Gender Bias and Crowd-Sourced Financial Information*

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Abstract

The capacity to aggregate information from diverse perspectives has positioned social finance forums as a potent source of signals that shape investors' beliefs and actions. We investigate how investors react to the information provided by male and female non-professional analysts on social platforms and the financial market consequences. Although male and female contributors exhibit similar informativeness and skills, female-authored perspectives receive significantly lower engagement, lower trust, and higher disagreement from platform users. The higher disagreement is subsequently associated with higher abnormal trading volume and lower price efficiency. Moreover, the platform consensus becomes less informative about future cash flows when female contributors quit due to their less favorable engagement.

Keywords: Gender Bias, Social Finance; Social Media; Information Aggregation; Disagreement; Price Efficiency

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1. Introduction

By the end of 2019, women accounted for over half of the college-educated labor force in the United States, as well as business-related master's degrees.[1] However, the proportion of women in the finance industry labor force remains much lower, at roughly 10% of mutual fund managers and financial analysts (Citywire, 2021; Jannati, 2021; Li and Wang, 2021; Niessen-Ruenzi and Ruenzi, 2019). One reason often cited for this gap is gender-based discrimination that manifests through institutional practices and implicit biases, i.e., social stereotypes (Adams and Lowry, 2022; Bayer and Rouse, 2016; Brown et al., 2023; Dupas et al., 2021; Ewens and Townsend, 2020; Lundberg and Stearns, 2019; Sherman and Tookes, 2022; Wu, 2020). However, existing studies on gender discrimination in finance primarily focus on either formal corporate or academic environments or study agents operating in such environments, making it hard to disentangle the role of institutional practices from "wired-in biases" in perpetuating gender discrimination. More so, the literature has made limited attempts to trace the broader market consequences of gender bias above and beyond its direct impacts on the individuals affected.

In this paper, we address the abovementioned issues. We document gender bias in how *everyday* investors process the financial information non-professional analysts provide on investment social media. This setting allows us to understand ordinary people's attitudes towards females on financial matters while ruling out plausible alternative interpretations. We then show that consistent with theory, the bias has relevant financial market implications for disagreement-based trading, price efficiency, and the efficient aggregation of information from diverse perspectives on social finance forums. Our analysis uses stock-specific articles and comments

[1] Pew Research Center; https://nces.ed.gov/programs/coe/indicator/ctb

posted by individuals on the Seeking Alpha platform to quantify the people's attitudes towards male and female non-professional analysts, *accounting for the information quality*.

Our use of Seeking Alpha (SA) is motivated by its status as a prominent social finance forum where anyone can contribute perspectives in a long-form article regarding the future performance of individual stocks. Earlier studies emphasize that interactions on SA are not a sideshow: discussion on SA embody cash flow-relevant information (Campbell et al., 2019; Chen et al., 2014), inform individual investors' trading (Farrell et al., 2022), and a sizeable proportion of the SA contributors are truly skilled (Dim, 2020). A crucial feature of the platform we exploit is that each SA article visibly displays the author's details, including the author's real name and a link to the author's bio page. The platform users (amounting to over 20 million unique users per month) read and engage with the articles, posting comments that align with, disparage or counter the views of an article's author. The article authors, in turn, receive financial compensation from SA based on their readership levels.[2] Crucially, the public and non-exclusive nature of the SA platform allows us to track people's attitudes towards male vs. female nonprofessional analysts in an information-rich environment where differential treatment based on gender can be reasonably traced. Moreover, the informal nature of the SA forum allows people to state their views freely without potential workplace repercussions, making SA an ideal setting for isolating gender discrimination in finance that is due to social stereotypes rather than institutional factors.

We analyze user engagement starting with the level and quality of interactions in the comments section that follow articles authored by male vs. female contributors. The article comments section is a primary medium through which other SA users express their thoughts on an author's perspective. More so, an article's number of comments proxies the article's impression,

[2] SA authors are also motivated to build a strong reputation through documented high-quality investment ideas that can lead to other professional opportunities (Crawford et al., 2018).

which determines a contributor's financial compensation on SA. SA encourages comments on articles, stating "questions and dissenting views in comments are a crucial part of Seeking Alpha".[3] In addition to the number of comments received, we analyze features of the comments' text, particularly the level of trust and disagreement expressed towards an author's viewpoint. We measure trust as the average fraction of words that signal trust used in an article's comment section and capture disagreement by the absolute value of the difference between an article's sentiment and the average sentiment of the comments, in line with recent papers that measure disagreement in the context of text data (Chen et al., 2014; Goldman et al., 2023).

