Working Paper 25-055

Generative AI Use by Capital Market Information Intermediaries: Evidence from Seeking Alpha

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Abstract

We study the use of generative AI for firm-specific financial analysis on the Seeking Alpha platform. We find that, after the initial launch of ChatGPT in November 2022, the share of AI-generated articles rose sharply to 13.4% of all articles, then declined in late 2023 after Seeking Alpha equated the use of AI to plagiarism and announced a prohibition on its use. Compared to human articles, AI articles elicit smaller trading volume and abnormal return responses, suggesting they are less informative to capital market participants. However, authors who adopt AI exhibit increased productivity, publishing more articles and covering more new firms than non-adopters. Moreover, the expansion of AI coverage is associated with improved liquidity for historically undercovered firms, but provides no incremental benefit for firms that are already well-covered. Our findings suggest that while AI-generated articles are currently perceived as less informative than human-written articles, their comparatively low cost may enable broader coverage of, and capital market benefits for, firms traditionally overlooked by capital market intermediaries.

Keywords: Generative AI; Seeking Alpha; equity research; large language models; GPT

JEL codes: D83, G14, M41, O33

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1. Introduction

Artificial intelligence (AI) broadly includes the use of computerized systems to automate both routine and, increasingly, non-routine tasks.[1] In short time, AI has impacted almost every aspect of society, including accounting and financial markets. Generative AI is a subset of AI that can generate original content such as text, software code, audio, and video, "unlocking new possibilities for financial analysis and decision-making" (Krause 2023). ChatGPT, which launched publicly in November 2022, is a generative AI chatbot that created threats and opportunities in numerous settings, including in the analysis of public firms that contributes to efficient capital markets (Bernstein 1975; Beaver 1981).[2] On one hand, the ability to synthesize large amounts of quantitative and qualitative data and create narratives using generative AI may disrupt traditional financial analysis and result in increased information production (Noy and Zhang 2023; Acemoglu 2024). On the other hand, AI has well-documented limitations translating data into output that provides compelling alternatives to human analysis and communication (Irons 2024; Levy 2024).

We join the early stages of research on the implications of generative AI in accounting and finance by investigating the implications of AI among capital market intermediaries, with a focus on the use and receptiveness of AI-based analyses among investors. In contrast to claims about the virtues of AI for capital markets, Seeking Alpha (SA) – the largest investor community platform in the world – has equated the use of AI in the context of financial analysis to "plagiarism," and

[1] According to H.R. 6216 (National Artificial Intelligence Initiative Act of 2020), "The term 'artificial intelligence' means a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments."
[2] OpenAI's ChatGPT release was followed by the introduction of Microsoft's Bing Chat (based on ChatGPT technology) and Google's Bard (based on its own technology) in early 2023, together referred to as 'the big three chatbots.' We highlight ChatGPT because it was the first that was widely available, but acknowledge that our analysis and sample period encompasses the availability of other AI tools.

initiated a policy prohibiting the use of AI by contributors to the platform.[3] We examine the incidence, determinants, characteristics, and capital market impacts of the use of AI for firm-specific research published on SA. Similar to emerging research in other settings, our analysis highlights challenges and opportunities for the integration of AI in financial analysis.

The rise of SA followed a long reliance by equity investors on professional financial analysis and investment advice. Numerous discrediting events such as the dot.com bubble (followed by Regulation FD in 2000 and the Global Analyst Research Settlement in 2003) and the global financial crisis (followed by the Occupy Wall Street movement in 2011) triggered a loss of trust in established financial intermediaries like investment banks and analysts. At the same time, technological advances and the rise of social media compelled disaffected investors to be receptive to alternative sources of financial analysis and advice, or inspired them to participate in the development of such alternatives. The outcomes include the expansion of investor-focused websites like The Motley Fool (Hirschey, Richardson and Scholz 2000), the creation of new crowdsourcing and investment analysis platforms such as SA (Chen et al. 2014; Gu, Yost and Zou 2025) and Estimize (Jame et al. 2016), and advent of ‘finfluencers’ on platforms like YouTube (Bradshaw, Koo and Zhao 2024; Campbell, Zheng and Zhou 2024).

Simultaneous with the negative market events mentioned above, changes in investor access to and participation in investment analysis have fostered a democratization of banking, financial analysis and investing. In a broad sense, Goldstein, Jiang and Karolyi (2019, p. 1658) argue, “It is no coincidence that FinTech came into prominence following the global financial crisis of 2008.”

[3] Equating AI use to plagiarism is consistent with a class action lawsuit filed in September 2023 by the Authors Guild against OpenAI, alleging that writers’ stories and characters were used in training models that now infringe on copyrighted work. Media outlets have filed similar suits. However, while still developing, in November 2024, a federal judge granted OpenAI a motion to dismiss the Authors Guild lawsuit, claiming, “The alleged injury for which plaintiffs truly seek redress is not the exclusion of copyright management information from defendants' training sets, but rather defendants' use of plaintiffs' articles to develop ChatGPT without compensation to plaintiffs” (Russell 2024).

Similarly, in a case-study analysis of Reddit's WallStreetBets, Gendron et al. (2024, p. 4) claim, "In the jurisdiction of finance, traditional experts are often considered as central information intermediaries, whose role is to convey influential investment narratives to other market participants … Yet, retail investors endeavored to challenge their traditional expertise, while developing their own expertise and investment narratives."

SA is widely regarded as one of the greatest success stories in the democratization of information production and dissemination in financial markets and is perhaps the most reputable crowdsourcing investment platform. SA is available via news distribution services and regularly discussed in mainstream financial media like *Forbes*, *Fortune* and *The Wall Street Journal*. The platform describes its mission as giving power to investors, and proclaims "Our research is created by investors, for investors." As the user base has expanded, SA has expanded its site content and diversified its revenue sources to include premium subscriptions, focused investing groups, stock and fund screening tools, and affiliate programs. Nevertheless, the mainstay of the site is firm-specific investment research, the influence of which has been documented in several studies.[4]

Being the dominant platform for user-generated firm-specific research, SA has a strong incentive to maintain the quality of the information housed on its site. Similar to the process of research studies submitted to academic journals, users submit articles to SA, and in-house editors carefully review the article, provide feedback and reach a publication decision.[5] The purpose of the review process is to ensure a minimum threshold of quality, which has solidified the popularity

[4] For example, see Chen et al. (2014), Campbell, DeAngelis and Moon (2019), Ding, Zhou and Li (2020), Farrell, Jame and Qiu (2020), Farrell et al. (2022), Umar (2022), Ding, Shi and Zhou (2023), Drake et al. (2023), Breuer, Knetsch and Sachsenhausen (2025), and Dim (2025).

[5] The SA article submission guideline discussion indicates: "Not every article that is submitted to us is published, but our editors will work with you if it's close to meeting our standards. Seeking Alpha receives a high volume of submissions each day and our team strives to provide quick turnaround times, with most articles reviewed or published within 10-14 hours of submission. New authors — those that have published less than three articles — should expect longer turnaround times" (https://about.seekingalpha.com/article-submission-guidelines).

of the site. In discussions with SA, representatives emphasized the importance of articles having a unique "investment thesis;" even before the availability of AI, editors would deny publication of an article if the thesis substantially overlapped with a previously published article.

As noted above, the rise of SA is in part attributable to the advancement of technology, but it now finds its prominence potentially threatened by continuing developments in technology, namely AI. In early 2023, SA editors were forced to address concerns related to AI use in these forums. For example (all quotes from SA editors on contributor forums that are only available to contributors),

> "Allowing authors to rely on AI software to generate investment content for our site would directly contravene our core purpose, and eliminate the crowdsourced nature of Seeking Alpha. Research and analysis prepared by 'bots' would reduce Seeking Alpha content to essentially a single view: the bot view. For this reason, opinion & analysis content submitted to Seeking Alpha cannot be sourced through, or constructed by, AI software (or any other automated means)."

Further, SA indicated a new policy regarding AI, clarified and justified as follows:

> "To be clear, under no circumstance should an automated tool be used to draft content for an article submitted to Seeking Alpha.
>
> While other sites may introduce generic AI-written content, SA readers can feel confident in knowing that our articles are written by human authors with their own unique talents, interests, perspectives, and voices.
>
> It's our belief that this is the best path forward for Seeking Alpha, its subscribers, and its valued contributors who remain SA's powerful source of unique differentiation.

An interpretation of the stance taken by SA is that it seeks to protect the value of its brand as the premier source of unique investing insights and its dominant market position.[6] We believe

[6] This reactionary policy appears consistent with the case study of 'fake news' documented by Kogan, Moskowitz and Niessner (2020), in which a whistleblower identified paid-for research appearing on sites like SA, which was followed by widespread attenuation in market reactions to SA articles. Another layer to the no-AI policy is that in December 2024, SA announced the launch of a new product, Virtual Analyst Reports, claiming, "With a single click, the Virtual Analyst Reports feature consolidates and synthesizes the renowned analysis from Seeking Alpha's platform and its market-beating Quant Ratings, delivering concise, easy-to-read reports on more than 3,000 U.S.-traded stocks. Each report highlights essential key metrics and insights, providing investors with the most important aspects of a stock to help them make informed investment decisions." Thus, in an interesting twist, SA now prohibits SA use by contributing authors but uses the technology to synthesize the authors' reports.

an analysis of the use of AI by SA authors and SA's reaction is thus informative to researchers, as it reflects the confluence of AI technology, financial analysis, and potential downstream impacts on market efficiency. Further, the SA stance on the use of AI is occurring in the midst of varying responses in other important fields like higher education, journalism and healthcare. For example, policies in higher education regarding student use of AI range from complete bans to encouragement (Zonjic 2024). Similarly, some news agencies are suing OpenAI for copyright infringement (e.g., *The New York Times*), whereas others are collaborating in formal partnerships (e.g., *Associated Press*, *The Wall Street Journal*'s parent, NewsCorp). The healthcare industry is diligently employing the use of AI while simultaneously struggling with the "ethical, moral, and legal debates" (Irwin, Jones, and Fealy 2023; Varghese and Chapiro 2024).

The global impact of ChatGPT was immediate and widespread, with over 100 million active users within the first two months after its release (Hu 2023). We capitalize on a natural experiment by examining SA research articles published from June 2022 through August 2024, a period including the introduction of ChatGPT and the enforcement of SA's no-AI policy. Our research approach is to examine changes in the characteristics of SA articles (i) during the baseline period before the introduction of ChatGPT in November 2022, (ii) after the introduction of ChatGPT but before SA's enforcement of its no-AI policy in October 2023, and (iii) after enforcement of the no-AI policy.

Our empirical analyses contrast differences across AI and human articles, and so require us to identify whether an article is written with the assistance of AI. In addition to scanning submitted articles for classic cases or plagiarism, SA now claims to have developed a proprietary tool for screening articles for use of AI and is unwilling to make that available for obvious reasons. As a proxy for SA's proprietary tool, we utilize an AI detector (Originality.ai) to identify articles that are likely written with the assistance of AI.[7] This tool utilizes a machine language algorithm based on the ubiquitous BERT model and, among other features, scores the probability that an article was written by AI rather than a human. Originality.ai claims to have an approximate 99% accuracy rate at detecting AI text (with a false positive rate of around 1%).

Our first analysis quantifies the frequency of AI-generated articles across time. We find a rapid and significant increase in the frequency of articles after the availability of ChatGPT, consistent with contributors either using AI to publish more articles on the existing breadth of firm coverage or expanding the coverage universe to additional firms. Beginning with the availability of ChatGPT to after SA's no-AI policy, we identify 8.1% of SA articles as AI-generated. The percentage of articles identified as AI rises from approximately 2% in the benchmark period before ChatGPT, peaking at 13.4% in October 2023 when SA initiated its no-AI policy enforcement, and then reverts back to approximately 4%. At the author (firm) level, the number of authors (firms) with an AI article rises from approximately 4% (1%) in the pre-ChatGPT period, spikes to approximately 17% (11%) before the no-AI policy, then declines but remains at approximately 9-11% (2-4%). Thus, consistent with the rapid adoption of ChatGPT, we find that contributors on the largest investor platform were enthusiastic adopters of AI for firm-specific research reports.

We perform univariate and multivariate determinants analysis to examine differences in AI and human articles across firm, article, and author characteristics. Although we find no reliable evidence of any firm characteristics being consistently associated with AI articles, we find robust

[7] There are numerous AI detectors, but Originality.ai and GPTZero appear to be the current leaders in terms of popularity and effectiveness. We replicate our analyses using GPTZero, finding similar results to those presented. See Akram (2023) and Dugan et al. (2024) for empirical comparisons of the performance of AI detectors. Also note that subsequent to the introduction of AI detectors, "bypass tools" were introduced that attempt to adapt AI-generated text to evade AI detection (e.g., Undetectable AI, Humanizey AI, Phrasly, StealthWriter, HIX Bypass, etc.). The landscape is akin to an AI arms race, with detectors like Originality.ai and GPTZero continuously adapting to bypasser entrants and updates. Also note that when we use AI detectors, we use the version as of the estimation date, not in effect during earlier months, which should enhance detection assuming continuous improvement in detection technology.

evidence that AI articles are more likely from novice authors with shorter tenures on the site. As a comparison with other studies examining AI text, we test for differences in textual characteristics such as readability, tone, and specificity (e.g., Blankespoor, deHaan and Li 2024). We find that, compared to human articles, AI articles are more complex, have a more positive tone, exhibit lower word strength, and are less quantitative. Our findings generally reflect well-documented characteristics of AI-generated versus human-generated text (e.g., Shah et al. 2023; Sardinha 2024).

Our primary results relate to differences in capital market effects of AI articles relative to human articles. These differences are large and significant, with AI articles accompanied by lower abnormal trading volume and smaller absolute cumulative abnormal returns. For investor impact measured on the SA platform, AI articles generate significantly fewer user comments and are less likely to be recognized by SA as "Editors' Picks." However, the latter result becomes insignificant if author fixed effects are included, likely reflecting minimal within-author variation for a concentrated group of authors using AI. In an alternative specification that extends the benchmarks from AI and human article days to no-article days, we find that AI articles are associated with positive abnormal trading volume and larger absolute cumulative abnormal returns relative to no-article days. Overall, we find that AI articles are predominantly written by less experienced SA authors and have significantly lower impacts on capital market outcomes relative to human articles, but are nevertheless beneficial relative to no-article days. The lower average impact of AI articles suggests some merit in SA's strategic choice to prohibit such articles from their platform.

Dwivedi et al. (2023) indicate the biggest disruption of AI is for 'knowledge work productivity,' and that "the biggest impact will be associated with its ability to create a first draft" (p. 7). We suspect that much of the increase in articles documented above might reflect this use of ChatGPT. Thus, we extend our analysis of the characteristics and impact of SA articles to focus on productivity at the individual author level. We examine two measures of productivity, the author's number of articles per month and whether the author covers a firm they had previously not covered. We first identify whether an author is an AI adopter based on the identification of that author's articles as generated by AI according to Originality.ai. We then employ a difference-in-differences research design that stratifies articles across the pre-ChatGPT, before the no-AI policy, and after the no-AI enforcement periods.

At the author level, AI adopters significantly increase the number of monthly articles after the introduction of ChatGPT, but the number decreases significantly after SA begins enforcing the no-AI policy. Similarly, authors expand coverage to new firms after ChatGPT was introduced, but the effect largely reverses after the no-AI enforcement. These results are consistent with individual authors using AI to increase productivity in terms of publishing more articles and covering more new firms until SA's prohibition curtailed their use of the tools. At the firm level, we show that the total number of SA articles covering a firm during a month is associated with lower bid-ask spreads and illiquidity, but the effect is driven by human articles. However, we document that AI articles for firms with lower coverage are also associated with lower bid-ask spreads and illiquidity. Thus, we find human articles are associated with firm-level capital market benefits, but that AI articles are also beneficial for firms with otherwise low coverage.

Our study makes two main contributions to the literature. We provide nuanced evidence on how new AI technologies are being used by some participants in the market for information, and the consequences of that use. Although our results show a significant increase in the use of AI to generate financial analysis, we find that the informativeness of these articles is, on average, attenuated relative to human-generated analysis. However, we document that relative to no-article days, AI articles nevertheless provide benefits to firm-level information flows and stock liquidity.

Also, we document that authors of SA articles exhibit varying abilities to integrate AI into impactful research outputs. Our study is related to Bertomeu et al. (2025), who examine the impact of a ban of ChatGPT in Italy on professional financial analysts, finding that the sudden withdrawal of the tool leads to fewer and less accurate earnings forecasts, a greater reliance on industry-specific information in analyst reports, and reduced market efficiency for affected firms. Whereas Bertomeu et al. (2025) focus on professional analysts, we examine non-professional analysts, who also serve an important role in promoting market efficiency but likely face lower career and reputational risks. Thus, we expect greater variation in the quality of their AI use – a prediction that seems borne out in our findings that AI articles are on average less informative than human-written articles, and that more experienced SA authors produce higher quality AI articles than less experienced authors. Moreover, whereas Bertomeu et al. (2025) are necessarily restricted to a small sample of analysts and firm-months surrounding Italy's brief ban of ChatGPT during April 2023, we exploit a setting allowing for longer-window observations of the productivity and market efficiency effects of AI availability.

