument	ChatGPT	Grok	Return Per Trade
1	AMD	$ 353.82		102.32%
2	NVDA	$ 56.47		7.44%
3	NVDA	$ 228.82		33.98%
4	AMD	$ 85.66		43.88%
5	TQQQ	$ 34.91		27.14%
6	NVDA	$ 29.46		8.00%
7	AAPL		$ 81.66	29.08%
8	XOM	$ 21.82		10.90%
9	AAPL		$ 39.30	12.35%
10	JNJ	$ 0.82		2.09%
11	NVDA	$ 19.65		8.14%
12	TSLA	$ 35.66		10.72%
13	AMD		$ 35.82	24.49%
14	AAPL	$ 17.82		10.00%
15	TSLA	$ 41.66		13.47%
16	NVDA		$ 31.64	10.20%
17	AMD			open
18	TSLA		$ 33.65	7.84%
Grand Total		**$ 926.57**	**$ 222.07**	
Average Return Per Trade		23%	17%	

Two weeks ago, I funded $400 over to robinhood to see if ChatGPT could trade better than me.

Day 1, boom, doubled my money faster than Kris Jenner can sign a new reality deal.

By day 4, I was feelin' spicy and decided to split my gains into two separate trades. Then I got this genius (or stupid) idea: let's pit ChatGPT and Grok against each other in the ultimate AI showdown and see who's the alpha when it comes to making me money without having to think.

I gave both of the AI bots a big fat list of nerdy data, and basically said, "Yo, filter through this mess and spit out trades that'll turn my beer and BBQ budget into Kardashian-level cash."

Then I even figured out that I can hand-feed them screenshots (of data) and upload spreadsheets, making sure they're using only primo data.

Fast-forward 10 trading days (two weeks): I've made 18 trades, closed out 17, and somehow these AI bros both have a flawless, 100% win rate.

ChatGPT has nailed 13, Grok has hit 5, and neither has let me down yet!

I'm hyped to see how far this YOLO AI adventure goes over the next six months. Stay tuned; It's time to crack another cold one—it's gonna be a wild ride!

4.5K 859 Share

Table IA.1 Alternative Retail Measure (Barber et al. 2024)

This table presents results for retail trading using the measure from Barber et al. (2024), which identifies retail trades from sub-penny prices and assigns trade direction using the quote midpoint. The sample period is 2021–2024. All specifications are identical to those in the main tables. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: AI and Retail Trading (replicates Table 2, Panel A)

	$RetailTrading_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.149**	-0.142**	-0.145**
	(0.054)	(0.052)	(0.051)
$AI\text{-}sentiment_{i,d}{*}After_d$	0.229***	0.228***	0.228***
	(0.054)	(0.053)	(0.054)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	34011	33994	33899
r2	0.063	0.060	0.060
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}{*}After_d$	0.080**	0.086**	0.083**
	(0.031)	(0.033)	(0.034)
p-value	0.023	0.019	0.027

Panel B: AI and Short-Window Retail Trading (replicates Table 3, Panel A)

	$RetailTrading_{i,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
$AI\text{-}sentiment_{i,d}$	-0.011	-0.124**
	(0.038)	(0.049)
$AI\text{-}sentiment_{i,d}{*}After_d$	0.012	0.200***
	(0.065)	(0.053)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	23133	32703
r2	0.020	0.033
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}{*}After_d$	0.001	0.076**
	(0.044)	(0.030)
p-value	0.972	0.022

Panel C: Cross-Sectional Heterogeneity in Retail-AI Alignment and Operating Uncertainty (replicates Table 4, Panel A)

	$RetailTrading_{i,[horizon]}$					
	Earnings Vol			Idiosyncratic Vol		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d]	[d+1:d+10]	[d+1:d+21]	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}*After_d$	0.161*	0.096	0.100	0.203**	0.136**	0.139**
	(0.080)	(0.068)	(0.068)	(0.072)	(0.056)	(0.056)
$AI\text{-}sentiment_{i,d}*After_d*HardToProcess_{i,d}$	0.242	0.399**	0.385**	0.144	0.242	0.239
	(0.169)	(0.163)	(0.168)	(0.183)	(0.164)	(0.166)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	16002	15991	15956	17004	16993	16958
r2	0.098	0.094	0.096	0.085	0.082	0.082