Consistent with gender bias in financial social media, we find that female-authored perspectives, on average, receive a significantly lower number of comments than males' by up to 40%. In addition, when female-authored perspectives receive comments from the platform users, the comments exhibit significantly lower trust and higher disagreement towards the female authors' viewpoints relative to males. More so, users express less uncertainty in their comments towards female viewpoints relative to males, indicating that they display more certainty in their dissenting attitudes towards females than males.

Importantly, these results are not driven by other author characteristics, such as academic/professional qualifications, writing style, and age on SA, nor by article and stock characteristics. Our tests directly control for relevant author, article and stock characteristics. In our most restrictive specification, we compare articles published by male and female authors on the same stock in the same quarter, and the results remain robust.[4] To the extent that article

[3] See, https://about.seekingalpha.com/community-guidelines.

[4] Ideally, we would use stock × date or stock × year-month fixed effects. However, for many stocks-days or stock-year-months there are no publications on the same stock by both male and female authors simultaneously. So, we are forced to compare male and female publications about a stock in the same quarter. While restrictive, this approach still yields a robust comparison, given that key information releases about firms, such as earnings announcements, that generate lots of investor interest and trading are quarterly and we control for daily variation in stock characteristics.

comments closely mirror article readership, which is proportional to SA financial compensation to contributors, our result implies that, on average, female authors likely earn significantly less than their male counterparts on SA due to the platform users' tendency to engage more with viewpoints authored by male versus female contributors.

A potential explanation for the above documented gender-based differences in engagement could be that female authors are less skilled than males at analyzing stocks' future performances and, as a result, receive less favorable user engagement. This skill-based interpretation can arise from two main channels. First, users might judge authors based on their past track record. Second, users could hold correct beliefs about the informativeness of a given article about the focal stock's future prospects. Fortunately, our setting is ideal for testing these potential gender-based skill and informativeness explanations since we can directly observe an objective measure that captures both past performance and informativeness about the future. Such a measure is the ability of each author's past and current SA articles to predict stock returns correctly.

We, therefore, investigate whether there is any difference in the predictability of stocks' future abnormal returns based on the bullishness of the articles interacted with the gender of the authors. We do not find supportive evidence for this differential informativeness explanation. While article bullishness positively and significantly predicts future abnormal returns, in line with the abovementioned evidence on SA opinion informativeness, we do *not* find any significant difference in this predictiveness conditional on the authors' gender. That is, the informativeness of female-authored SA publications is no different than that of males. What matters for the value-relevance of an SA article is the quality of its signals, which is unrelated to the author's gender in our sample. This crucial result indicates that the documented differences in user engagement with female-authored articles are unlikely to be explained by differences in author quality.

In a battery of tests, we investigate several other potential alternative explanations for the differential engagement male and female contributors experience on the social finance platform. Precisely, we augment our primary specifications with an interaction of gender with several potential drivers of user engagement, including author characteristics (academic/professional qualifications, age on SA, average past abnormal returns, and number of prior publications on SA) article characteristics, and stocks' ex-post abnormal returns. In all cases, these additional interaction terms are either insignificant or solidify the message that female contributors are treated less favorably than males in terms of lower engagement with their viewpoints and conditional on engagement, lower levels of trust and higher disagreement.[5]

Next, we investigate the implications of this gender bias observed on SA for financial markets and efficient information aggregation on the platform. Models of investor disagreement suggest that besides exposure to different information sets, investors can disagree due to differential interpretations of the same information (Hong and Stein, 2007). Differential interpretation of information could stem from, among other things, investors' technological and cognitive capacity constraints or psychological biases such as stereotypes. Importantly, theory suggests that such stereotype-based disagreement can result in trading in financial markets and could facilitate or impede price discovery depending on the magnitude of noise in the trades.