We also contribute broadly to the burgeoning literature on accounting and labor markets (e.g., Barrios et al. 2024), and more specifically to research examining the effects of technology adoption on human performance in the financial decision-making domain (e.g., Costello, Down and Mehta 2020; Liu 2022; Dyer, Guest, and Yu 2025). We find that SA authors who adopt generative AI tools increase their productivity, publishing more articles and covering more new firms compared to non-adopting authors. Moreover, the productivity advantage of AI-adopters fades after SA's prohibition on AI use. The magnitude of the productivity boost for AI-adopting SA authors is comparable to effects found for AI-adopting professionals in other fields, including software developers (Cui et al. 2024), consultants (Dell'Acqua et al. 2023), and customer support professionals (Brynjolfsson, Li and Raymond 2025). In addition to extending research on AI-induced productivity effects to financial professionals, we complement these studies by bringing to light a unique setting featuring both the introduction and withdrawal of generative AI tools.[8]

Our study is subject to several caveats. First, as noted above, our sample period is restricted to the immediate periods before and after the widespread availability of ChatGPT. Generative AI and tools that detect the use of generative AI continue to evolve, and there is a ‘cat and mouse” game between AI and AI detection. As these technologies are refined, the associations we document may also change. Second, our evidence about AI articles being interpreted as, on average, less impactful relative to human articles is similarly subject to the continuing development of AI and human proficiency at effectively deploying such tools; indeed, some of our results indicate incremental benefits to firms by the use of AI by a subset of authors. Finally, our ability to identify AI usage by SA authors is limited to the final versions of written articles. It is possible (or likely) that competent SA authors use AI tools to screen stocks, perform background financial analysis or summarize large amounts of data prior to writing an analysis, and these activities are unobservable. Nevertheless, we believe our evidence on the immediate use of AI in writing of SA articles to be evidence of the enthusiastic use of AI in financial analysis, which is sure to continue.

2. Background and Hypothesis Development

2.1 AI and Financial Analysis

Research on AI and financial analysis is relatively new. However, prior studies that attempt to harness computing power to optimize analysis of financial statements goes back decades. These studies can be loosely interpreted as ‘generative’ given a predominant focus on predicting changes

[8] Cui et al. (2024) note that “to date, there is still a dearth of experimental studies examining the effects of generative AI in a field setting” (p. 3).

in earnings, prices, or infrequent events like bankruptcy. For example, Ou and Penman (1989) 'let the data speak' on whether a statistical model can be developed from 68 financial statement variables to predict the sign of the next annual earnings change. Similarly, numerous studies have used time-series models to predict levels of future earnings (e.g., Brown and Rozeff 1978; Fried and Givoly 1982). Studies on fundamental analysis have also used statistical modelling to predict either future earnings or price changes (Lev and Thiagarajan 1993; Abarbanell and Bushee 1998). Finally, researchers have used statistical analysis to predict outcomes such as bankruptcy (Altman 1968) and accounting fraud (Beneish 1999).

With the evolution of machine learning, data analytics, and AI capabilities, researchers have revisited similar questions to the above studies. For example, Shen (2012) employs neural network analysis and Chen et al. (2022) apply machine learning tools to predict the sign of the next annual earnings change. Qianyu et al. (2021) use neural networks to show that prediction accuracy for future earnings is superior to forecasts by financial analysts. Amel-Zadeh et al. (2020) use machine learning and Cao et al. (2024) use AI to predict future abnormal returns. AI has the potential to reveal the value of context in the numeric interpretations learned from the deep interactions between numeric and textual information (Kim and Nikolaev 2024). Finally, recent studies have used tools such as neural networks, random forests, vector machines, swarm optimization and advanced textual analysis for bankruptcy prediction (e.g., Agarwal and Taffler 2008; Kostopoulos et al. 2017; Mai et al. 2019). A parallel literature uses similar tools to predict accounting fraud (e.g., Omar, Johari and Smith 2017; Brown, Crowley and Elliott 2020; Wyrobek 2020; Bertomeu et al. 2021).

An issue lurking in the background of these studies is understanding of what happens inside the 'black box' of these advanced data analytics and generative AI techniques. Researchers can to some extent control the parameters of the prediction process, but interpreting the output requires understanding the generative algorithms. Further, a looming concern is that a convergence of generative algorithms may lead to a herding of analytic outcomes, which can actually reduce the information content yielded by such tools. This concern is reflected in the justification by SA, discussed earlier, to prohibit the use of AI for articles submitted to the platform.

2.2 Timeline of Seeking Alpha's No-AI Policy

To better understand the timeline of SA's policy on AI use, we met with SA senior management and manually reviewed SA developer chat room forums. Although SA officially addressed the use of AI on its platform as early as February 2023, users continued to ask questions. For example, a February 2023 thread titled "Elephant in the Room: ChatGPT" contained the following,

> "Sorry if SA has already addressed this somewhere, but what do we do about ChatGPT? The platform is impressive, it has saved me tons of time already writing content on another (non-SA) site. … are we allowed to leverage the AI tool here?"

A March 2023 thread titled "Plagiarism and Attribution Policy - ChatGPT/AI Software" clarified,

> "Seeking Alpha considers the use of Artificial Intelligence tools to create content to be a form of plagiarism. … opinion & analysis content submitted to Seeking Alpha **cannot** be sourced through, or constructed by, AI software."

A notable development occurred in October 2023, when SA made key changes to their enforcement approach that improved their ability to detect and deter AI-generated submissions.[9] SA also refined how it communicated its no-AI policy to contributors and how it disciplined violators. For instance, SA published enforcement statistics in January 2024 indicating that numerous authors were caught and penalized. SA's forum post noted,

[9] Private communication with SA senior management confirms that enforcement changes made around October 2023 enabled SA to better detect and deter AI-generated submissions.

> “A depressing stat: **25 analysts** were suspended or removed from the Seeking Alpha platform during 2023 due to plagiarism violations. … Our team is monitoring for, and tracking suspicions of plagiarism and AI usage very closely, as the times demands us to.”

Finally, in May 2024, a thread titled “Submission Update: New AI Disclosure Requirement” highlights a new submission requirement for authors to acknowledge, which reads:

> “I verify that I have not used, and will not use, an artificial intelligence (AI) tool in the creation of this article. I understand that using AI – even to rewrite sentences or paragraphs – is prohibited and can lead to my account being suspended or permanently banned from the platform.”

2.3 Research on Seeking Alpha

Given the launch of SA in 2004, there is now a well-developed literature on the platform. Research on the impact of SA coverage falls into three main areas: (1) market pricing, (2) trading, especially among retail traders, and (3) other firm-level outcomes.

Chen et al. (2014), the first SA study, documents that SA articles predict both future returns and earnings surprises. Ding, Zhou and Li (2020) show that firm-specific information production on SA is associated with a reduction in stock return comovement. Ding, Shi and Zhou (2023) find that SA coverage helps attenuate market underreactions to earnings announcements (especially for low-visibility firms), whereas Gomez et al. (2024) find that SA coverage is linked to lower bid-ask spreads during earnings announcements. Campbell, DeAngelis and Moon (2019) find that SA authors’ disclosures of stock positions lead to enhanced credibility and informativeness of articles by those authors.

With regard to the impact of SA articles on trading, Farrell et al. (2022) examine whether SA articles specifically affect retail trading and draw causal inferences by comparing intraday trading between the pre- to post-article publication date (as the counterfactual). They highlight that informed retail trading is a driver of the post-article publication trading activity. In contrast, Umar (2022) conducts a novel field experiment with SA, where different titles for the same article are randomized across SA users. The results suggest SA users are more likely to click a link to articles with less complex titles. Similarly, Breuer, Knetsch and Sachsenhausen (2024) conclude that retail investors are more likely to rely on superficial characteristics of articles and show that only 3% of articles are associated with significant announcement returns.

The above studies document clear impacts of SA articles. However, Kogan, Moskowitz and Niessner (2020) examine a countervailing force by highlighting an undercover investigation that revealed fake news on crowdsourcing platforms. They find attenuated market reactions to all articles after the revelation, suggesting a loss of credibility and impact of SA contributors. Mitts (2020) studies a different form of manipulation, showing that negative articles by authors using anonymous pseudonyms coincided with elevated put option trading in the targeted firms, consistent with informed trading. However, Dyer and Kim (2021) find muted responses to SA articles by authors who use pseudonyms, even after controlling for article content.

Finally, recent evidence shows firm-level impacts from SA articles. He et al. (2024) argue that SA coverage of innovation activities reduces financing constraints, leading in turn to increased spending on innovation. Gu, Yost and Zou (2025) show that SA coverage of relatively small firms increases their visibility such that they are more likely to be acquired.

2.4 Hypotheses

After establishing that AI is used extensively in SA articles after the launch of ChatGPT (shown in Section 3 below), we first seek to understand any differences in the information content of AI and human articles. We proxy for article informativeness using: (1) the capital market consequences (abnormal trading volume and stock returns), and (2) the reception by the SA community (user comments and Editors' Picks, i.e., articles determined by the editors to have "the most compelling stock analysis"). Because research on the quality of AI-generated analysis is still developing, we do not make a directional prediction about differences between AI and human articles. Accordingly, we state our first hypothesis as follows:

H1: There is no difference in the informativeness of AI and human articles.

Having considered the average quality of AI articles, we next examine the role of author type in AI article quality. Our analysis is motivated by the idea that SA contributors include both "good" and "bad" users of AI. For instance, a good AI user may input into ChatGPT a detailed prompt with a clearly stated thesis and supporting bullet points for analysis, and merely ask the AI tool to help write the thesis into the style of a SA article. Moreover, a good user carefully checks the output and makes any revisions necessary to ensure the article's accuracy and quality. On the other hand, a bad AI user may lack a clear thesis and simply rely on AI to generate an article from scratch. We expect that AI articles by good users are more informative than those by bad users.

Because we cannot directly observe how SA contributors use AI, we use two proxies to identify good and bad AI users. First, we predict that authors with substantial experience have incentives to maintain their good reputation within the SA community by writing articles with high quality insights, even when using AI (i.e., good AI users). Second, we predict that authors who first begin publishing on SA just after the launch of ChatGPT are more likely to be opportunists seeking compensation for articles requiring relatively little effort (i.e., bad AI users). Thus, we state the following directional hypotheses:

H2a: Experienced authors publish higher-quality AI articles than less-experienced authors.

H2b: Opportunistic AI authors (i.e., authors who first publish on SA just after the launch of ChatGPT) publish lower-quality AI articles than other authors.

Next, we examine the productivity effects of generative AI for authors. While such research is nascent, recent studies have found that AI enables increased productivity in various contexts. Cui et al. (2024) describe field experiments at Microsoft, Accenture, and an anonymous Fortune

100 electronics manufacturing company where random subsets of software developers were provided access to an AI-based coding assistant, and found that such developers exhibit a 26% increase in the number of completed tasks. Dell'Acqua et al. (2023) find that consultants at Boston Consulting Group who were given access to generative AI tools improved productivity by 12%-25% on a series of day-to-day tasks. In the domain of writing, both Noy and Zhang (2023) and Kaisen, Li and Lu (2024) find that professionals who were given access to ChatGPT increase their productivity relative to those who were not. Intuitively, we expect that generative AI enables SA authors to reduce the amount of time required to publish an article, allowing them to publish more and cover more new firms. Thus, we state our H3 as:

H3: SA authors who adopt AI exhibit increased productivity compared to those who do not.

Last, we consider the impact of generative AI on: (1) aggregate firm coverage, and (2) firm liquidity. If AI enables SA authors to write more articles, we expect that more firms receive SA coverage after the launch of ChatGPT. Although this prediction may seem intuitive, SA authors may simply publish more articles on the set of already-covered firms. This may occur, for example, if AI tools struggle to produce insights about low-visibility firms with a poor information environment. As a follow-up question, we explore whether AI coverage benefits firms by leading to improved liquidity. In particular, if the use of AI enables information intermediaries to cover firms that historically have received little coverage, we predict such coverage will lead to increased visibility, lower information asymmetry, and improved liquidity. We state our final hypotheses as:

H4a: Firm coverage by SA articles increases after the launch of ChatGPT, and decreases after SA's improved enforcement of its no-AI policy.

H4b: Coverage by AI articles is associated with improved liquidity, particularly for firms with historically low coverage.

3. Sample, Variables, and Descriptive Evidence

3.1 Seeking Alpha Article Collection

The SA website provides firm-related content in two separate sections. One section contains in-depth articles by outside contributors focused on firm-level fundamental analysis (i.e., the Analysis section), whereas the other section contains information on news events such as earnings announcements, dividend announcements, etc. (i.e., the News section). Because we are interested in studying the incremental informativeness of AI-generated articles to investors (as opposed to simply the dissemination of existing information), we focus on articles in the Analysis section (e.g., Chen et al. 2014; Dyer and Kim 2021; Farrell et al. 2022).

As shown in Table 1 Panel A, we collect all such articles published from June 1, 2022 through August 31, 2024, including the article's title, publication date, author name, main text, user comments on the article, "Editor's Pick" flag, and company ticker associated with the article. We exclude articles with fewer than 100 words, firms we are unable to match to Compustat or CRSP, and articles for firms missing data required to construct control variables. We match articles to firms based on ticker symbols and publication dates. To avoid skewing our tests on the capital market impact of AI articles, we exclude articles on very small firms (i.e., firms with a stock price below $1 per share or with a total market capitalization less than $100 million), as well as articles for firms missing information related to trading volume or market returns. The above steps yield a sample of 75,637 SA articles, of which 59,881 are published after the launch of ChatGPT (i.e., from December 1, 2022 to August 31, 2024). Based on our procedure to identify AI articles (which we describe in detail in the next subsection), we find that out of 59,881 SA articles, 4,877 are primarily AI-generated and 55,004 are human-written.

3.2 Identifying AI-generated Articles

We identify the use of generative AI in SA articles using Originality.ai, a commercial AI content detection tool that employs a fine-tuned, high-dimensional language model. Originality.ai was commercially released in April 2023 and is considered to be one of the most accurate AI content detectors available (e.g., Irons 2024).[10] Originality.ai claims that the model we employ in our study, the Lite 1.0.0 model released in July 2024, exhibits a 99% accuracy rate in detecting AI-generated content with a false positive rate under 1%. Moreover, existing testing suggests this model is well-calibrated in that it correctly detects AI-generated text even if it has been paraphrased (e.g., Dugan et al. 2024), but does not flag content as AI-generated when an AI writing assistant (e.g., Grammarly) has been used only for spelling or grammatical errors.[11]

We scan each SA article individually using Originality.ai. Prior to scanning, we remove boilerplate language (e.g., Editor's note, disclaimers) and noisy text (e.g., image captions and ticker parentheses) to improve detection accuracy. Scanning the resulting text yields a confidence score that the content scanned was produced by an AI tool. We consider an article to be AI-generated if its AI confidence score from Originality.ai's content detector exceeds 95%.[12] We label such articles "AI articles" and all other SA articles as human-written ("human articles").

Our approach to detecting and classifying AI-generated articles sets a high threshold for identification as AI, as our coding requires the author to have inserted AI-generated text (either verbatim or only lightly edited). Consequently, our estimate of AI usage likely represents a lower bound of the true scope of AI usage by SA authors. To the extent that authors use AI for tasks such

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[10] For details on the relative performance accuracy of Originality.ai and other AI detection tools, see the following link: https://originality.ai/blog/empirical-study-ai-generated-text-detection.

[11] Originality.ai claims that it "allows for lightly edited AI-content (like Grammarly's grammar and spelling suggestions) while still differentiating between light AI editing and fully generated AI content." See the following link for more details: https://originality.ai/blog/ai-content-detection-accuracy.

[12] An above-95% threshold for classifying articles as AI-generated is necessarily ad hoc. In untabulated robustness tests, we obtain similar inferences using alternative thresholds (e.g., 90%, 99%).

as idea generation, financial information processing, first draft generation, or text polishing that is not detected by Originality.ai (or falls below our confidence threshold), our classification of AI articles may understate the prevalence of AI use.

3.3 Prevalence of AI-generated Articles Over Time

Table 2 displays the monthly distributions of the total number of SA articles (columns 1-3), authors (columns 4-6), and firms covered (columns 7-9), as well as the prevalence of AI use in each category. For instance, column 2 shows that in December 2022 there were 119 AI articles published, comprising 4.6% of total SA articles. The share of AI articles rose rapidly in subsequent months to a peak of 13.4% (433 articles) in October 2023, before a sharp decline that bottoms out at approximately 4% of total articles in April to August 2024. Similarly, columns 4-6 show that the percentage of SA authors who published an AI article increased from 7.8% (37 authors) in December 2022 to 17.0% (86 authors) in October 2023, before declining to approximately 10.5% (49 authors) in April to August 2024. In addition, columns 7-9 show that the percentage of public firms covered by an AI article increased from 3.5% (112 firms) in December 2022 to 11.3% (363 firms) in October 2023, before declining to approximately 2.8% (89 firms) in April to August 2024.

The above patterns are illustrated in Figure 1. In Panel A, the x-axis represents calendar-months and the y-axis is the percentage of total SA articles that are AI-generated. We include data for six months prior to the ChatGPT launch on November 30, 2022 (i.e., June through November 2022) to establish a baseline of articles classified as AI-generated before generative AI tools were broadly available. An average of 1.6% of articles are deemed to be AI-generated in the pre-ChatGPT months, consistent with a false positive rate of approximately 1.6%. After the ChatGPT launch, the share of AI-generated articles rises until October 2023 when it exhibits a downturn that bottoms out in April 2024. The reversal of AI articles in late 2023 reflects changes in SA's enforcement efforts that improved their ability to detect and deter AI-generated submissions. Panels B and C show a similar pattern of rising AI use by authors and AI coverage of firms in the months after the ChatGPT launch followed by a swift drop in late 2023 and early 2024, when SA intensified enforcement of its no-AI policy.

3.4 Variable Measurement

3.4.1 Article Informativeness

We examine two sets of outcome variables to gauge the informativeness of AI and human articles. First, we study the capital market effects by examining (1) the firm's abnormal trading volume for the 3-day window from the article publication date (*Abnormal Trading Volume*$_{(0,+2)}$) and (2) the absolute value of the firm's 3-day cumulative abnormal returns ($|CAR_{(0,+2)}|$). Second, we consider the reception of an article by the SA community using: (1) the number of user comments an article receives in the 30 days after publication (*User Comments*), and (2) whether it is selected as a top (i.e., "most compelling") article by an editor (*Editor's Pick*). Appendix A contains details on variable construction.