Panel D: Cross-Sectional Heterogeneity in Retail-AI Alignment and Information Environment Quality (replicates Table 4, Panel B)

	$RetailTrading_{i,[horizon]}$		
	Analyst Dispersion		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}*After_d$	0.111*	0.108*	0.113*
	(0.055)	(0.053)	(0.053)
$AI\text{-}sentiment_{i,d}*After_d*HardToProcess_{i,d}$	0.266*	0.278**	0.264**
	(0.133)	(0.121)	(0.116)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	16660	16645	16570
r2	0.064	0.058	0.060

Panel E: AI and Information Asymmetry (replicates Table 5)

	$BidAskSpread_{i,[horizon]}$			
	(1)	(2)	(3)	(4)
	[d EA, d Call Start]	[d Call Start, d Close]	[d+1:d+10]	[d+1:d+21]
$Treat_i^{AI}$	34.282	-3.198	19.706	21.396
	(184.947)	(21.555)	(14.156)	(14.218)
*$Treat_i^{AI}$*$After_d$*	167.685	-113.407***	-75.109***	-76.310***
	(144.388)	(21.156)	(13.896)	(13.464)
Control	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24	21-24
N	23666	26662	28166	28072
r2	0.212	0.389	0.428	0.440

Panel F: AI and Retail Trading Profitability (replicates Table 6, Panel A)

	$CAR_{i,[horizon]}$					
	High Alignment			Low Alignment		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]
$RetailTrading_{i,d}$	-0.419**	-0.880***	-2.932***	-0.225	0.019	-1.126
	(0.175)	(0.224)	(0.476)	(0.255)	(0.421)	(0.922)
*$RetailTrading_{i,d}$*$After_d$*	0.795*	0.974	5.676	-0.123	-1.385**	-1.776
	(0.396)	(0.774)	(3.240)	(0.400)	(0.592)	(1.580)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	15142	15141	14400	15141	15140	14145
r2	0.012	0.012	0.020	0.007	0.007	0.006

Table IA.2 Restricted Sample Period of 2022–2023

This table presents results for Table 1–3 using sample period of 2022–2023. All specifications are identical to those in the main tables. *AI-sentiment* is the sentiment score of earnings call transcripts computed by GPT-3.5-Turbo-16k model (demeaned and rescaled by the inter-decile range). Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: 2022-2023 Sample (replicates Table 1)

Variable	N	Mean	P1	P50	P99	Std Dev
AI-sentiment (demeaned and rescaled)	17177	0.000	-0.650	-0.020	0.360	0.280
Return (%)	17177	-0.288	-28.190	-0.119	26.998	9.887
Beta	17177	1.260	0.150	1.180	3.030	0.590
BM	17177	0.500	-0.490	0.390	2.810	0.680
MVE	17177	14.250	9.140	14.350	19.260	2.220
Mom12m	17177	-0.020	-0.870	-0.050	1.680	0.530
SUE	17177	0.050	-0.440	0.000	0.790	1.210
RetailTrading	17177	-0.0004	-0.0322	-0.0005	0.0326	0.0136
RetailTradingIntensity	17177	2.465	0.165	1.815	10.600	2.120
ShortSelling	16683	0.290	0.020	0.150	3.480	0.620
BidAskSpread (time by 100)	15387	0.390	0.004	0.101	4.195	0.795

Panel B: AI and Retail Trading (replicates Table 2, Panel A)

	$RetailTrading_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.139**	-0.115*	-0.111*
	(0.056)	(0.055)	(0.054)
$AI\text{-}sentiment_{i,d}*After_d$	0.252**	0.230**	0.226**
	(0.073)	(0.078)	(0.080)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	22-23	22-23	22-23
N	17177	17176	17176
r2	0.013	0.013	0.013
$AI\text{-}sentiment_{i,d} + AI\text{-}sentiment_{i,d}*After_d$	0.113*	0.115	0.115
	(0.055)	(0.061)	(0.063)
p-value	0.079	0.100	0.109

Panel C: AI and Short Selling (replicates Table 2, Panel B)