3.4.2 Firm, Timing, and Author Characteristics

We consider three sets of characteristics for AI and human articles to be used primarily as control variables in our analyses. First, we examine characteristics of firms covered by SA articles, including firm size (*Size*), book-to-market value of equity (*BTM*), performance (*ROA*), leverage (*Leverage*), R&D and advertising expenditures (*R&D* and *Advertising*), firm age (*Firm Age*), analyst following (*Analyst Follow*), institutional ownership (*Institutional Own*), and recent stock returns (*Past Return*). Second, we consider article timing, such as whether an article is published just after the firm announces its quarterly earnings (*Recent EA*), files a Form 8-K (*Recent 8-K*), is covered by a traditional media article (*Recent Press*), and whether an article is published within a three-day window of another, human-written article (*Concurrent Article*). Third, we consider author-level characteristics such as the span of time the author has been a SA contributor (*Author Tenure*), the number of articles published (*Author Article History)*, and whether an author remains publicly anonymous (*Author Anonymous*) (e.g., Dyer and Kim 2021).

3.4.3 Article Textual Characteristics: Readability, Tone, and Specificity

We examine textual characteristics of AI and human SA articles along three dimensions: readability, tone, and specificity (e.g., Blankespoor, deHaan and Li 2024). We employ two proxies to capture each dimension. For readability, we measure *Complexity*, defined as the Gunning Fog Index, and *Length*, defined as the natural log of the number of words in an article (e.g., Li 2008; Miller 2010). For tone, we use the Loughran and McDonald (2011) tonal dictionary to capture *Sentiment*, defined as the proportion of net positive words to total words, and *Word Strength*, defined as the proportion of net strong words to total words. For specificity, we use *Quantitative*, defined as the proportion of numerical information (count of numbers) to total words (e.g., Campbell, Zheng and Zhou 2024), and *Named Entities*, defined as the proportion of 7-class entities by the Stanford Named Entity Recognizer (NER) to total words (Hope, Hu and Lu 2016; Dyer, Lang and Stice-Lawrence 2017).

3.5 Descriptive Statistics

Table 3 Panel A presents descriptive statistics for the sample of 59,881 SA articles. The mean value of *AI Article* indicates that 8.1% of articles are AI-generated. The average article length is 1,328 words, has positive tone (mean *Sentiment* of 0.575), and uses more weak than strong words (mean *Word Strength* of -0.182). The average article contains a ratio of 0.028 numbers to words (mean *Quantitative* value of 2.794) and a ratio of 0.081 named entities to words (mean *Named Entities* value of 8.105). For article timing, 20.7% (32.9%) of articles are published within six days after a quarterly earnings announcement (Form 8-K filing), and a mean (median) of 4.7 (0) media articles are published in the six days prior to a SA article. The mean (median) article is published by an author with 5.2 (4.4) years of SA experience who has written 745 (280) articles, and 24.5% of articles are published by anonymous authors. The average article receives 22 user comments, and approximately 1.9% of articles are selected as an "Editor's Pick."

Table 3 Panel B presents mean values of the above characteristics separately for the groups of AI articles (column 1) and human articles (column 2), as well as the results of t-tests comparing the two groups. AI articles are more complex, longer, have a more positive tone and use weaker words, and include less quantitative and specific information. In terms of coverage, AI articles tend to cover firms that are larger, have lower book-to-market equity values, worse profitability, and lower leverage. Firms covered in AI articles have higher R&D and advertising expenditures, are younger, and have greater analyst following and institutional ownership. Compared to human articles, AI articles are less likely to occur immediately after an earnings announcement or Form 8-K filing. In terms of author characteristics, authors of AI articles have shorter tenures, have written fewer articles, and are more likely to be anonymous.

Examining article impact, AI articles give rise to smaller trading volume and market return responses than human articles (although the difference in market returns is not statistically significant). Relative to human articles, AI articles also receive fewer user comments and are less likely to be selected as an Editor's Pick. Overall, these findings provide preliminary evidence that AI articles have lower impact than human articles.

3.6 Determinants Analysis and Textual Characteristics of AI Articles

Two sets of multivariate regression analysis help to formalize some of our inferences from the univariate comparison in the previous subsection. First, we conduct a determinants test by regressing the variable *AI Article* on the array of firm, timing, and author characteristics described above as well as various sets of fixed effects including: (1) month; (2) firm and month; and (3) firm, month, and author. The results, displayed in Table A1 of the online appendix, indicate few systematic differences between AI and human articles in the characteristics of firms covered and article timing. However, one notable difference is that AI articles are more likely to be written by authors with less experience on SA (i.e., authors with shorter tenures and fewer historical articles). A possible interpretation is that generative AI serves as a crutch to inexperienced authors who lack the ability to write compelling articles. Alternatively (or in addition), the availability of generative AI tools may have led to a wave of opportunistic new authors seeking compensation for publishing articles requiring relatively little effort.[13] We consider these possibilities in further analysis below.

In a second set of multivariate regression tests, we explore differences in textual attributes between AI and human articles. As shown in Table A2 of the online appendix, we regress proxies for article readability, tone, and specificity on the variable *AI Article*, controlling for firm, timing, and author characteristics as well as an array of fixed effects. Compared to human articles, we find that AI articles have a higher Fog score (indicating greater complexity), more positive sentiment, use weaker words, and include less numeric information.[14] On the other hand, AI and human articles exhibit no differences in length or in the frequency of named entities. The findings indicate

[13] Another possibility is that inexperienced authors who rely on generative AI are more likely to successfully pass SA's rigorous review and screening process than those who do not (i.e., a selection effect causes inexperienced authors to be overrepresented among AI-generated articles).

[14] The findings on complexity align with recent studies showing that AI-generated summaries of medical guidance are difficult to read and require a high level of reader sophistication, making them unsuitable for most laypeople (e.g., Gencer 2024; Onder et al. 2024; Hanci et al. 2024; Yan et al. 2024). Moreover, the findings on tone are consistent with those from a study at the Gillmore Center for Financial Technology at Warwick Business School, which finds that LLMs shift text sentiment towards neutrality, reducing both positive and negative sentiment. However, the reduction in negative sentiment is more pronounced, leading to a general shift towards positive sentiment. The study is summarized at the link: https://itbrief.co.uk/story/warwick-study-reveals-sentiment-shifts-in-text-rewritten-by-ai#:~:text=Revolutionary%20research%20from%20academics%20at,the%20sentiment%20of%20original%20text.

that, on average, AI articles are less readable than human-written articles, skew more positive in tone but refrain from using strong language, and contain less quantitative information.

4. Informativeness of AI Articles

4.1 AI Articles vs. Human Articles

To begin our main analysis, we examine differences in the informativeness of AI and human articles by studying their capital market impact and reception by the SA community. To do so, we estimate the following OLS regression at the article level:

$$Informative_{i,t,j} = \alpha + \beta_1 AI\ Article_{i,t,j} + \beta_k Controls_{i,t,j} + \theta FE + \epsilon_{i,t,j} \quad (1)$$

In Eq. (1), *i*, *t*, and *j* index the firm covered by an article, the publication date, and the author, respectively. *Informative* represents the proxies for an article's informativeness and reception by the SA community, as discussed above. *AI Article* is an indicator equal to one if the article is AI-generated, and zero otherwise. *Controls* represents a vector of firm, article timing, and author characteristics. We include the following sets of fixed effects: (1) firm and month; and (2) firm, month, and author. Standard errors are clustered at the firm and month levels.

Table 4 Panel A displays the results from estimating Eq. (1) for $Abnormal\ Trading\ Volume_{(0,+2)}$ (columns 1-2) and $|CAR_{(0,+2)}|$ (columns 3-4). Column 1 shows a significantly negative coefficient on *AI Article* (coef.= -0.029; t-stat.= -3.61), indicating that AI articles lead to smaller trading volume responses than human articles, on average. Column 2, controlling for author fixed effects, also shows a negative coefficient on *AI Article* (coef.= -0.025; t-stat.= -2.23), confirming a robust negative link between AI articles and trading volume. Columns 3-4, examining $|CAR_{(0,+2)}|$, show significantly negative coefficients on *AI Article*, denoting smaller abnormal return responses to AI articles than to human articles. Economically, cumulative abnormal returns around AI articles are 7.0% smaller than for human articles. Overall, the findings for trading volume and abnormal returns suggest that AI articles are less informative to investors than human articles.

Table 4 Panel B presents the results examining the link between AI articles and SA user comments (columns 1-2) and Editor's Pick articles (columns 3-4). Columns 1 and 2 show significantly negative coefficients on *AI Article* (coef.= -2.930; t-stat.= -7.53, and coef.= -1.028; t-stat.= -2.01), indicating that AI articles receive fewer comments than human articles, even after including author fixed effects. Economically, AI articles receive 5.0% fewer user comments than human articles, on average. Examining articles selected as an Editor's Pick, column 3 shows a significantly negative coefficient on *AI Article* (coef.= -0.008; t-stat.= -3.45), but column 4 shows that the effect turns insignificant after including author fixed effects (coef.= -0.003; t-stat.= -1.19). The findings suggest that while AI articles are less likely to be selected as Editor's Picks than human articles, the effect may be due to a difference in the quality of authors submitting the articles rather than the authors' use of AI, per se (in other words, the type of author that submits AI articles may produce lower-quality articles than the type of author that does not).[15]

The findings in Table 4 indicate that AI articles give rise to smaller trading volume and abnormal return responses than human articles, spur less user engagement, and are less likely to be selected as an Editor's Pick. Collectively, the results suggest that market participants perceive AI articles as less informative than human articles, leading us to reject our null H1 hypothesis that there is no difference in the informativeness of the two article types. Moreover, the findings lend preliminary support to SA's decision to implement a no-AI policy for its contributors.

[15] Another possible interpretation is that some SA authors may utilize AI to compose articles for firms or events of lesser importance, which is consistent with an interpretation that AI use is associated with lower capital market impacts.

4.2 AI and Human Articles vs. No Article Days

While the findings in the previous subsection suggest that AI articles are less informative than human articles, they do not necessarily imply that AI articles lack information content entirely. To investigate the possibility that AI articles have some capital market impact, we conduct tests using a firm-day sample with which we benchmark the effects of human and AI articles against days with no SA articles. Specifically, we estimate the following regressions at the firm-day level:

$$Informative_{i,t} = \alpha + \beta_1 SA\ Article\ Day_{i,t} + \beta_k Controls_{i,t} + \theta FE + \epsilon_{i,t} \quad (2a)$$

$$\begin{aligned} Informative_{i,t} = \alpha + \beta_1 AI\ Article\ Day_{i,t} + \beta_2 Human\ Article\ Day_{i,t} \\ + \beta_k Controls_{i,t} + \theta FE + \epsilon_{i,t} \end{aligned} \quad (2b)$$

In Eq. (2a) and (2b), *i* and *t* index firm and trading day, respectively. $Informative_{i,t}$ represents either $Abnormal\ Trading\ Volume_{(0,+2)}$ or $|CAR_{(0,+2)}|$ for firm *i* on day *t*. $SA\ Article\ Day_{i,t}$ is an indicator equal to one if firm *i* is covered by any SA article on day *t*. $AI\ Article\ Day_{i,t}$ ($Human\ Article\ Day_{i,t}$) is an indicator equal to one if firm *i* is covered by an AI article (human article) on day *t*. *Controls* represents a vector of control variables similar to Eq. (1) with author-level controls excluded because many firm-days contain no SA article. Firm and day fixed effects are included, and standard errors are clustered at the firm and month levels.

Table 5 displays the results from estimating Eq. (2a) and (2b) for $Abnormal\ Trading\ Volume_{(0,+2)}$ (columns 1-2) and $|CAR_{(0,+2)}|$ (columns 3-4). Column 1 shows a significantly positive coefficient on *SA Article Day* (coef.= 0.054; t-stat.= 17.40), indicating that firm-days with a SA article exhibit significantly higher abnormal trading volume than days without SA articles. Column 2, showing the effects of AI and human article days separately, reveals significantly positive coefficients on both *AI Article Day* (coef.= 0.022; t-stat.= 3.01) and *Human Article Day* (coef.= 0.056; t-stat.= 17.22), denoting that both AI and human article coverage are linked to higher abnormal trading volume than days without such articles. An F-test comparing the coefficients indicates that the impact of *AI Article Day* is significantly lower than that of *Human Article Day* (p-value < 0.01). Columns 3-4, showing the results for $|CAR_{(0,+2)}|$, reveal a similar pattern.

The results in Table 5 indicate that while AI-generated articles have a smaller capital market impact than human-written articles, they still contain some information content that market participants find useful. These findings suggest that, to the extent that AI-generated articles are less costly to produce than human-written articles, there may be capital market benefits to the expansion of AI coverage. We explore this possibility in later tests.

4.3 Experienced Authors and Opportunistic Authors

In this subsection, we examine the role of author type in the quality of AI articles. As discussed in Section 2.4, we posit that SA contributors include "good" and "bad" AI users, and we expect that articles by good AI users are more informative than those by bad AI users. Since we cannot directly observe how SA authors use AI, we rely on two proxies to identify good and bad AI users. First, we predict that authors with substantial experience have an incentive to maintain their good reputation in the SA community by publishing articles with high quality insights, even when using AI (i.e., good AI users). Second, we predict that authors who first begin publishing on SA just after the launch of ChatGPT are more likely to be opportunists aiming to be compensated for articles requiring relatively little effort (i.e., bad AI users).

To operationalize our predictions, we first define the variable *Experienced Author* as an indicator equal to one for authors with two or more years of experience prior to the launch of ChatGPT, and zero otherwise. We also define the variable *Opportun AI Author* as an indicator equal to one for authors whose first article appeared in the three months after the launch of ChatGPT (i.e., Dec. 2022 – Feb. 2023), and zero otherwise. We test our predictions by estimating a modified Eq. (1) that includes our proxies for experienced and opportunistic AI authors.

Table 6 Panel A presents the results for experienced authors. Column 1, examining abnormal trading volume, shows a significantly negative coefficient on *AI Article* (coef.= -0.035; t-stat.= -3.77), consistent with our previous findings that AI articles are on average less informative than human articles. However, the coefficient on the interaction term *AI Article* × *Experienced Author* is significantly positive (coef.= 0.034; t-stat.= 2.23), indicating that AI articles by experienced authors are higher quality than AI articles by other authors. Column 2, controlling for firm fixed effects, also shows a positive coefficient on *AI Article* × *Experienced Author* (coef.= 0.026; t-stat.= 1.52), although the effect falls short of statistical significance. Columns 3 and 4 find that AI articles by experienced authors elicit significantly higher abnormal return responses than AI articles by other authors. The findings imply that author experience can mitigate the tendency to produce lower-quality AI articles.

Table 6 Panel B shows the results for opportunistic authors. Column 1 shows a significantly negative coefficient on *AI Article* × *Opportun AI Author* (coef.= -0.067; t-stat.= -2.40), indicating that AI articles by authors who first began contributing to SA just after the launch of ChatGPT elicit lower abnormal trading volume than AI articles by other authors. Column 2 shows a similar result after controlling for firm fixed effects, and columns 3-4 reveal a similar pattern for abnormal return responses. The findings indicate that authors who first began contributing to SA just after the launch of ChatGPT produce lower-quality AI articles, consistent with such authors being "bad" AI users. Overall, the findings in Table 6 provide evidence that the quality of AI use (as manifested in the quality of AI articles produced) varies depending on the author.

5. Author-Level and Firm-Level Effects of Generative AI Use

5.1 AI Use and Author Productivity

5.1.1 Productivity of AI Adopters and Non-Adopters Over Time

Having examined the content and consequences of AI articles, we turn to the potential link between AI use and the productivity of SA authors. We posit that using generative AI has the potential to improve authors' efficiency in producing articles, enabling them to accomplish more in the same amount of time. To test our prediction, we construct a sample of author-months from June 2022 through August 2024. We extend the start of our sample back in time to include six months before the ChatGPT launch to establish a baseline level of productivity for authors before generative AI tools were broadly available.

As shown in Table 1 Panel C, a total of 1,894 authors published at least one article during this window. Because we aim to study changes in author productivity over time, we require authors to have published articles in at least six different months during our sample period; a restriction yielding 744 authors that we partition into three groups: (1) authors who never adopt AI (Non-Adopters); (2) existing authors who publish at least one AI article (AI Adopters); (3) new authors who published AI articles in their first month on SA (AI-Starters). We focus on the first two groups (Non-Adopters and AI Adopters) because our research design, which is described below, compares changes in productivity for these authors. Thus, our final sample comprises 711 authors (491 Non-Adopters and 220 AI Adopters) and 17,612 author-months from June 2022 through August 2024.

Figure 2 Panel A provides graphical evidence of the change in author productivity over time for AI Adopters (black line) and Non-Adopters (gray dashed line). The x-axis represents calendar months and the y-axis the average number of monthly articles by authors in each group. Whereas average monthly articles by the two groups are fairly similar and move in tandem in the pre-ChatGPT months, they diverge after the ChatGPT launch, with AI Adopters publishing more articles than before and Non-Adopters publishing fewer. After SA begins enforcing its no-AI policy around October 2023, the number of articles by AI Adopters falls back into closer alignment with Non-Adopters. Figure 2 Panel B shows the proportion of monthly articles comprising non-AI articles (striped gray area) and AI articles (solid black area) for AI Adopters, revealing that much of the gap in article frequency between AI Adopters and Non-Adopters after the ChatGPT launch can be attributed to AI. This figure provides preliminary evidence that AI adoption increased productivity for AI Adopters relative to Non-Adopters.