	$ShortSelling_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.280***	-0.309***	-0.310***
	(0.073)	(0.083)	(0.081)
$AI\text{-}sentiment_{i,d}*After_d$	0.170	0.191	0.202*
	(0.094)	(0.107)	(0.105)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	22-23	22-23	22-23
N	16683	16682	16680
r2	0.186	0.183	0.181
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	-0.110*	-0.118*	-0.108*
	(0.054)	(0.055)	(0.053)
p-value	0.082	0.068	0.079

Panel D: AI and Short-Window Retail Trading (replicates Table 3, Panel A)

	$RetailTrading_{i,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
$AI\text{-}sentiment_{i,d}$	-0.043	-0.192*
	(0.048)	(0.085)
$AI\text{-}sentiment_{i,d}*After_d$	-0.022	0.279**
	(0.069)	(0.100)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	22-23	22-23
N	8790	16940
r2	0.033	0.008
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	-0.065	0.087
	(0.071)	(0.049)
p-value	0.391	0.119

Panel E: AI and Short-Window Short Selling (Table 3, Panel B)

	$ShortSelling_{i,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
$AI\text{-}sentiment_{i,d}$	-0.096	-0.225***
	(0.056)	(0.041)
$AI\text{-}sentiment_{i,d}*After_d$	-0.036	0.084
	(0.057)	(0.066)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	22-23	22-23
N	10864	16449
r2	0.042	0.103
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	-0.132	-0.141**
	(0.092)	(0.059)
p-value	0.192	0.048

Table IA.3 AI and Trading: Difference-in-Differences

This table presents the relation between AI deployment and retail trading relative to short selling in a difference-in-differences (DiD) setting. The sample period is 2021–2024. We include both long-window (Panel A) and short-window trading (Panel B). The dataset includes both retail trading (treatment group) and short selling (control group) for each stock in each quarter. In Panel A, *StandardizedTrading* includes both retail trading and short selling. We invert the sign of *ShortSelling* and separately standardize both *ShortSelling* and *RetailTrading* (demeaned and with unit standard deviation). We scale trading in each interval by its duration (in hours) to ensure comparability and then standardize short-window trading to have zero mean and unit standard deviation. In Panel B, we compute *RetailTrading* (*ShortSelling*), the abnormal retail (short-seller) holdings as defined in Sections 1.3 (1.4), over two intervals on earnings call day d: from the earnings announcement to call start [d EA, d Call Start], and from call start to market close [d Call Start, d Close]. We then construct the short-window *StandardizedTrading* in the same way as Panel A. $Treat^{IsRetail}$ is a dummy variable that equals one if the trading variable for a stock in a given quarter is retail trading and zero if it is short selling. *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter-firm and trader fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Long-Window

	$StandardizedTrading_{i,g,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	0.254**	0.320***	0.338***
	(0.090)	(0.077)	(0.077)
$AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g}$	-0.289***	-0.317***	-0.321***
	(0.089)	(0.088)	(0.085)
$AI\text{-}sentiment_{i,d}*After_{d}$	-0.361**	-0.279***	-0.300***
	(0.130)	(0.082)	(0.087)
$AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g}*After_{d}$	0.351***	0.370***	0.366***
	(0.094)	(0.096)	(0.092)
Control	Yes	Yes	Yes
Year-Quarter-Firm FE	Yes	Yes	Yes
Trader FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	66266	66254	66083
r2	0.40	0.40	0.41
$AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g} + AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g}*After_{d}$	0.062	0.053	0.045
	(0.063)	(0.066)	(0.065)
p-value	0.342	0.434	0.499

Panel B: Short-Window

	$StandardizedTrading_{i,g,[horizon]}$	
	(1)	(2)
	[d EA, d Call Start]	[d Call Start, d Close]
$AI\text{-}sentiment_{i,d}$	0.734	0.376***
	(0.718)	(0.079)
$AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g}$	0.030	-0.297***
	(0.077)	(0.098)
$AI\text{-}sentiment_{i,d}*After_{d}$	-0.811	-0.345***
	(0.716)	(0.093)
$AI\text{-}sentiment_{i,d}*After_{d}*Treat^{IsRetail}_{g}$	0.071	0.326***
	(0.101)	(0.102)
Control	Yes	Yes
Year-Quarter-Firm FE	Yes	Yes
Trader FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	33745	60533
r2	0.342	0.301
$AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g} + AI\text{-}sentiment_{i,d}*Treat^{IsRetail}_{g}*After_{d}$	0.101	0.029
	(0.072)	(0.047)
p-value	0.184	0.539