To assess the robustness of the univariate results on the link between AI use and author productivity, we estimate the following OLS regression at the author-month level:

$$\begin{aligned} Productive_{j,t} = \alpha + \beta_1 Post\ GPT_t \times AI\ Adopter_j + \beta_2 Post\ No\ AI\ Policy_t \times AI\ Adopter_j \\ + \beta_3 AI\ Adopter_j + \beta_k Controls_{j,t} + \theta FE + \epsilon_{j,t} \end{aligned} \tag{3a}$$

In Eq. (3a), *j* and *t* index author and month, respectively. *Productive* represents our two proxies for author productivity: (1) *Monthly Articles*, defined as the natural log of one plus the number of articles published by the author, and (2) *Newly Covered Firms*, defined as the natural log of one plus the number of firms covered by the author for the first time. *Post GPT* is an indicator equal to one if month *t* is December 2022 or later, and zero otherwise. *Post No-AI Policy* is an indicator equal to one if month *t* is November 2023 or later, and zero otherwise. *AI Adopter* is an indicator equal to one if author *j* publishes at least one AI article during the sample period, and zero otherwise. *Controls* is a vector of firm, article timing, and author characteristics.[16] We include the following sets of fixed effects: (1) month; (2) month and author. Standard errors are clustered at the author and month levels. We predict $\beta_1 > 0$, indicating that AI-adopters increase productivity

[16] For the tests using author-months as the unit of observation, firm-level control variables are constructed as average values for the firms covered by the author in that month. If an author covers no firms in that month, we use values for the most recent month in which the author covered firms.

after the launch of ChatGPT, compared to non-adopters. Moreover, we predict $\beta_2 < 0$, indicating that AI-adopting authors suffer reduced productivity after SA enforces its no-AI policy.

The results from estimating Eq. (3a) are displayed in Table 7 Panel A. Column 1, showing results for *Monthly Articles*, reveals a positive and significant coefficient on *Post GPT* × *AI Adopter* (coef.= 0.284; t-stat.= 5.24), denoting that AI-adopting authors publish more articles after the launch of ChatGPT. Further, the coefficient on *Post No-AI Policy* × *AI Adopter* is significantly negative (coef.= -0.186; t-stat.= -3.09), indicating that AI-adopting authors publish fewer articles after SA tightens enforcement around AI use. Compared to non-adopting authors, AI-adopting authors exhibit an increase of 39.9% in published articles after the ChatGPT launch.[17] However, AI-adopting authors exhibit a subsequent decrease of 20.6% in published articles after no-AI enforcement is tightened. Column 2 shows similar results after controlling for author fixed effects. Columns 3 and 4, examining *Newly Covered Firms*, reveal findings consistent with those for *Monthly Articles*; AI-adopting authors cover more new firms after the launch of ChatGPT, but fewer new firms after SA tightens its no-AI enforcement.[18]

Overall, the findings in Figure 2 and Table 7 Panel A support our prediction that the use of generative AI tools enables authors to increase their productivity. After the launch of ChatGPT, AI-adopting authors publish more articles and more new firms compared to non-adopting authors. However, this pattern reverses after no-AI enforcement is tightened in October 2023, reversing some of the productivity gains of AI-adopters relative to non-adopting authors.

[17] We compute the economic magnitude for AI Adopters after the launch of ChatGPT by deriving an implied change in *Monthly Articles* relative to its untransformed mean value in the pre-ChatGPT months (i.e., 4.63 articles) as follows: we solve for r such that 0.284 = ln(1+4.63*(1+r))-ln(1+4.63). Here, r = 39.9%.
[18] In untabulated analysis, we estimate Eq. (3a), (3b), and (4) using Poisson regressions (e.g., Cohn, Liu and Wardlaw 2022) and find that our results are qualitatively unchanged.

5.1.2 Productivity of AI Adopters in Event-Time

To provide an aggregated picture of the link between AI use and individual author productivity, we conduct an event-time analysis examining the productivity of AI-adopting authors in the months surrounding their initial adoption of AI, and in the months after they cease using AI. For this analysis, we restrict our focus to AI-adopting authors (AI Adopters), yielding a sample of 220 authors and 5,248 author-months.

Figure 3 provides graphical evidence of the link between AI adoption and author productivity in event-time. In Panel A, the x-axis represents the month relative to when the author first begins using generative AI in a published article (which occurs in month t = 0), and the y-axis represents the average number of articles published by AI-adopting authors in each month. In the nine months prior to adopting AI (months t = -9 to t = -1), authors publish an average of five articles per month. In month t = 0, the average number of published articles spikes upwards to 8.39 and remains at an elevated level in subsequent months. On average, the number of monthly articles increases from 5.12 in the pre-AI adoption period to 7.09 in the post-AI adoption period; an increase of 38.5%. Panel B shows the proportion of monthly articles comprising human articles (striped gray area) and AI articles (solid black area). This figure reveals that most of the increase in article production reflects AI articles.

To test the event-time link between AI adoption and author productivity, we estimate the following OLS regression at the author-month level:

$$Productive_{j,t} = \alpha + \beta_1 Post\ AI\ Adoption_{j,t} + \beta_2 Post\ AI\ Exit_{j,t} + \beta_k Controls_{j,t} + \theta FE + \epsilon_{j,t} \quad (3b)$$

In Eq. (3b), *j* and *t* index author and month, respectively. *Productive* represents our two proxies for author productivity (*Monthly Articles*, *Newly Covered Firms*). *Post AI Adoption* is an indicator equal to one for all months on or after author *j* publishes their first AI article, and zero otherwise.

Post Exit is an indicator equal to one for all months after author *j* publishes their last AI article in the sample period, and zero otherwise. *Controls* represents a vector of firm, article timing, and author characteristics. We include author and month fixed effects, and cluster standard errors at the author and month levels. We predict $\beta_1 > 0$, indicating that authors increase their productivity after they begin using AI. In addition, we predict $\beta_2 < 0$, denoting that authors become less productive after they cease using AI.

The results from estimating Eq. (3b) are displayed in Table 7 Panel B. Column 1 reveals a significantly positive coefficient on *Post AI Adoption* (coef.= 0.592; t-stat.= 9.00), denoting an increase in published articles after an author begins using AI. In contrast, the coefficient on *Post AI Exit* is significantly negative (coef.= -0.223; t-stat.= -2.48), indicating that authors publish fewer articles after they stop using AI. Column 2 shows a similar result for *Newly Covered Firms*; authors cover more new firms after they begin using AI, but the effect reverses once they cease using AI.

Overall, the findings in Table 7 and Figure 3 indicate that AI-adopting authors are more productive after they begin using AI to produce articles and less productive after they stop using it. The estimated magnitude of the impact from AI use suggests that AI-adopting authors increase their output (published articles) by 38.5%-39.9%, or approximately two additional articles per month. These effect sizes are in line with recent work examining the effect of generative AI use on productivity in other contexts. For instance, Cui et al. (2024) describe field experiments conducted at Microsoft, Accenture, and an anonymous Fortune 100 electronics manufacturing company where randomly selected subsets of software developers were provided access to an AI-based coding assistant. They find that developers who were given access to the new tool exhibited a 26% increase in the number of completed tasks relative to those who were not.[19] Dell'Acqua et

[19] Cui et al. (2024) also document that less experienced developers showed higher adoption rates and greater productivity gains; results in line with our findings that AI-adopting authors are less experienced than non-adopters.

al. (2023) find that consultants at Boston Consulting Group who were given access to generative AI tools improved productivity by 12%-25% on a series of day-to-day tasks. Similarly, Brynjolfsson, Li and Raymond (2025) find that an AI-based conversational assistant increases the productivity of customer chat support agents by 14%. Our results provide evidence of similar productivity improvements for information intermediaries (i.e., SA authors) who adopt generative AI tools.

5.2 AI Use and Seeking Alpha Coverage of Firms Over Time

Having shown the effects of generative AI on author productivity, we next consider the impact on overall firm coverage by SA. We conjecture that the increased efficiency and productivity made possible by generative AI leads to an increase in the total number of firms covered by SA articles, which has previously been an explicitly stated goal of SA (Gu, Yost and Zou 2025). To test our conjecture, we construct a sample of firm-months from June 2022 through August 2024. We exclude firm-months that are missing information required to construct control variables as well as very small firms (i.e., firms with a stock price below $1 per share or with a total market capitalization less than $100 million), to match our sample of SA articles. The above steps yield a sample of 3,529 firms with 86,077 firm-months from June 2022 through August 2024.

Figure 4 Panel A provides graphical evidence of the link between generative AI availability and SA coverage over time. The x-axis represents calendar months and the y-axis the percentage of public firms covered by an SA article in that month. The figure shows that, although the share of covered firms fluctuates by month, a higher percentage of firms are covered in the months between the launch of ChatGPT and SA's no-AI policy. The share of firms with SA coverage increases from 40.6% in the pre-ChatGPT months (June to November 2022) to 48.1% after the ChatGPT launch but prior to SA's no-AI policy (December 2022 to October 2023), before falling back down to 42.9% in the post-enforcement period (November 2023 to August 2024). Figure 4 Panel B shows the share of firms covered by non-AI articles only (striped gray area), the share covered by AI articles only (solid black area), and the share covered by both AI and non-AI articles (dotted gray area). The share of firms covered only by non-AI articles stays relatively stable over time, whereas the share covered by AI articles or both AI and non-AI articles grows after the ChatGPT launch before shrinking upon enforcement of the no-AI policy.

To assess the robustness of expanded firm coverage to the inclusion of control variables, we estimate the following OLS regression at the firm-month level:

$$SA\ Cover_{i,t} = \alpha + \beta_1 Post\ GPT_t + \beta_2 Post\ No\ AI\ Policy_t + \beta_k Controls_{i,t} + \theta FE + \epsilon_{i,t} \quad (4)$$

In Eq. (4a), *i* and *t* index firm and month, respectively. *SA Cover* represents our two proxies for firm coverage: (1) *SA Coverage*, an indicator equal to one if firm *i* is covered by a SA article in month *t*, and zero otherwise, and (2) *SA Articles*, defined as the natural log of one plus the number of articles covering firm *i* in month *t*. *Post GPT* is an indicator equal to one if month *t* is December 2022 or later, and zero otherwise. *Post No-AI Policy* is an indicator equal to one if month *t* is November 2023 or later, and zero otherwise. *Controls* represents a vector of firm characteristics described previously. Firm fixed effects are included, and standard errors are clustered at the firm and month levels. We predict that $\beta_1 > 0$ and $\beta_2 < 0$, indicating that firms receive more coverage after the launch of ChatGPT, but less coverage after SA tightens enforcement around AI use.

The results from estimating Eq. (4) are displayed in Table 8. Column 1, showing results for *SA Coverage*, reveals a significantly positive coefficient on *Post GPT* (coef.= 0.068; t-stat.= 3.15), and a significantly negative coefficient on *Post No-AI Policy* (coef.= -0.054; t-stat.= -3.35), denoting that firms are more likely to receive coverage after the launch of ChatGPT, but that effect disappears after SA tightens enforcement of its no-AI policy. Economically, firms experience a

6.8 percentage point increase in coverage likelihood after the launch of ChatGPT, a relative increase of 16.9%. However, SA's no-AI enforcement leads to a 5.4 percentage point decrease in coverage likelihood, bringing coverage levels approximately back to where they were before ChatGPT was available. Column 2 shows a similar pattern after controlling for firm fixed effects. Columns 3-4 demonstrate generally similar results for *SA Articles*; namely that firms receive more article coverage after the ChatGPT launch but less coverage after SA's no-AI enforcement.

Viewed together, the results in Figure 4 and Table 8 suggest that the availability of generative AI tools enabled SA authors to expand their coverage of public firms; coverage which subsequently contracted when SA stepped-up its no-AI policy enforcement. On average, the number of firms with monthly coverage increased from 1,299 in pre-ChatGPT months to 1,531 after the launch of ChatGPT, then fell back to 1,373 after SA's no-AI policy. Our results suggest that generative AI tools led to a 17.8% increase in overall firm coverage. The findings are consistent with generative AI improving the productivity of SA authors on the scale of productivity enhancements in other domains (e.g., software development, consulting, customer assistance), leading in turn to a broader reach of information intermediaries in the capital markets.

5.3 Seeking Alpha Coverage and Firm Liquidity

Motivated by our findings that the adoption of generative AI by information intermediaries enables increased firm coverage, we seek to understand whether firms benefit from such coverage. We conjecture that increased SA coverage raises the visibility of a firm and reduces information asymmetry among investors, potentially leading to improved liquidity. Moreover, we expect that SA coverage is more impactful for firms that historically have received relatively low coverage.

We test our first prediction at the firm-month level by examining the link between a firm's monthly AI and human article coverage and its stock illiquidity in the subsequent month. We use two proxies for illiquidity, taking firm-month averages of: (1) the weighted average daily bid-ask spread, *Bid-Ask Spread*, and (2) the weighted average daily price impact, *Illiquidity*. We define *# SA Articles* as the natural log of one plus the monthly number of SA articles about the firm, and *# AI Articles* (*# Human Articles*) as the natural log of one plus the monthly number of AI (human) articles about the firm. We control for firm characteristics as well as firm and month fixed effects. Standard errors are clustered at the firm and month.

Table 9 Panel A shows the results of our tests for *Bid-Ask Spread* (columns 1-2) and *Illiquidity* (columns 3-4). In column 1, the coefficient on *# SA Articles* is significantly negative (coef.= -0.004; t-stat.= -5.99), indicating that greater SA coverage in month t is linked to lower bid-ask spreads in month t+1, consistent with SA coverage improving liquidity. Column 2, which separates AI and human articles, shows a significantly negative coefficient on *# Human Articles* (coef.= -0.004; t-stat.= -5.51) but an insignificant coefficient on *# AI Articles* (coef.= -0.002; t-stat.= -1.03). These findings suggest that the negative link between SA coverage and bid-ask spreads is driven primarily by human-written articles rather than by AI articles. Columns 3-4, examining Illiquidity, reveal a similar pattern. The results suggest that, on average, human articles improve firms' liquidity while AI articles do not.

Next, we test our prediction that SA coverage is more impactful for firms with historically low coverage. We construct a variable, *Low Coverage*, defined as an indicator equal to one for firms with below-sample-median SA article coverage in the past 90 calendar days, and zero otherwise. As an alternative proxy for firm coverage, we employ the number of analysts' annual EPS forecasts. We modify the specification from Table 9 Panel A by interacting *# AI Articles* with *Low Coverage*, and present the results in Table 9 Panel B.

Column 1 of Table 9 Panel B shows a significantly negative coefficient on *# AI Articles* × *Low Coverage* (coef.= -0.007; t-stat.= -2.65), denoting that AI articles are associated with lower future bid-ask spreads for firms with historically low SA coverage. The coefficient for the main effect, *# AI Articles*, is insignificantly different from zero (coef.= 0.000; t-stat.= 0.11), indicating that AI articles have no incremental impact on bid-ask spreads for firms that are already well-covered. Column 2 reveals similar findings when using analysts' forecasts as a proxy for firm coverage. The results in columns 3-4 for *Illiquidity* are consistent with those for *Bid-Ask Spread* – AI article coverage is associated with reduced illiquidity for undercovered firms, but has no effect on well-covered firms.

Overall, the findings in Table 9 suggest that AI use by information intermediaries leads to capital market benefits (i.e., improved liquidity) for some firms. While we do not find evidence that AI article coverage improves liquidity for the average firm, we find improved liquidity for firms that would otherwise receive little or no coverage by information intermediaries. Viewed in combination with our earlier findings that AI use enables SA authors to publish more articles and cover more firms (i.e., AI lowers the cost of covering a firm), these findings imply that the expansion of AI use among information intermediaries has the potential to lead to improved overall capital market outcomes.

6. Conclusion

We investigate generative AI use by contributors to the largest investor community platform in the world – Seeking Alpha (SA). Employing a state-of-the-art AI detection tool, we find that the prevalence of AI-generated SA articles ramped up quickly after the launch of ChatGPT and peaked at 13.4% of all articles (covering over 11% of public firms) in October 2023 before dropping off in the face of SA's no-AI policy. Compared to human articles, we find that AI articles elicit smaller capital market responses than human articles, suggesting that investors find them less informative, and they are less likely to generate SA user engagement or be selected as a SA Editor's Pick. However, the informativeness of AI articles varies by author, and more experienced authors produce relatively higher-quality AI articles. Authors who adopt AI benefit from increased productivity compared to non-adopters, publishing more articles and covering more new firms. Consequently, the widespread availability of generative AI tools led temporarily to an overall expansion in firm coverage, but this trend has been halted and largely reversed since SA's ban on AI use. Finally, we find that AI coverage of historically undercovered firms leads to improved liquidity for those firms, although such coverage provides no incremental benefit for firms that are already well-covered by information intermediaries.

Our study makes two primary contributions to the literature. First, we provide early evidence on how new AI technologies are used by information intermediaries and the challenges and opportunities created by such use. Although AI articles appear, on average, less informative to market participants than human articles, they can provide liquidity benefits to firms that would not otherwise receive coverage. To the extent that AI use enables information intermediaries to expand their coverage at lower cost, the capital markets may benefit from AI use. Our second contribution is to the literature on accounting and labor markets. Our finding that AI-adopting SA authors exhibit increased productivity adds to recent work examining how financial professionals use technology to improve decision-making in contexts such as lending decisions and quantitative investing. Moreover, we extend recent studies examining the effects of AI on productivity in fields such as medicine, consulting, and customer service through our analysis of capital market information intermediaries.

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Appendix A
Variable definitions

This table provides a detailed description of the variables used in the analyses. Data come from the Seeking Alpha website, Compustat, CRSP, WRDS Intraday Indicators, I/B/E/S, RavenPack, and Thomson/Refinitiv. All continuous variables except for $|CAR_{(0,+2)}|$ are winsorized at the 1st and 99th percentiles of their distributions.

Dependent variables:

Variable	Definition
Abnormal Trading Volume$_{(0,+2)}$	The natural log of average daily trading volume over trading window [0, +2] relative to the current date scaled by average daily trading volume over days [-41,-11]. Daily trading volume is the number of shares traded on a given day scaled by shares outstanding.
$\lvert CAR_{(0,+2)}\rvert$	The absolute value of the market-adjusted cumulative stock return during a three-day window [0, +2] relative to the current date. Multiplied by 100 to ease interpretation.
User Comments	The number of Seeking Alpha user comments received by an article within 30 calendar days after its publication.
Editor's Pick	An indicator variable equal to one for Seeking Alpha articles selected as an "Editor's Pick"; zero otherwise.
Monthly Articles	The natural log of one plus the number of Seeking Alpha articles published by a given author in the current month.
Newly Covered Firms	The natural log of one plus the number of firms covered by an author in the current month that the author has not previously covered.
SA Coverage	An indicator variable equal to one if a firm is covered by one or more Seeking Alpha articles in the current month; zero otherwise.
SA Articles	The natural log of one plus the number of Seeking Alpha articles covering a firm in the current month.
Bid-Ask Spread$_{t+1}$	The weighted average daily spread in month t+1, where daily spread is average percent effective spread. Daily spreads are weighted based on the total number of trades during market hours.
Illiquidity$_{t+1}$	The weighted average daily price impact in month t+1, where daily price impact is average percent effective price impact of each trade over a 5-min window. Daily price impacts are weighted based on the total number of trades during market hours.

Primary independent variables:

Variable	Definition
AI Article	An indicator variable equal to one if an article's AI confidence score from Originality.ai's content detector exceeds 95%; zero otherwise.
SA Article Day	An indicator variable equal to one if at least one Seeking Alpha article covering the firm is published on that day; zero otherwise.
AI Article Day	An indicator variable equal to one if at least one AI article covering the firm is published on that day; zero otherwise. An article is classified as AI-generated if its AI confidence score from Originality.ai's content detector exceeds 95%.
Human Article Day	An indicator variable equal to one if at least one human article covering the firm is published on that day; zero otherwise. An article is classified as human-generated if its AI confidence score from Originality.ai's content detector is 95% or below.
Experienced Author	An indicator variable equal to one if an author had at least two years of experience publishing on Seeking Alpha prior to the launch of ChatGPT; zero otherwise.
Opportun AI Author	An indicator variable equal to one if an author first published on Seeking Alpha within the three-month window following the launch of ChatGPT; zero otherwise.
Post GPT	An indicator variable equal to one for months starting with December 2022 and afterwards; zero otherwise.
Post No-AI Policy	An indicator variable equal to one for months starting with November 2023 and afterwards; zero otherwise.
AI Adopter	An indicator variable equal to one if an author initially published one or more articles without AI and published at least one AI article in a subsequent month; zero otherwise.

Post AI Adoption	An indicator variable equal to one for all future months starting with the first month an author publishes an AI article; zero otherwise.
Post AI Exit	An indicator variable equal to one for all future months starting in the month after an author publishes their last AI article during the sample period; zero otherwise.
# SA Articles$_t$	The natural log of one plus the number of Seeking Alpha articles covering the firm published in month t.
# AI Articles$_t$	The natural log of one plus the number of AI articles covering the firm published in month t. An article is classified as AI-generated if its AI confidence score from Originality.ai's content detector exceeds 95%.
# Human Articles$_t$	The natural log of one plus the number of human articles covering the firm published in the current month. An article is classified as human-generated if its AI confidence score from Originality.ai's content detector is 95% or below.
Low Coverage	An indicator variable equal to one for firm-months with a below-sample-median number of SA articles (analyst annual EPS estimates) in the past 90 calendar days prior to the start of the month; zero otherwise.

Control variables:

Variable	**Definition**
Size	The natural log of the firm's market value of equity as of the fiscal quarter end prior to the article publication date.
BTM	The ratio of the firm's book value of equity to market value of equity as of the fiscal quarter end prior to the article publication date.
ROA	The ratio of the firm's net income before extraordinary items and discontinued operations (the sum over the most recent four quarters before the article publication date) to total assets as of the fiscal quarter end prior to the article publication date.
Leverage	The ratio of the firm's total debt (debt in current liabilities plus long-term debt) to total assets as of the fiscal quarter end prior to the article publication date. Missing values for debt are assumed to be zero.
R&D	The ratio of the firm's R&D expenditures (the sum over the most recent four quarters before the article publication date) to total assets as of the fiscal quarter end prior to the article publication date. Missing values for R&D expenditures are assumed to be zero.
Advertising	The ratio of the firm's advertising expenses to total assets as of the fiscal year end prior to the article publication date. Missing values for advertising expenses are assumed to be zero.
Firm Age	The natural log of one plus the number of years since the firm first appeared on Compustat, as of the fiscal quarter end prior to the article publication date.
Analyst Follow	The natural log of one plus number of unique analysts issuing annual EPS forecasts for the firm in the 365 calendar days prior to the article publication date.
Institutional Own	The percentage of the firm's outstanding shares held by institutional investors as of the fiscal quarter end prior to the article publication date.
Past Return	The market-adjusted cumulative return in the 90 calendar days prior to the article publication date.
Recent EA	An indicator variable equal to one if the firm announces quarterly earnings during trading days [-6, 0] relative to the article publication date; zero otherwise.
Recent 8-K	An indicator variable equal to one if the firm files a Form 8-K during trading days [-6, 0] relative to the article publication date; zero otherwise.
Recent Press	The number of RavenPack Dow Jones news articles with a relevance score of 95 or higher covering a firm during trading days [-6, 0] relative to the article publication date.
Concurrent Article	An indicator variable equal to one if a human article is published during trading days [0, +2] relative to the article publication date; zero otherwise.
Author Tenure	The natural log of one plus the number of months since an author's first SA publication.
Author Article History	The total number of SA articles an author has published historically.
Author Anonymous	An indicator variable equal to one if an author provides no attributable information in their biographical profile; zero otherwise (e.g., Dyer and Kim 2021). Attributable information includes social media links, email address, university/geography reference, business name, and company reference.

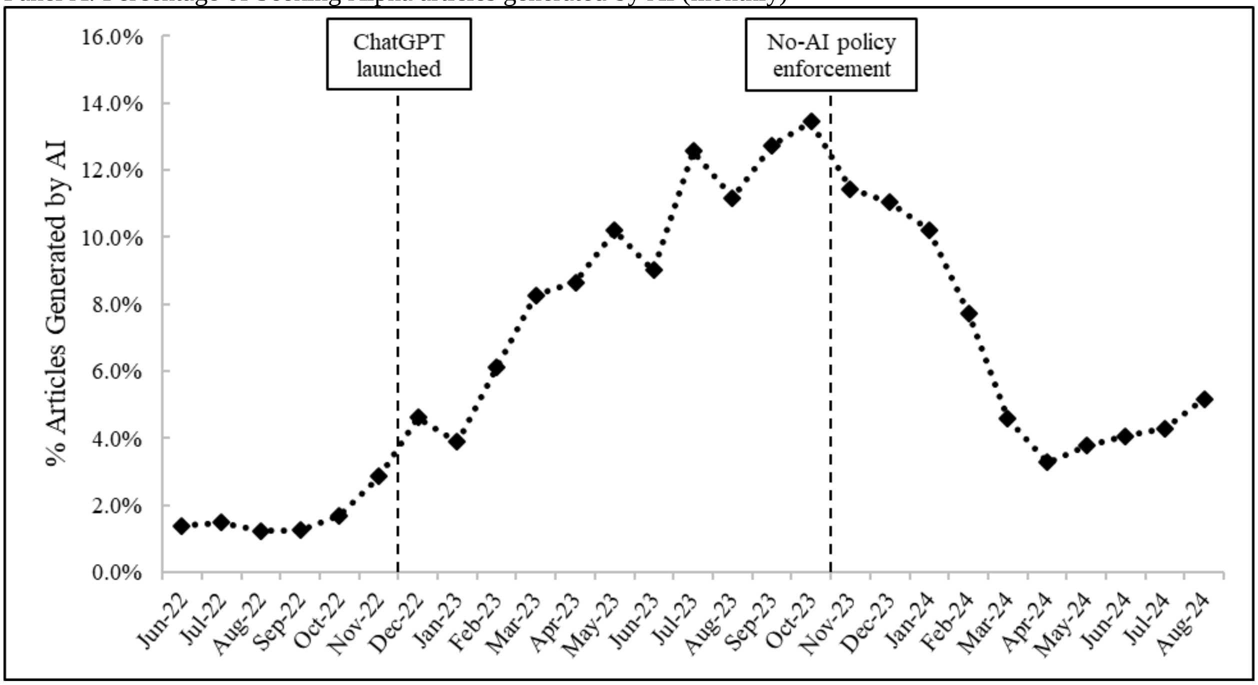
Textual characteristics:

Complexity	The Gunning Fox Index, measured as: 0.4 × [(#Words / #Sentences) + 100 × (#Complex Words / #Words)].
Length	The natural log of the number of words in an article.
Sentiment	The proportion of net positive words (positive words minus negative words) to the total number of words. The word dictionary for sentiment is based on Loughran and McDonald (2011). Multiplied by 100 to ease interpretation.
Word Strength	The proportion of net strong words (strong words minus weak words) to the total number of words. The word dictionary for modality is based on Loughran and McDonald (2011). Multiplied by 100 to ease interpretation.
Quantitative	The proportion of numerical information, computed as the count of numbers divided by total words (Campbell, Zheng and Zhou 2024). Multiplied by 100 to ease interpretation.
Named Entities	The proportion of 7-class entities by the Stanford Named Entity Recognizer (NER) to the total number of words. The 7-class entities contain the location, person, organization, money, percent, date and time. Multiplied by 100 to ease interpretation.

Figure 1
Generative AI Use in Seeking Alpha Articles Over Time

The figures below provide a visual representation of the prevalence of generative AI use in Seeking Alpha articles by month from June 2022 to August 2024. Panel A shows the percentage of total articles generated by AI. Panel B shows the percentage of total authors who publish one or more AI articles. Panel C shows the percentage of total firms covered by one or more AI articles. ChatGPT was launched on November 30, 2022. Seeking Alpha implemented stricter measures to enforce its no-AI policy beginning in October 2023.

Panel A: Percentage of Seeking Alpha articles generated by AI (monthly)



Panel B: Percentage of Seeking Alpha authors publishing AI articles (monthly)

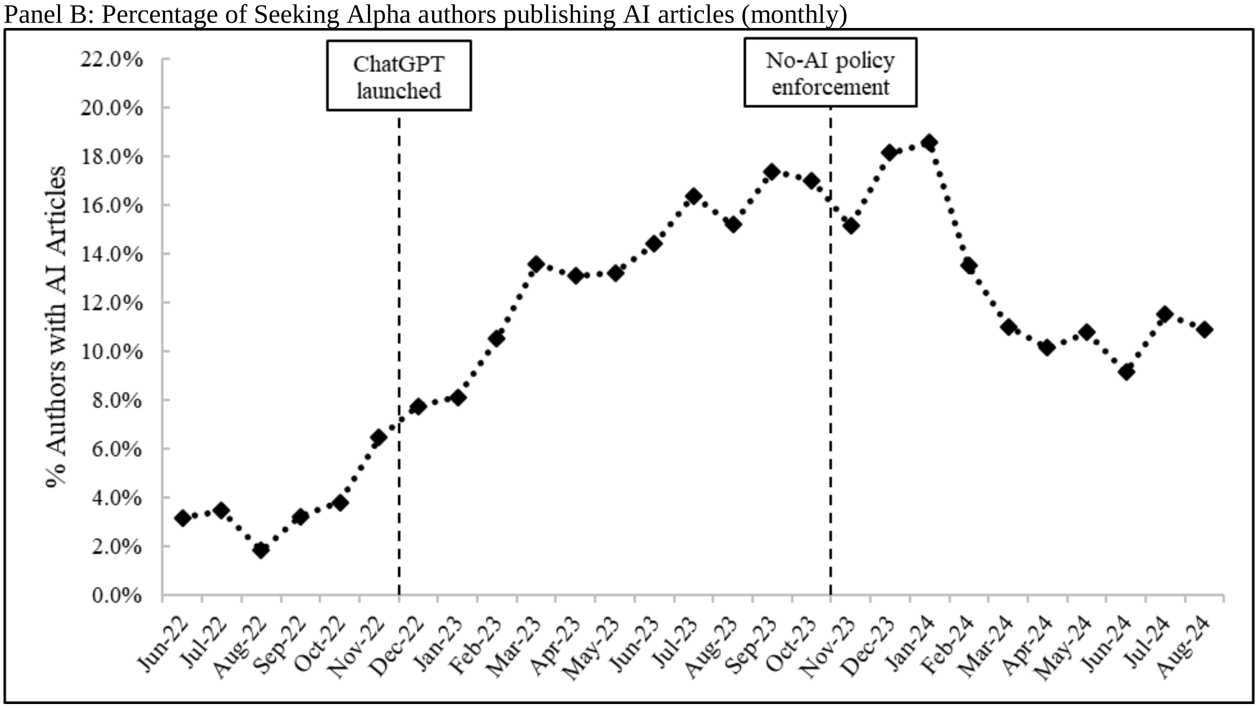


Figure 1 (continued)

Panel C: Percentage of firms covered by an AI article (monthly)

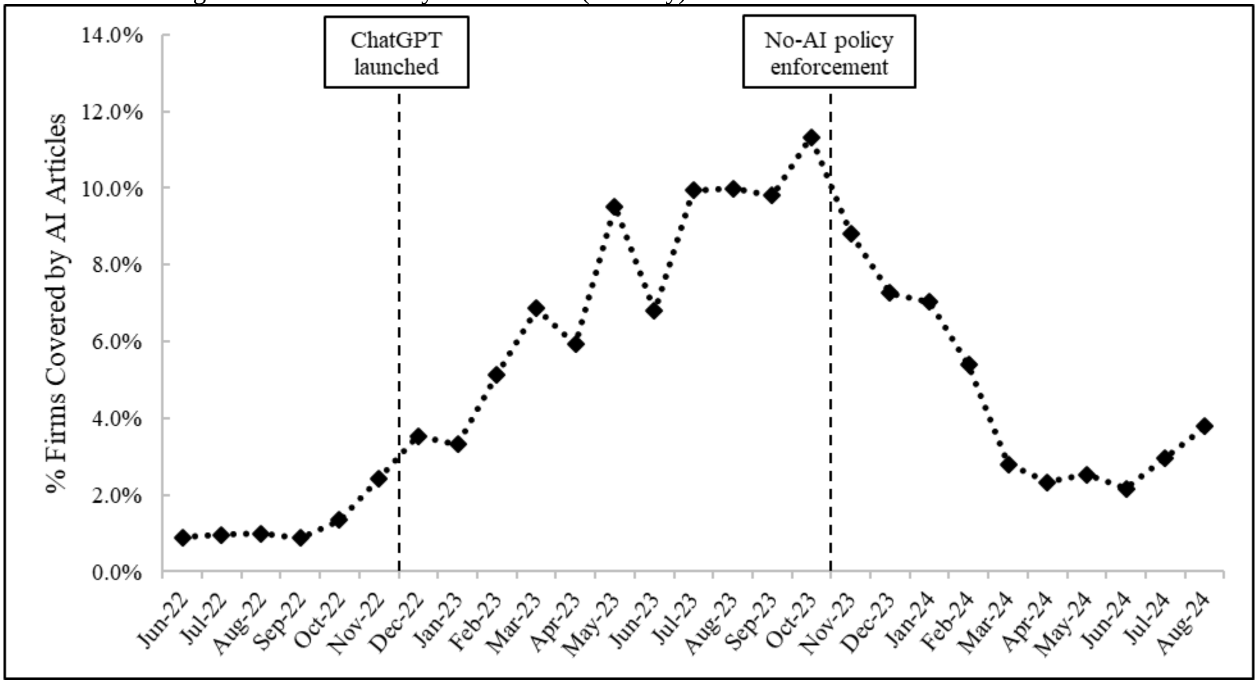
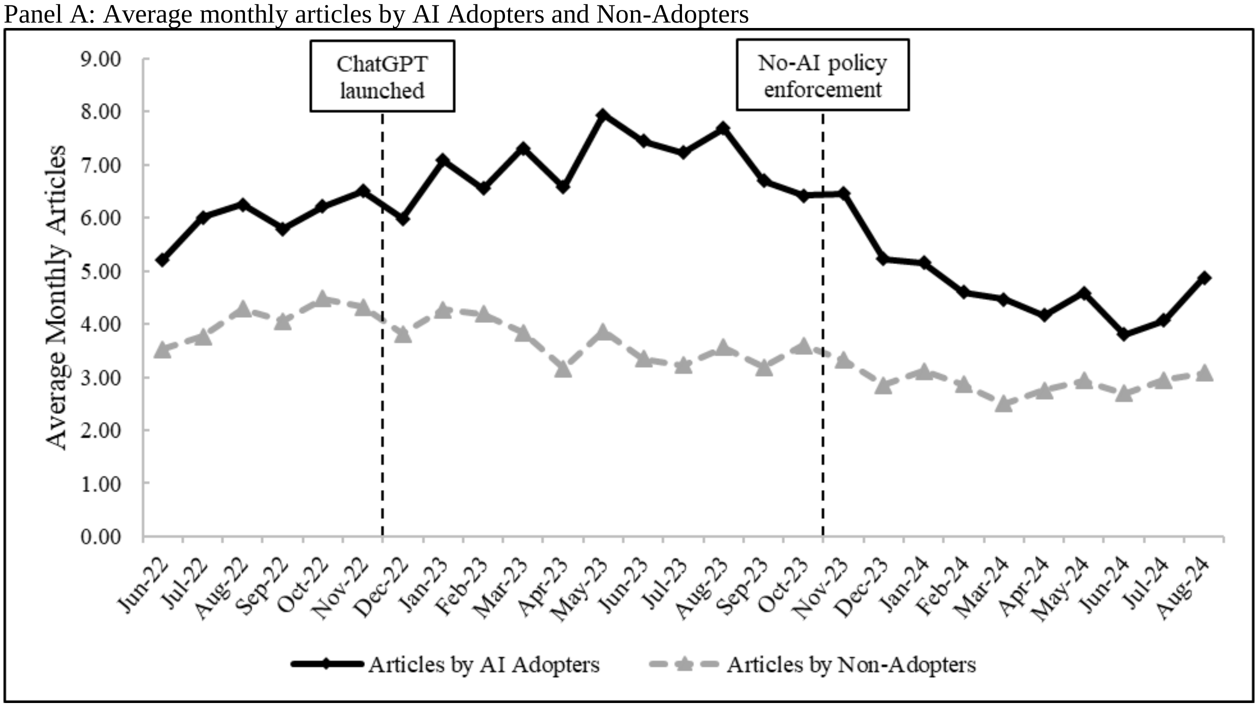


Figure 2

Generative AI Use and Author Productivity: AI Adopters and Non-Adopters Over Time

The figures illustrate the link between generative AI use and author productivity by month from June 2022 to August 2024. Panel A shows the average number of monthly articles published by AI Adopters (authors who publish at least one AI article during the sample period) and Non-Adopters (authors who never publish an AI article). The average number of monthly articles published by AI Adopters (Non-Adopters) is shown by the solid black line (dashed gray line). Panel B shows average monthly articles published by AI Adopters partitioned into human articles (striped gray area) and AI articles (solid black area). ChatGPT was launched on November 30, 2022. Seeking Alpha implemented stricter measures to enforce its no-AI policy beginning in October 2023.