Table IA.4 Propensity Score Matching

This table presents the summary statistics of variables before and after propensity score matching (PSM). All variables are defined in Appendix A. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	Unmatched				Matched			
	Mean (High Alignment Group)	Mean (Low Alignment Group)	Difference	t-stat	Mean (High Alignment Group)	Mean (Low Alignment Group)	Difference	t-stat
Beta	1.266	1.287	-0.021**	-2.280	1.271	1.264	0.007	0.740
BM	0.474	0.524	-0.050***	-4.070	0.496	0.487	0.009	0.880
MVE	14.269	14.092	0.177***	5.000	14.222	14.262	-0.040	-1.130
Mom12m	-0.025	-0.030	0.005	0.590	-0.027	-0.022	-0.004	-0.530
SUE	-0.032	0.029	-0.061***	-3.900	-0.025	-0.043	0.017	1.210

Table IA.5 AI and Trading Profitability: Difference-in-Differences

This table presents the relation between AI deployment and retail trading profitability relative to short selling profitability in a difference-in-differences (DiD) setting. The sample period is 2021–2024. We focus on two subsamples: stocks with high and low retail-AI alignment. We define high (low) retail-AI alignment if a stock's retail-AI alignment is above (below) the median. Retail-AI alignment is the coefficient of *AI-sentiment*After*, obtained by running regressions in Table 2 Panel A on a stock-by-stock basis on the earnings call day. The high and low alignment groups are balanced using propensity score matching. The dataset includes both retail trading (treatment group) and short selling (control group) for each stock in each quarter. *StandardizedTrading* includes both retail trading and short selling. We invert the sign of *ShortSelling* and separately standardize both *ShortSelling* and *RetailTrading* (demeaned and with unit standard deviation). $Treat^{IsRetail}$ is a dummy variable that equals one if the trading variable for a stock in a given quarter is retail trading and zero if it is short selling. *CAR* is cumulative abnormal returns calculated following the DGTW method (Daniel et al., 1997). *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

	$CAR_{i,[horizon]}$					
	High Alignment			Low Alignment		
	(1)	(2)	(3)	(4)	(5)	(6)
	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]	[d+1:d+10]	[d+1:d+21]	[d+1:d+126]
$StandardizedTrading_{i,g,d}$	0.656**	1.254**	5.574***	0.401	0.750*	3.922***
	(0.245)	(0.541)	(0.912)	(0.319)	(0.406)	(1.162)
$Treat^{IsRetail}_g$	0.042	0.084	0.288	0.057	0.096*	0.477**
	(0.030)	(0.054)	(0.194)	(0.042)	(0.049)	(0.180)
$StandardizedTrading_{i,g,d}*Treat^{IsRetail}_g$	-1.041**	-2.235***	-8.172***	-0.603	-0.686	-4.803**
	(0.380)	(0.722)	(1.424)	(0.589)	(0.810)	(1.740)
$StandardizedTrading_{i,g,d}*After_d$	-0.417	-0.730	-4.066**	-0.133	-0.292	-2.722
	(0.498)	(0.817)	(1.483)	(0.355)	(0.534)	(1.708)
$Treat^{IsRetail}_g*After_d$	-0.019	-0.029	-0.028	-0.099*	-0.166**	-0.608***
	(0.063)	(0.103)	(0.247)	(0.048)	(0.058)	(0.185)
$StandardizedTrading_{i,g,d}*Treat^{IsRetail}_g*After_d$	1.137*	2.417*	10.142**	-0.150	-0.656	1.781
	(0.630)	(1.149)	(3.487)	(0.663)	(0.972)	(2.499)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	21-24	21-24	21-24	21-24	21-24	21-24
N	30191	30190	28636	30189	30187	28169
r2	0.011	0.012	0.023	0.007	0.006	0.007