Panel A: Average monthly articles by AI Adopters and Non-Adopters



Panel B: Average monthly AI and human articles by AI Adopters

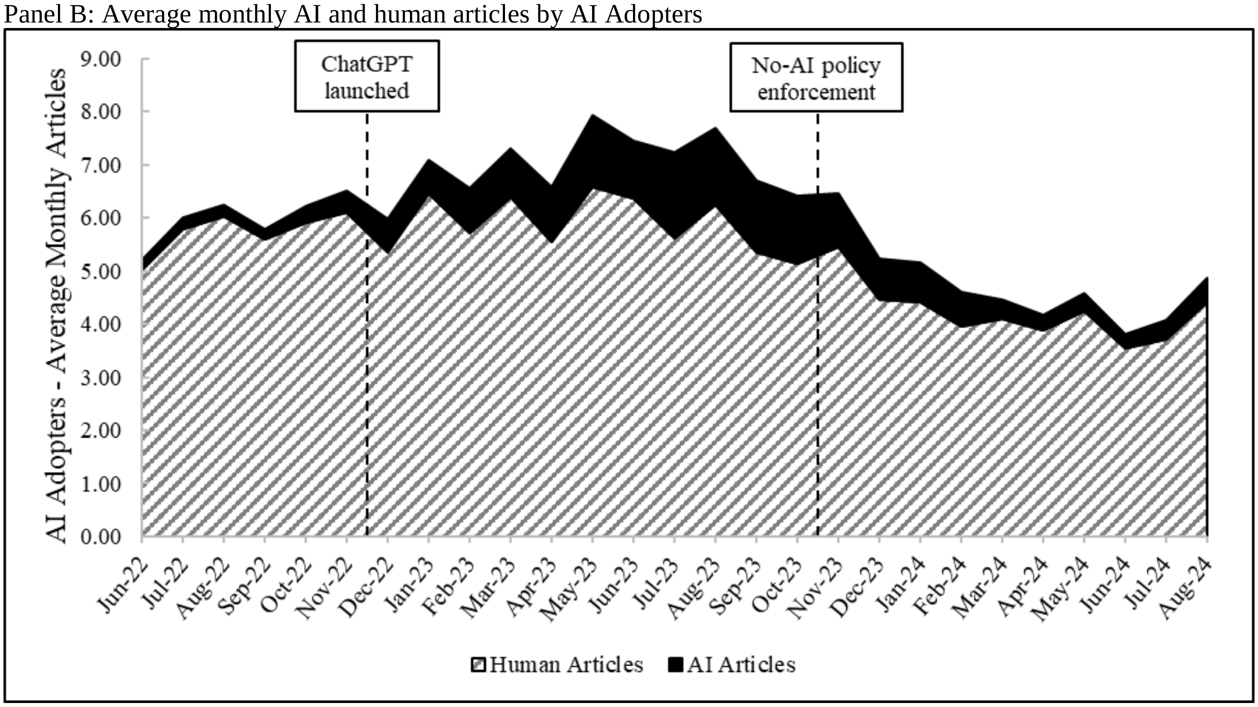
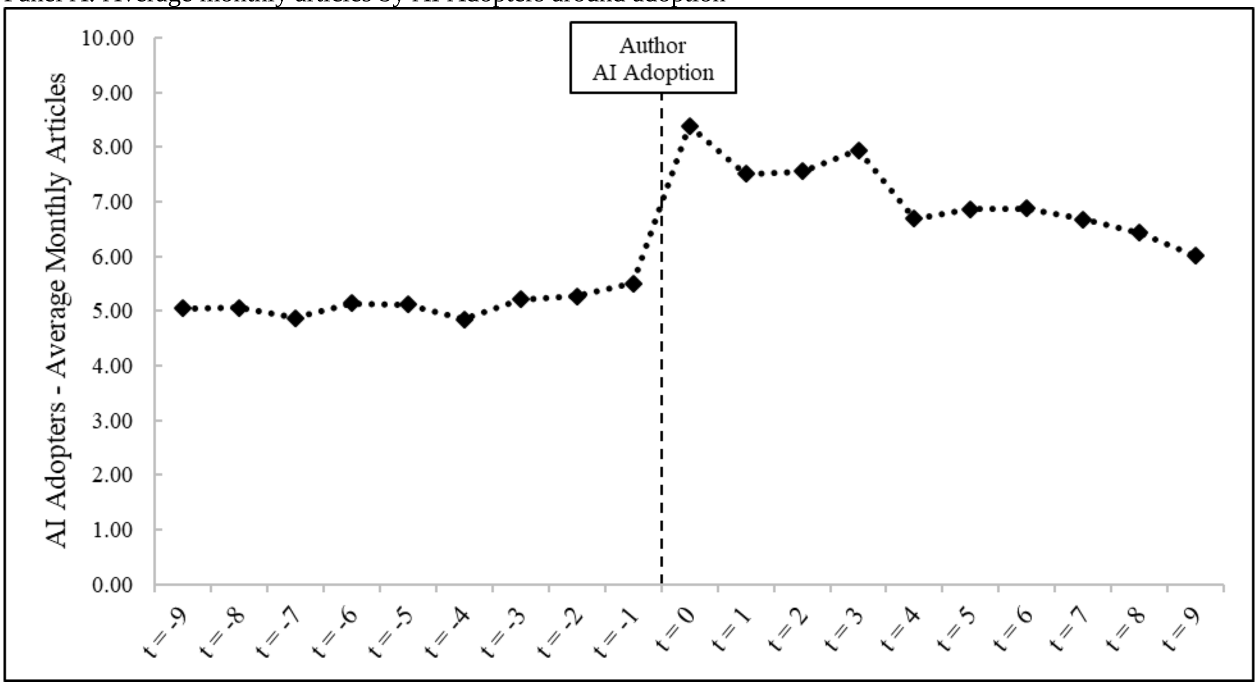


Figure 3
Generative AI Use and Author Productivity: AI Adopters in Event-Time

The figures below provide a visual representation of generative AI use on author productivity by month in event-time. Panel A shows the average number of monthly articles published by AI Adopters (authors who publish at least one AI article during the sample period) around the months when they first begin using AI to generate articles (in month t = 0). Panel B shows the average number of monthly articles published by AI Adopters partitioned into human articles (striped gray area) and AI articles (solid black area).

Panel A: Average monthly articles by AI Adopters around adoption



Panel B: Average monthly AI and human articles by AI Adopters around adoption

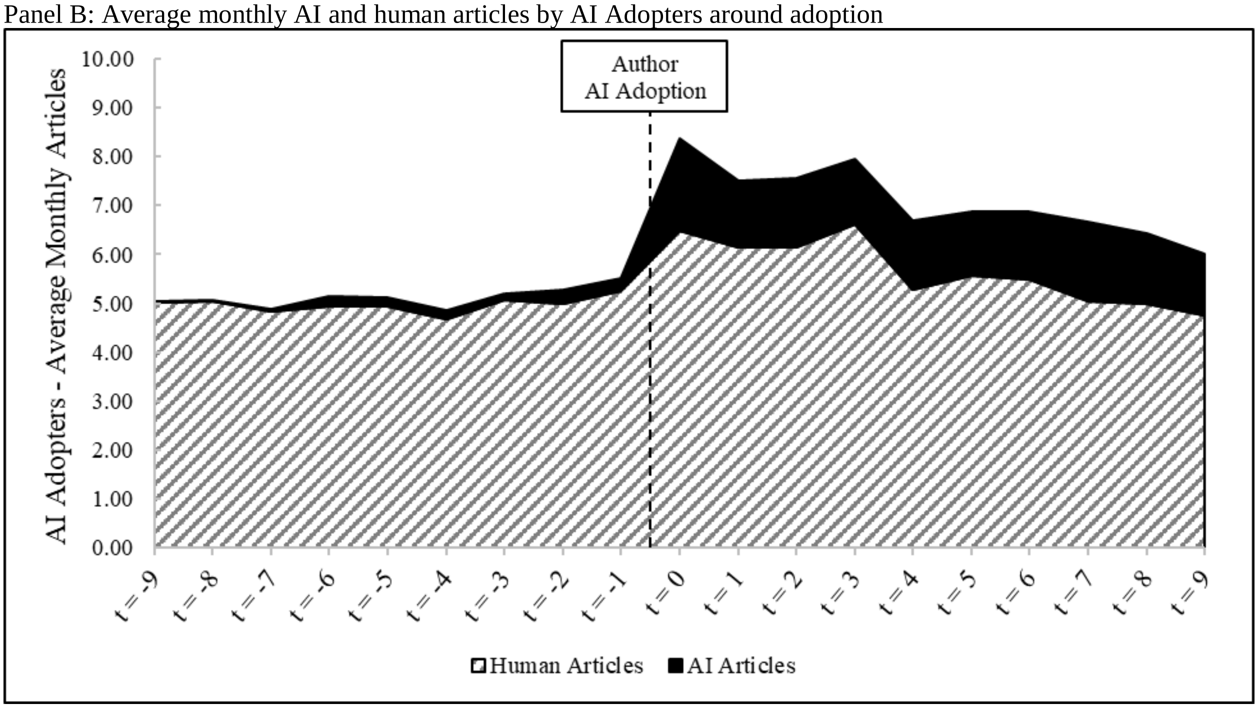
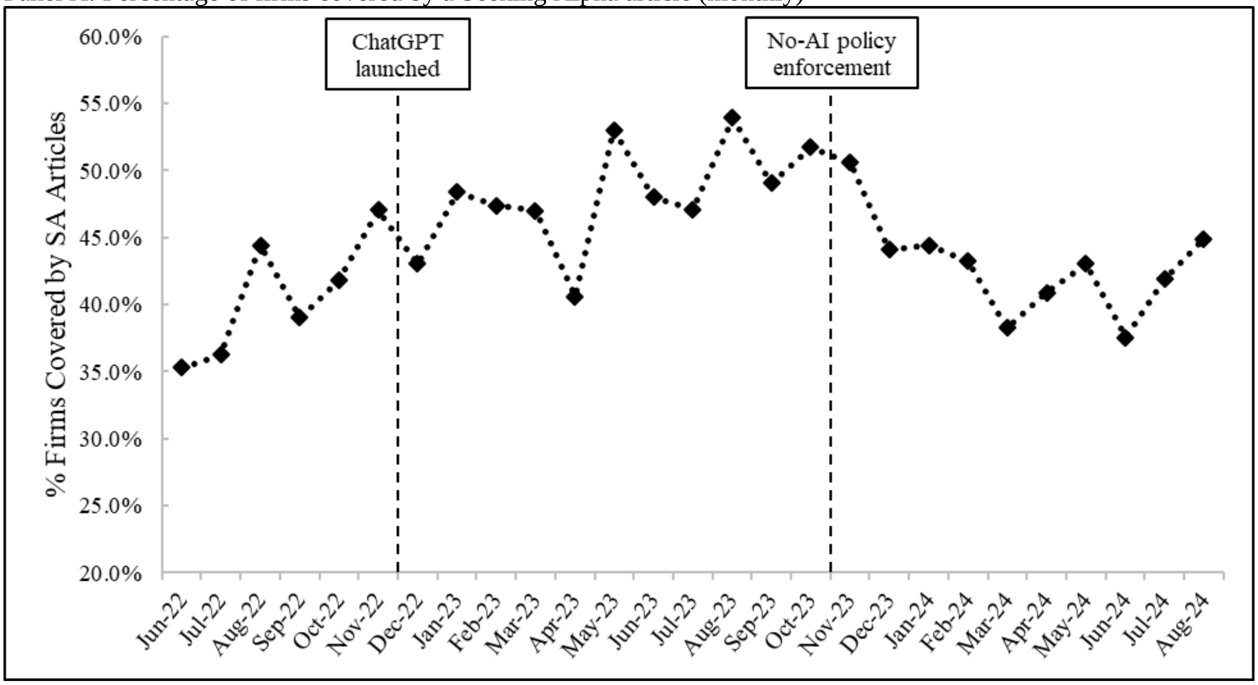


Figure 4
Seeking Alpha Coverage of Firms Over Time

The figures below provide a visual representation of the monthly coverage of firms by Seeking Alpha articles from June 2022 to August 2024. Panel A shows the percentage of total firms covered by one or more Seeking Alpha articles each month. Panel B shows the percentage of total firms covered by human articles only (striped gray area), AI articles only (solid black area), or both AI and human articles (dotted gray area). ChatGPT was launched on November 30, 2022. Seeking Alpha implemented stricter measures to enforce its no-AI policy beginning in October 2023.

Panel A: Percentage of firms covered by a Seeking Alpha article (monthly)



Panel B: Percentage of firms covered by an AI article, a human article, or both (monthly)

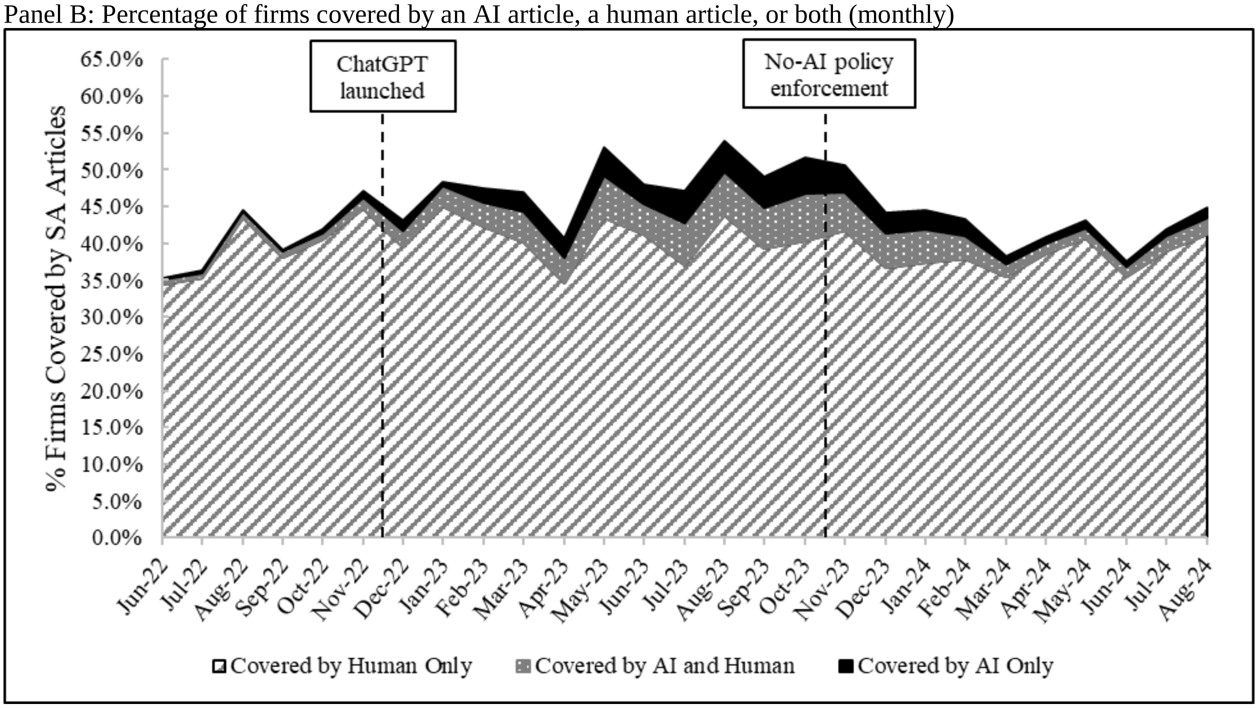


Table 1
Sample Selection

Panel A: Article-level sample

	SA Articles
Seeking Alpha articles with tickers from 6/1/2022 to 8/31/2024	85,401
Exclude:	
Items that are not original equity research (e.g., podcasts, news, talks, transcripts)	(794)
Articles with fewer than 100 words	(3)
Articles unable to match to Compustat and CRSP	(2,449)
Articles for firms missing information for variable construction	(4,545)
Articles for firms with stock price <= $1 or market cap <= $100 million	(1,973)
	75,637
Number of pre-GPT articles (from 6/1/2022 to 11/30/2022)	15,756
Number of post-GPT articles (from 12/1/2022 to 8/31/2024)	59,881
	75,637
Post-GPT Articles:	
Number of AI articles	4,877
Number of Human articles	55,004
Sample of AI and Human articles	**59,881**

Panel B: Firm-day sample

	Firms	Firm-Days
Firms in Compustat/CRSP/WRDS Intraday Indicator from 12/1/2022 to 8/31/2024	5,496	2,176,692
Exclude:		
Firm-days missing information for variable construction	(94)	(156,517)
Firms with minimum stock price <= $1 or market cap <= $100 million	(1,963)	(625,766)
Sample of firm-days	**3,439**	**1,394,409**

Panel C: Author-month sample

	SA Authors	Author-Months
Seeking Alpha authors who publish at least one article from 6/1/2022 to 8/31/2024	1,894	41,340
Exclude:		
Authors who do not publish articles in at least six different months	(1,150)	(23,272)
	744	18,068
Author groups:		
(1) Non-Adopters (authors who never adopt AI)	491	12,364
(2) AI Adopters (existing authors who adopt AI)	220	5,248
(3) AI-Starters (new authors whose first articles are AI-generated)	33	456
	744	18,068
Sample of Non-Adopters and AI Adopters (author groups (1) and (2))	**711**	**17,612**

Table 2
Generative AI Use in Seeking Alpha Articles Over Time

This table presents the prevalence of generative AI use in Seeking Alpha articles by month from December 2022 to August 2024. Columns 1-3 show the number and percentage of articles generated by AI. Columns 4-6 show the number and percentage of Seeking Alpha authors who publish one or more AI articles. Columns 7-9 show the number and percentage of firms covered by one or more AI articles. Seeking Alpha implemented stricter measures to enforce its no-AI policy beginning in October 2023.

Month	Total Articles	AI Articles	% Articles Generated by AI	Total Authors	Authors with AI Articles	% Authors with AI Articles	Total Firms	Firms Covered by AI Articles	% Firms Covered by AI Articles
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dec-22	2,579	119	4.6%	477	37	7.8%	3,166	112	3.5%
Jan-23	3,090	120	3.9%	529	43	8.1%	3,170	105	3.3%
Feb-23	3,017	185	6.1%	514	54	10.5%	3,171	163	5.1%
Mar-23	3,001	248	8.3%	523	71	13.6%	3,188	219	6.9%
Apr-23	2,659	230	8.6%	474	62	13.1%	3,173	188	5.9%
May-23	3,345	341	10.2%	522	69	13.2%	3,170	302	9.5%
Jun-23	3,073	277	9.0%	507	73	14.4%	3,194	217	6.8%
Jul-23	3,007	378	12.6%	489	80	16.4%	3,191	317	9.9%
Aug-23	3,364	376	11.2%	533	81	15.2%	3,191	319	10.0%
Sep-23	3,055	389	12.7%	501	87	17.4%	3,183	312	9.8%
Oct-23	3,222	433	13.4%	506	86	17.0%	3,202	363	11.3%
Seeking Alpha begins more strictly enforcing no-AI policy									
Nov-23	3,145	360	11.4%	515	78	15.1%	3,194	282	8.8%
Dec-23	2,611	288	11.0%	458	83	18.1%	3,177	231	7.3%
Jan-24	2,760	282	10.2%	507	94	18.5%	3,184	224	7.0%
Feb-24	2,650	205	7.7%	511	69	13.5%	3,186	172	5.4%
Mar-24	2,358	108	4.6%	454	50	11.0%	3,187	89	2.8%
Apr-24	2,436	80	3.3%	454	46	10.1%	3,209	75	2.3%
May-24	2,670	101	3.8%	464	50	10.8%	3,207	81	2.5%
Jun-24	2,310	94	4.1%	437	40	9.2%	3,198	69	2.2%
Jul-24	2,609	112	4.3%	460	53	11.5%	3,241	96	3.0%
Aug-24	2,920	151	5.2%	504	55	10.9%	3,228	122	3.8%
Average	2,851	232	8.1%	492	65	13.2%	3,191	193	6.1%

Table 3
Summary Statistics

This table presents summary statistics for the sample of Seeking Alpha articles from December 2022 to August 2024. Panel A shows statistics for all Seeking Alpha articles. Panel B compares the differences in mean values for variables of interest for the sample of AI articles (column 1) and Human articles (column 2). Details of variable construction are contained in Appendix A.

Panel A: All articles

Variable	**N**	**Mean**	**SD**	**p25**	**p50**	**p75**
AI Article	59,881	0.081	0.274	0.000	0.000	0.000
Textual Characteristics:						
Complexity	59,881	10.849	1.670	9.690	10.780	11.900
Length	59,881	7.118	0.372	6.851	7.084	7.351
Sentiment	59,881	0.575	2.130	-0.747	0.624	1.976
Word Strength	59,881	-0.182	0.361	-0.380	-0.160	0.000
Quantitative	59,881	2.794	1.379	1.806	2.620	3.575
Named Entities	59,881	8.105	3.174	5.812	7.699	9.980
Covered Firm Characteristics:						
Size	59,881	16.157	2.275	14.428	16.035	17.824
BTM	59,881	0.535	0.557	0.146	0.382	0.767
ROA	59,881	0.013	0.169	-0.009	0.034	0.091
Leverage	59,881	0.310	0.226	0.132	0.286	0.442
R&D	59,881	0.051	0.088	0.000	0.002	0.077
Advertising	59,881	0.013	0.030	0.000	0.000	0.010
Firm Age	59,881	3.008	0.868	2.303	3.168	3.683
Analyst Follow	59,881	2.521	1.011	1.946	2.708	3.296
Institutional Own	59,881	0.658	0.265	0.526	0.713	0.854
Past Return	59,881	0.003	0.228	-0.123	-0.020	0.092
Article Timing:						
Recent EA	59,881	0.207	0.405	0.000	0.000	0.000
Recent 8-K	59,881	0.329	0.470	0.000	0.000	1.000
Recent Press	59,881	4.704	13.406	0.000	0.000	3.000
Concurrent Article	59,881	0.318	0.466	0.000	0.000	1.000
Author Characteristics:						
Author Tenure	59,881	3.596	1.280	2.773	3.989	4.663
Author Article History	59,881	744.648	1088.902	75.000	280.000	902.000
Author Anonymous	59,881	0.245	0.430	0.000	0.000	0.000
Article Impact:						
Abnormal Trading Volume $_{(0,+2)}$	59,881	0.030	0.502	-0.291	-0.032	0.282
$\lvert CAR_{(0,+2)} \rvert$	59,881	3.442	5.164	0.897	2.041	4.075
User Comments	59,881	20.542	37.524	2.000	7.000	21.000
Editor's Pick	59,881	0.019	0.137	0.000	0.000	0.000

Table 3 (continued)

Panel B: AI articles vs. Human articles

	AI Articles (N = 4,877)	Human Articles (N = 55,004)	
	Mean	Mean	Difference in means
	(1)	(2)	(1) - (2)
Textual Characteristics:			
Complexity	11.697	10.774	0.922***
Length	7.129	7.117	0.012**
Sentiment	1.078	0.531	0.547***
Word Strength	-0.260	-0.175	-0.085***
Quantitative	2.503	2.820	-0.317***
Named Entities	7.598	8.150	-0.553***
Covered Firm Characteristics:			
Size	16.218	16.151	0.067**
BTM	0.430	0.544	-0.113***
ROA	-0.004	0.014	-0.018***
Leverage	0.294	0.312	-0.018***
R&D	0.072	0.049	0.023***
Advertising	0.014	0.012	0.002***
Firm Age	2.928	3.015	-0.087***
Analyst Follow	2.633	2.511	0.122***
Institutional Own	0.676	0.656	0.020***
Past Return	0.001	0.003	-0.002
Article Timing:			
Recent EA	0.192	0.209	-0.016***
Recent 8-K	0.309	0.331	-0.022***
Recent Press	4.469	4.725	-0.256
Concurrent Article	0.316	0.318	-0.001
Author Characteristics:			
Author Tenure	2.985	3.650	-0.665***
Author Article History	286.473	785.273	-498.799***
Author Anonymous	0.313	0.239	0.074***
Article Impact:			
Abnormal Trading Volume $_{(0,+2)}$	-0.004	0.033	-0.038***
$\|CAR_{(0,+2)}\|$	3.383	3.448	-0.064
User Comments	14.736	21.057	-6.321***
Editor's Pick	0.015	0.020	-0.005**

Table 4
Informativeness of AI Articles

This table presents the results from tests examining differences in the informativeness of AI and human articles. The sample consists of Seeking Alpha articles published from December 2022 to August 2024. Panel A (B) shows the results for the capital market effects (reception) of AI articles. In Panel A, the dependent variable in columns 1-2 (3-4) is *Abnormal Trading Volume*$_{(0,+2)}$ ($|CAR_{(0,+2)}|$). In Panel B, the dependent variable in columns 1-2 (3-4) is *User Comments* (*Editor's Pick)*. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Capital market effects

Dep. Var. =		*Abnormal Trading Volume* $_{(0,+2)}$		$\|CAR_{(0,+2)}\|$	
	Pr. Sign	(1)	(2)	(3)	(4)
AI Article	?	-0.029***	-0.025**	-0.151**	-0.240*
		(-3.61)	(-2.23)	(-2.52)	(-1.83)
Size		-0.035	-0.033	-0.830***	-0.845***
		(-1.42)	(-1.31)	(-4.18)	(-4.24)
BTM		-0.052	-0.047	0.232	0.246
		(-1.60)	(-1.38)	(0.66)	(0.70)
ROA		-0.006	0.001	0.943	0.901
		(-0.07)	(0.02)	(1.00)	(0.94)
Leverage		0.002	-0.014	3.898***	3.633***
		(0.02)	(-0.14)	(3.90)	(3.50)
R&D		0.909***	0.830***	8.891**	8.282**
		(3.66)	(3.26)	(2.76)	(2.51)
Advertising		1.005	0.743	1.353	0.389
		(1.24)	(0.84)	(0.16)	(0.05)
Firm Age		-0.049	-0.059	-2.893***	-3.142***
		(-0.24)	(-0.29)	(-3.08)	(-3.39)
Analyst Follow		-0.024	-0.023	-0.234	-0.217
		(-1.17)	(-1.08)	(-1.56)	(-1.37)
Institutional Own		-0.153**	-0.150**	0.129	0.198
		(-2.38)	(-2.18)	(0.21)	(0.32)
Past Return		-0.004	-0.006	0.018	-0.023
		(-0.17)	(-0.27)	(0.07)	(-0.09)
Recent EA		0.248***	0.235***	0.871***	0.778***
		(11.60)	(11.52)	(6.28)	(5.67)
Recent 8-K		0.103***	0.098***	0.550***	0.523***
		(8.28)	(7.76)	(6.14)	(5.76)
Recent Press		0.006***	0.006***	0.034***	0.033***
		(3.29)	(3.33)	(4.45)	(4.37)
Concurrent Article		0.041***	0.044***	0.098*	0.107*
		(5.11)	(5.30)	(1.82)	(1.84)
Author Tenure		0.010***	0.001	0.082***	-0.032
		(5.08)	(0.11)	(4.33)	(-0.73)
Author Article History		0.000***	0.000	0.000	0.000
		(4.59)	(0.51)	(1.56)	(0.26)
Author Anonymous		-0.016***		-0.127***	
		(-4.07)		(-2.92)	
Month FE		Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes
Author FE		No	Yes	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		59,665	59,299	59,665	59,299
Adjusted R2		17.00%	18.70%	20.74%	21.65%

Table 4 (continued)

Panel B: Article reception

Dep. Var. =		*User Comments*		*Editor's Pick*	
	Pr. Sign	(1)	(2)	(3)	(4)
AI Article	?	-2.930***	-1.028*	-0.008***	-0.003
		(-7.53)	(-2.01)	(-3.45)	(-1.19)
Size		3.935***	4.412***	0.002	0.003
		(3.26)	(3.95)	(0.84)	(1.32)
BTM		5.360***	4.463***	0.003	0.003
		(5.30)	(5.26)	(0.47)	(0.64)
ROA		8.278**	8.893**	0.018	0.017
		(2.25)	(2.40)	(1.43)	(1.31)
Leverage		10.794**	11.214**	0.066***	0.071***
		(2.30)	(2.57)	(3.69)	(4.43)
R&D		13.958	15.421*	-0.019	-0.024
		(1.57)	(1.77)	(-0.78)	(-0.82)
Advertising		61.636**	35.291	0.224**	0.215**
		(2.56)	(1.33)	(2.38)	(2.31)
Firm Age		15.915**	12.263**	0.021	0.005
		(2.60)	(2.31)	(0.85)	(0.20)
Analyst Follow		-0.115	0.455	-0.003	-0.001
		(-0.10)	(0.51)	(-0.87)	(-0.22)
Institutional Own		-1.931	-3.436	0.015	0.005
		(-0.51)	(-1.05)	(1.28)	(0.48)
Past Return		-4.789**	-4.519**	-0.001	0.001
		(-2.69)	(-2.76)	(-0.21)	(0.25)
Recent EA		-4.030***	-3.969***	-0.002	-0.002
		(-6.46)	(-6.45)	(-1.04)	(-0.96)
Recent 8-K		0.615	0.538	0.003	0.002
		(1.24)	(1.09)	(1.72)	(1.52)
Recent Press		0.098**	0.094**	-0.000	-0.000
		(2.65)	(2.71)	(-0.38)	(-1.51)
Concurrent Article		-2.445***	-1.916***	-0.001	0.000
		(-4.42)	(-3.97)	(-0.81)	(0.29)
Author Tenure		1.775***	-0.049	0.001*	-0.000
		(10.82)	(-0.09)	(2.06)	(-0.02)
Author Article History		0.000	0.004***	-0.000***	0.000
		(0.05)	(3.17)	(-9.49)	(1.05)
Author Anonymous		-2.574***		-0.006***	
		(-8.08)		(-3.47)	
Month FE		Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes
Author FE		No	Yes	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		59,665	59,299	59,665	59,299
Adjusted R2		42.96%	53.18%	-0.81%	5.51%

Table 5
Capital Market Impact of AI and Human Articles compared to No Article Days

This table presents the results from tests examining the capital market impact of AI and human articles, relative to days with no articles. The sample consists of firm-days from December 2022 to August 2024. The dependent variable in columns 1-2 (3-4) is *Abnormal Trading Volume*$_{(0,+2)}$ (|*CAR*$_{(0,+2)}$|). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dep. Var. =			*Abnormal Trading Volume* $_{(0,+2)}$		|*CAR* $_{(0,+2)}$|	
	Coef.	Pr. Sign	(1)	(2)	(3)	(4)
SA Article Day	β_1	+	0.054***		0.265***	
			(17.40)		(10.70)	
AI Article Day	β_2	+		0.022***		0.133*
				(3.01)		(1.87)
Human Article Day	β_3	+		0.056***		0.279***
				(17.22)		(10.59)
Size			0.011	0.011	-0.699***	-0.699***
			(0.83)	(0.83)	(-7.31)	(-7.31)
BTM			-0.053***	-0.053***	0.105	0.105
			(-2.89)	(-2.89)	(0.93)	(0.93)
ROA			0.028	0.028	-0.580**	-0.580**
			(0.74)	(0.74)	(-2.43)	(-2.43)
Leverage			-0.072**	-0.072**	1.030***	1.030***
			(-2.40)	(-2.39)	(4.09)	(4.09)
R&D			0.167	0.167	2.025**	2.025**
			(1.23)	(1.22)	(2.19)	(2.19)
Advertising			0.100	0.100	3.251	3.252
			(0.27)	(0.27)	(0.70)	(0.70)
Firm Age			0.003	0.003	-1.535***	-1.536***
			(0.02)	(0.02)	(-3.04)	(-3.04)
Analyst Follow			-0.005	-0.005	-0.007	-0.007
			(-0.50)	(-0.50)	(-0.13)	(-0.13)
Institutional Own			-0.248***	-0.248***	0.154	0.154
			(-4.24)	(-4.24)	(0.72)	(0.72)
Past Return			-0.071**	-0.071**	-0.460***	-0.460***
			(-2.73)	(-2.73)	(-3.23)	(-3.23)
Recent EA			0.249***	0.249***	0.805***	0.805***
			(15.41)	(15.41)	(11.86)	(11.86)
Recent 8-K			0.064***	0.064***	0.232***	0.232***
			(15.75)	(15.75)	(8.29)	(8.30)
Recent Press			0.011***	0.011***	0.031***	0.031***
			(7.31)	(7.30)	(5.90)	(5.88)
p -Value: $\beta_2 <= \beta_3$				< 0.01		0.04
Day FE			Yes	Yes	Yes	Yes
Firm FE			Yes	Yes	Yes	Yes
S.E. clustered by firm and month			Yes	Yes	Yes	Yes
No. of observations			1,394,409	1,394,409	1,394,409	1,394,409
Adjusted R2			17.63%	17.64%	15.64%	15.64%

Table 6
Heterogeneity in Author Type

This table presents the results from tests examining the role of heterogeneity in author type on the capital market impact of AI and human articles. The sample consists of Seeking Alpha articles published from December 2022 to August 2024. Panel A examines authors with at least two years of experience publishing on Seeking Alpha prior to the launch of ChatGPT (*Experienced Author*). Panel B examines authors who first published on Seeking Alpha within the three-month window following the launch of ChatGPT (*Opportun AI Author*). In both panels, the dependent variable in in columns 1-2 (3-4) is *Abnormal Trading Volume*$_{(0,+2)}$ (|*CAR*$_{(0,+2)}$|). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Experienced Authors

Dep. Var. =		*Abnormal Trading Volume* $_{(0,+2)}$		|*CAR* $_{(0,+2)}$|	
	Pr. Sign	(1)	(2)	(3)	(4)
AI Article	-	-0.035***	-0.040***	-0.248***	-0.201***
		(-3.77)	(-4.20)	(-2.97)	(-2.89)
AI Article × Experienced Author	+	0.034**	0.026	0.436***	0.125*
		(2.23)	(1.52)	(4.47)	(1.73)
Experienced Author		0.009	0.015	-0.047	0.055
		(1.09)	(1.72)	(-0.49)	(0.64)
Controls		Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes
Firm FE		No	Yes	No	Yes
Author FE		No	No	No	No
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		59,881	59,665	59,881	59,655
Adjusted R2		13.06%	17.01%	11.47%	20.74%