Table IA.6 AI Access Shocks: Evidence from ChatGPT Outages

This table presents estimates from the specifications that exploit the effect of unexpected ChatGPT outages as exogenous shocks to AI access on retail-AI alignment. The sample period is 2021–2024. Panel A (Panel B) presents the effect of ChatGPT outages on short-window retail-AI alignment (information asymmetry). $RetailTrading_{i,[d\ Call\ Start,\ d\ Close]}$ is abnormal retail holding from call start to market close [d Call Start, d Close]. We scale trading in each interval by its duration (in hours) to ensure comparability and then standardize short-window trading to have zero mean and unit standard deviation. $BidAskSpread_{i,[d\ Call\ Start,\ d\ Close]}$ is the bid–ask spread calculated from call start to market close [d Call Start, d Close]. *After&Outage* is measured either as a dummy equal to one if a major outage occurs on the earnings call day and zero otherwise, or by the total outage duration (in hours) of all major outages occur on the earnings call day. $Treat^{AI}$ is a dummy variable that equals one if the stock's retail-AI alignment is above the median and zero otherwise. Retail-AI alignment is the coefficients of *AI-sentiment*After*, obtained by running regressions in Table 2, Panel A, on a stock-by-stock basis on the earnings call day. The high and low alignment groups are balanced using propensity score matching. *AI-sentiment* is the sentiment score of earnings call transcripts computed by ChatGPT (demeaned and rescaled by the inter-decile range). *After* is a dummy variable equals one for periods subsequent to January 1, 2023. We control for *Beta*, *BM*, *MVE*, *Mom12m*, and *SUE* as defined in Appendix A. We include year-quarter fixed effect. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: Short-Window Retail Trading

	$RetailTrading_{i,[d\ Call\ Start,\ d\ Close]}$	
	(1)	(2)
	Dummy	Duration
$AI\text{-}sentiment_{i,d}*After_d$	0.285***	0.286***
	(0.079)	(0.079)
$AI\text{-}sentiment_{i,d}*After\&Outage_{i,d}$	-0.108	-0.136**
	(0.072)	(0.059)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	33552	33552
r2	0.010	0.010

Panel B: Short-Window Bid–Ask Spread

	$BidAskSpread_{i,[d\ Call\ Start,\ d\ Close]}$	
	(1)	(2)
	Dummy	Duration
$Treat_i^{AI}*After_d$	-0.081***	-0.076***
	(0.022)	(0.022)
$Treat_i^{AI}*After\&Outage_{i,d}$	0.080*	0.029
	(0.041)	(0.022)
Control	Yes	Yes
Year-Quarter FE	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24
N	27914	27914
r2	0.404	0.404

Table IA.7 Additional Control Variables of ROA and ROE

This table replicates Table 2 with additional controls of *ROA* and *ROE*. The sample period is 2021–2024. All other settings are the same as the main tables. Standard errors are two-way clustered by firm and year-quarter. Standard errors are reported in parentheses. *, **, and *** represent significance at the 10%, 5% and 1% levels, respectively.

Panel A: AI and Retail Trading (replicates Table 2, Panel A)

	$RetailTrading_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.077	-0.067	-0.063
	(0.059)	(0.056)	(0.053)
$AI\text{-}sentiment_{i,d}*After_d$	0.244***	0.236***	0.227***
	(0.064)	(0.062)	(0.060)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	34128	34127	34126
r2	0.017	0.016	0.015
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	0.167***	0.169***	0.164***
	(0.041)	(0.041)	(0.040)
p-value	0.001	0.001	0.001

Panel B: AI and Short Selling (replicates Table 2, Panel B)

	$ShortSelling_{i,[horizon]}$		
	(1)	(2)	(3)
	[d]	[d+1:d+10]	[d+1:d+21]
$AI\text{-}sentiment_{i,d}$	-0.223**	-0.245**	-0.246**
	(0.076)	(0.086)	(0.085)
$AI\text{-}sentiment_{i,d}*After_d$	0.104	0.115	0.114
	(0.080)	(0.091)	(0.090)
Control	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Cluster	Firm&YrQtr	Firm&YrQtr	Firm&YrQtr
Sample Period	21-24	21-24	21-24
N	33128	33122	33032
r2	0.239	0.238	0.239
$AI\text{-}sentiment_{i,d}$ + $AI\text{-}sentiment_{i,d}*After_d$	-0.119***	-0.130***	-0.132***
	(0.035)	(0.036)	(0.036)
p-value	0.004	0.002	0.002