Panel B: Opportunistic AI Authors

Dep. Var. =		*Abnormal Trading Volume* $_{(0,+2)}$		|*CAR* $_{(0,+2)}$|	
	Pr. Sign	(1)	(2)	(3)	(4)
AI Article	-	-0.015*	-0.024**	0.005	-0.107*
		(-1.94)	(-2.77)	(0.07)	(-1.85)
AI Article × Opportun AI Author	-	-0.067**	-0.056**	-0.816***	-0.474***
		(-2.40)	(-2.34)	(-5.31)	(-3.00)
Opportun AI Author		0.004	0.004	0.235**	-0.028
		(0.34)	(0.42)	(2.46)	(-0.32)
Controls		Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes
Firm FE		No	Yes	No	Yes
Author FE		No	No	No	No
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		59,881	59,665	59,881	59,655
Adjusted R2		13.06%	17.00%	11.48%	20.74%

Table 7
Generative AI Use and Author Productivity

This table presents the results for author productivity over time for AI adopters and non-adopters. The sample consists of author-months from June 2022 to August 2024. Panel A shows the results for AI adopters compared to non-adopters around the launch of ChatGPT and Seeking Alpha's tightened enforcement of its no-AI policy. Panel B shows the results for AI adopters after they first adopt AI to generate articles and when they cease doing so. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by author and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Productivity of AI Adopters and Non-Adopters over time

Dep. Var. =		*Monthly Articles*		*Newly Covered Firms*	
	Pr. Sign	(1)	(2)	(3)	(4)
Post GPT × AI Adopter	+	0.284***	0.281***	0.170***	0.187***
		(5.24)	(4.73)	(3.81)	(4.05)
Post No-AI Policy × AI Adopter	-	-0.186***	-0.189***	-0.202***	-0.186***
		(-3.09)	(-2.84)	(-4.13)	(-3.75)
AI Adopter		0.150**		0.155***	
		(2.07)		(3.10)	
Size		-0.094***	-0.052***	-0.090***	-0.045***
		(-6.43)	(-4.64)	(-8.94)	(-4.90)
BTM		0.036	0.004	-0.033	0.002
		(0.96)	(0.14)	(-1.42)	(0.10)
ROA		-0.001	0.155	-0.007	0.080
		(-0.01)	(1.56)	(-0.08)	(1.02)
Leverage		0.030	-0.004	0.005	0.013
		(0.33)	(-0.05)	(0.09)	(0.23)
R&D		0.098	0.041	0.045	-0.004
		(0.35)	(0.21)	(0.22)	(-0.03)
Advertising		-0.887*	0.030	-0.607*	-0.119
		(-1.86)	(0.09)	(-1.84)	(-0.43)
Firm Age		0.200***	0.085***	0.144***	0.067***
		(7.27)	(3.84)	(7.45)	(3.91)
Analyst Follow		0.258***	0.142***	0.142***	0.099***
		(9.38)	(6.18)	(8.32)	(5.84)
Institutional Own		-0.294***	-0.079	0.002	0.009
		(-3.42)	(-1.13)	(0.03)	(0.16)
Past Return		0.004	-0.070	0.041	-0.026
		(0.04)	(-1.08)	(0.74)	(-0.57)
Author Tenure		-0.119***	0.046	-0.154***	-0.130***
		(-5.76)	(0.93)	(-10.11)	(-2.97)
Author Article History		0.001***	-0.000	0.000***	-0.001***
		(9.11)	(-0.35)	(5.67)	(-4.27)
Author Anonymous		-0.008		0.023	
		(-0.15)		(0.65)	
Month FE		Yes	Yes	Yes	Yes
Author FE		No	Yes	No	Yes
S.E. clustered by author and month		Yes	Yes	Yes	Yes
No. of observations		17,612	17,612	17,612	17,612
Adjusted R2		26.48%	60.31%	14.88%	42.98%

Table 7 (continued)

Panel B: Productivity of AI Adopters in event time

Dep. Var. =		*Monthly Articles*	*Newly Covered Firms*
	Pr. Sign	(1)	(2)
Post AI Adoption	+	0.592***	0.493***
		(9.00)	(7.78)
Post AI Exit	-	-0.223**	-0.286***
		(-2.48)	(-3.76)
Size		-0.059**	-0.059***
		(-2.56)	(-3.18)
BTM		-0.009	-0.022
		(-0.15)	(-0.54)
ROA		0.421**	0.276
		(2.16)	(1.70)
Leverage		-0.027	-0.022
		(-0.19)	(-0.18)
R&D		0.529	0.362
		(1.35)	(1.11)
Advertising		-0.573	-0.204
		(-0.95)	(-0.39)
Firm Age		0.090*	0.074**
		(2.05)	(2.29)
Analyst Follow		0.159***	0.095**
		(3.38)	(2.74)
Institutional Own		-0.103	0.034
		(-0.75)	(0.29)
Past Return		-0.101	-0.089
		(-0.76)	(-0.83)
Author Tenure		0.116	-0.102
		(1.67)	(-1.60)
Author Article History		-0.000	-0.001***
		(-0.88)	(-4.10)
Month FE		Yes	Yes
Author FE		Yes	Yes
S.E. clustered by author and month		Yes	Yes
No. of observations		5,248	5,248
Adjusted R2		60.32%	42.66%

Table 8
Seeking Alpha Coverage of Firms Over Time

This table presents the results for Seeking Alpha coverage of firms over time. The sample consists of firm-months from June 2022 to August 2024. The dependent variable in columns 1-2 (3-4) is *SA Coverage* (*SA Articles*). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dep. Var. =		*SA Coverage*		*SA Articles*	
	Pr. Sign	(1)	(2)	(3)	(4)
Post GPT	+	0.068***	0.056***	0.062***	0.053***
		(3.15)	(2.82)	(3.08)	(2.88)
Post No-AI Policy	-	-0.054***	-0.063***	-0.058***	-0.066***
		(-3.35)	(-3.37)	(-3.62)	(-3.52)
Size		0.078***	0.045***	0.117***	0.050***
		(25.19)	(3.22)	(21.08)	(3.23)
BTM		0.031***	0.033***	0.058***	0.044***
		(4.58)	(3.19)	(5.66)	(3.47)
ROA		0.112***	0.128***	0.116**	0.150***
		(3.77)	(3.88)	(2.34)	(4.68)
Leverage		0.119***	0.019	0.119***	0.042
		(8.05)	(0.67)	(5.72)	(1.28)
R&D		0.284***	0.202**	0.416***	0.216***
		(5.57)	(2.55)	(5.00)	(2.82)
Advertising		1.191***	0.561***	1.503***	0.648*
		(9.08)	(3.46)	(7.59)	(1.83)
Firm Age		0.002	0.150*	-0.002	0.168*
		(0.31)	(1.82)	(-0.25)	(1.96)
Analyst Follow		0.064***	0.030***	0.099***	0.035***
		(11.02)	(5.43)	(12.10)	(6.28)
Institutional Own		-0.140***	0.001	-0.265***	-0.002
		(-8.96)	(0.03)	(-11.49)	(-0.04)
Past Return		-0.024	-0.011	-0.036*	-0.020**
		(-1.70)	(-1.29)	(-1.71)	(-2.12)
Month FE		No	No	No	No
Firm FE		No	Yes	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		86,077	86,063	86,077	86,063
Adjusted R2		12.20%	22.17%	22.34%	48.78%

Table 9
Seeking Alpha Coverage and Firm Liquidity

This table presents the results from tests examining the link between Seeking Alpha article coverage and the liquidity of a firm's stock. The sample consists of firm-months from June 2022 to August 2024. Panel A shows the results for all firms, whereas Panel B shows the results conditional on a firm's recent coverage by Seeking Alpha and traditional equity analysts. In both panels, the variable *# SA Articles*$_t$ (*# AI Articles*$_t$, *# Human Articles*$_t$) is defined as the natural log of one plus the total number of Seeking Alpha articles (number of AI articles, number of Human articles) covering a firm during month *t*. In both panels, the dependent variable in columns 1-2 (3-4) is *Bid-Ask Spread*$_{t+1}$ (*Illiquidity*$_{t+1}$). In columns 1 and 3 (2 and 4) of Panel B, *Low Coverage* is an indicator variable set equal to one for firm-months with a below-median number of Seeking Alpha articles (number of analyst estimates) in the 90 calendar days prior to the start of the month, and zero otherwise. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: All firms

Dep. Var. =		*Bid-Ask Spread* $_{t+1}$		*Illiquidity* $_{t+1}$	
	Pr. Sign	(1)	(2)	(3)	(4)
# SA Articles $_t$	-	-0.004***		-0.002***	
		(-5.99)		(-4.81)	
# AI Articles $_t$	?		-0.002		-0.000
			(-1.03)		(-0.49)
# Human Articles $_t$	-		-0.004***		-0.001***
			(-5.51)		(-4.44)
Size		-0.044***	-0.044***	-0.027***	-0.027***
		(-10.37)	(-10.36)	(-11.61)	(-11.60)
BTM		0.020***	0.020***	0.008***	0.008***
		(3.38)	(3.38)	(2.89)	(2.89)
ROA		-0.039***	-0.039***	-0.017***	-0.017***
		(-2.91)	(-2.91)	(-3.11)	(-3.11)
Leverage		-0.009	-0.009	0.004	0.004
		(-0.52)	(-0.52)	(0.57)	(0.56)
R&D		-0.039	-0.039	-0.006	-0.006
		(-0.69)	(-0.69)	(-0.26)	(-0.26)
Advertising		0.180	0.180	0.066	0.066
		(0.98)	(0.98)	(0.96)	(0.96)
Firm Age		-0.161***	-0.161***	-0.107***	-0.107***
		(-6.49)	(-6.49)	(-8.62)	(-8.61)
Analyst Follow		-0.009**	-0.009**	-0.003**	-0.003**
		(-2.27)	(-2.27)	(-2.15)	(-2.15)
Institutional Own		-0.069***	-0.069***	-0.027***	-0.027***
		(-3.98)	(-3.98)	(-3.74)	(-3.74)
Past Return		-0.022***	-0.022***	-0.014***	-0.014***
		(-5.03)	(-5.03)	(-6.23)	(-6.23)
Month FE		Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		85,754	85,754	85,754	85,754
Adjusted R2		85.79%	85.78%	82.61%	82.61%

Table 9 (continued)

Panel B: Low-coverage firms

Dep. Var. =		*Bid-Ask Spread* $_{t+1}$		*Illiquidity* $_{t+1}$	
Low Coverage proxy:		Low SA Articles	Low Analysts	Low SA Articles	Low Analysts
	Pr. Sign	(1)	(2)	(3)	(4)
# AI Articles $_t$	0	0.000	0.000	0.001	0.001
		(0.11)	(0.19)	(1.24)	(1.09)
# AI Articles $_t$ × *Low Coverage*	-	-0.007**	-0.008*	-0.006***	-0.006**
		(-2.65)	(-1.94)	(-3.20)	(-2.55)
Low Coverage	+	0.003***	0.002	0.001***	0.002*
		(3.16)	(1.44)	(2.91)	(1.96)
# Human Articles $_t$	-	-0.004***	-0.004***	-0.002***	-0.001***
		(-5.64)	(-5.51)	(-4.50)	(-4.49)
Size		-0.044***	-0.044***	-0.027***	-0.027***
		(-10.34)	(-10.37)	(-11.59)	(-11.62)
BTM		0.020***	0.020***	0.008***	0.008***
		(3.39)	(3.39)	(2.90)	(2.92)
ROA		-0.038***	-0.039***	-0.017***	-0.017***
		(-2.86)	(-2.90)	(-3.07)	(-3.11)
Leverage		-0.009	-0.009	0.004	0.004
		(-0.51)	(-0.51)	(0.58)	(0.58)
R&D		-0.039	-0.038	-0.006	-0.005
		(-0.68)	(-0.68)	(-0.25)	(-0.24)
Advertising		0.181	0.180	0.066	0.066
		(0.99)	(0.99)	(0.97)	(0.97)
Firm Age		-0.160***	-0.160***	-0.107***	-0.107***
		(-6.48)	(-6.49)	(-8.61)	(-8.60)
Analyst Follow		-0.009**	-0.008**	-0.003**	-0.002*
		(-2.27)	(-2.10)	(-2.15)	(-1.85)
Institutional Own		-0.069***	-0.069***	-0.027***	-0.027***
		(-3.96)	(-3.98)	(-3.72)	(-3.72)
Past Return		-0.022***	-0.022***	-0.014***	-0.015***
		(-5.05)	(-5.04)	(-6.24)	(-6.25)
Month FE		Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes
No. of observations		85,754	85,754	85,754	85,754
Adjusted R2		85.79%	85.79%	82.61%	82.61%

Online Appendix

for

“Generative AI Use by Capital Market Information Intermediaries:

Evidence from Seeking Alpha”

Table A1
Determinants of Generative AI Use in Seeking Alpha Articles

This table presents the results of a determinants model for whether a Seeking Alpha article is produced using generative AI. The sample consists of Seeking Alpha articles published from December 2022 to August 2024. The dependent variable, *AI Article*, equals one if the probability that the article is AI-generated is greater than 0.95, and zero otherwise. All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Dep. Var. =		*AI Article*	
	(1)	(2)	(3)
Size	-0.001	0.014**	0.003
	(-1.12)	(2.31)	(0.66)
BTM	-0.017***	-0.005	-0.003
	(-4.88)	(-0.42)	(-0.38)
ROA	-0.002	0.003	0.002
	(-0.14)	(0.13)	(0.11)
Leverage	-0.025***	0.038	0.010
	(-3.24)	(1.23)	(0.46)
R&D	0.204***	-0.022	-0.012
	(4.72)	(-0.29)	(-0.23)
Advertising	-0.008	-0.259	-0.165
	(-0.11)	(-0.91)	(-0.63)
Firm Age	0.000	-0.101	-0.078
	(0.07)	(-1.64)	(-1.50)
Analyst Follow	0.006***	0.005	0.001
	(3.20)	(0.56)	(0.11)
Institutional Own	0.013*	0.004	0.016
	(1.93)	(0.14)	(1.10)
Past Return	-0.012	-0.017**	-0.014**
	(-1.40)	(-2.18)	(-2.71)
Recent EA	0.005	0.002	-0.003
	(1.06)	(0.47)	(-1.06)
Recent 8-K	-0.001	0.000	0.002
	(-0.23)	(0.01)	(0.82)
Recent Press	-0.000*	-0.000	-0.000
	(-1.75)	(-0.79)	(-0.47)
Concurrent Article	-0.001	0.010**	0.001
	(-0.56)	(2.39)	(0.24)
Author Tenure	-0.022***	-0.022***	-0.021**
	(-5.39)	(-5.75)	(-2.74)
Author Article History	-0.000***	-0.000***	0.000
	(-5.79)	(-6.54)	(0.01)
Author Anonymous	-0.002	-0.003	
	(-0.20)	(-0.39)	
Month FE	Yes	Yes	Yes
Firm FE	No	Yes	Yes
Author FE	No	No	Yes
S.E. clustered by firm and month	Yes	Yes	Yes
No. of observations	59,881	59,665	59,299
Adjusted R2	4.61%	6.36%	45.63%

Table A2
Textual Characteristics of AI Articles

This table presents the results from tests examining differences in textual characteristics between AI and human articles. The sample consists of Seeking Alpha articles published from December 2022 to August 2024. Panel A (B, C) shows the results for article readability (tone, specificity). In Panel A, the dependent variable in columns 1-3 (4-6) is *Complexity* (*Length*). In Panel B, the dependent variable in columns 1-3 (4-6) is *Sentiment* (*Word Strength*). In Panel C, the dependent variable in columns 1-3 (4-6) is *Quantitative* (*Named Entities*). All variables are defined in Appendix A. The *t*-statistics are reported below coefficient estimates in parentheses and are calculated based on standard errors clustered by firm and month. *, **, *** indicate statistical significance at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed *t*-test.

Panel A: Readability

Dep. Var. =		*Complexity*			*Length*		
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
AI Article	?	0.699***	0.644***	0.472***	-0.030**	-0.031**	-0.005
		(10.58)	(10.97)	(11.34)	(-2.83)	(-2.77)	(-0.55)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		No	Yes	Yes	No	Yes	Yes
Author FE		No	No	Yes	No	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		59,881	59,665	59,299	59,881	59,665	59,299
Adjusted R2		8.14%	16.66%	68.00%	8.70%	13.84%	68.36%

Panel B: Tone

Dep. Var. =		*Sentiment*			*Word Strength*		
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
AI Article	?	0.343***	0.309***	0.097**	-0.084***	-0.080***	-0.063***
		(4.40)	(4.71)	(2.22)	(-7.91)	(-8.36)	(-10.01)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		No	Yes	Yes	No	Yes	Yes
Author FE		No	No	Yes	No	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		59,881	59,665	59,299	59,881	59,665	59,299
Adjusted R2		9.00%	21.25%	36.17%	1.22%	3.57%	24.58%

Panel C: Specificity

Dep. Var. =		*Quantitative*			*Named Entities*		
	Pr. Sign	(1)	(2)	(3)	(4)	(5)	(6)
AI Article	?	-0.165***	-0.158***	-0.069***	0.031	0.038	-0.035
		(-4.51)	(-4.52)	(-3.36)	(0.42)	(0.56)	(-0.59)
Controls		Yes	Yes	Yes	Yes	Yes	Yes
Month FE		Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		No	Yes	Yes	No	Yes	Yes
Author FE		No	No	Yes	No	No	Yes
S.E. clustered by firm and month		Yes	Yes	Yes	Yes	Yes	Yes
No. of observations		59,881	59,665	59,299	59,881	59,665	59,299
Adjusted R2		6.22%	14.19%	62.93%	9.64%	19.99%	67.78%