We directly test these implications of gender-based disagreement in information processing in social forums by first regressing future stock abnormal trading volume on the next day following article publications on the disagreement expressed towards the articles' viewpoints controlling for several other potential drivers of abnormal trading. Across different specifications, we consistently

[5] Based on its content moderation policy, Seeking Alpha sometimes remove user comments that are deemed abusive or overtly offensive. Such moderation suggest that the results we document are likely a lower bound on the magnitude of unfavorable engagement female contributors face on the platform.

find that higher disagreement with authors to the tune of one standard deviation (SD) is associated with significantly higher abnormal trading on the focal stock by roughly 0.36 to 0.85 percentage points over the next day. We repeat the exercise with price efficiency around earnings announcements, measured as the Intraperiod Price Efficiency (Blankespoor et al., 2020, 2018). We find a significantly lower speed of incorporating earnings announcement information into stock prices (by 3.4% to 5.4% of its SD) when platform users disagree more with contributors over the week before earnings announcement by one SD. This result indicates that, to a reasonably large extent, the higher abnormal trading that trails higher disagreement on the social forum likely impedes rather than facilitates price discovery. Importantly, because female contributors experience significantly higher disagreement than males on the social forum, the results suggest that stocks disproportionately covered by females could experience higher uninformative trading due to gender-driven disagreement, which, in turn, slows price discovery.

Our last set of tests examines the implications of the less favorable treatment female contributors face on SA on the informativeness of the crowd-sourced SA consensus view. Previous studies have praised the wisdom of the social media crowd (Chen et al., 2014; Dim, 2020; Jame et al., 2016) that stems from the diverse viewpoints individuals contribute to the social forum's consensus view. We, therefore, assess the usefulness of incorporating female viewpoints into such consensus and the effect on the consensus informativeness about firms' future cash flow should female contributors quit SA due to the less favorable engagement they experience. Precisely, we regress firms' future earnings and earnings surprises, respectively, on the SA consensus bullishness, calculated as the average bullishness of articles published over the prior 30-day window ending two days before earnings announcement, interacted with the number of female-authored perspectives incorporated into the consensus. Across different specifications, the SA

consensus is significantly more informative about future firm cash flows when incorporating more female viewpoints. Therefore, female contributors bring forth novel, non-redundant perspectives that complement those of males.

We conduct additional complementary analysis using natural language processing techniques to assess the novelty of female-authored articles about a stock relative to those of males. We find similar levels of novelty across both genders on average, again solidifying the interpretation that female contributors produce useful perspectives that result in more efficient information aggregation on SA when combined with males'. Consequently, the departure of female contributors from SA due to the less favorable engagement they face will adversely impact the platform's informativeness.

Taken together, our results indicate users', possibly unintentional, tendency to favor male viewpoints over those of females on investment social media. Consequently, many female voices could be discouraged from participating on these platforms, diminishing inclusivity and jeopardizing the efficiency of information aggregation. Such consequences likely apply in other domains beyond social forums, where subtle forms of discrimination discourage the participation of certain demographics. Our result echoes and extends recent findings in other finance domains that female CEOs receive fewer analysts following even though their earnings forecasts are more accurate than male CEOs' (Francoeur et al., 2023), that the market response to female professional analyst forecasts is weaker and slower (Gu, 2020), and that mutual fund flows sensitivity to performance is lower for female fund managers (Rau and Wang, 2022). Our results suggest that the preference for male voices on financial matters is a systematic pattern also exhibited by ordinary people on social finance forums, with significant market implications.

1.1. Related Literature

This paper contributes to the literature on gender issues in finance and top corporate positions (Du, 2023; Ewens and Townsend, 2020; Fang and Huang, 2017; Gu, 2020; Huang and Kisgen, 2013; Kumar, 2010; Niessen-Ruenzi and Ruenzi, 2019; Raina, 2021; Sherman and Tookes, 2022), as well as the labor market in general (Goldin, 2014; Hochberg et al., 2023; Niederle and Vesterlund, 2007).[6] In contrast to the existing papers that focus on formal corporate environments or financiers who are often corporate entities, we provide new evidence based on an informal online environment emblematic of today's increasingly social media-based mode of information production and assimilation in financial markets. Our findings indicate that gender bias in finance is not simply due to the finance industry's institutional structure. Instead, the bias appears deep-rooted and much more widespread than perhaps earlier thought. It manifests even among younger, ordinary investors who share investment ideas online, contributing to the enduring underrepresentation of women in the finance industry.

We contribute novel insights to the literature on the sources and implications of investor disagreement in financial markets (Ajinkya et al., 1991; Atmaz and Basak, 2018; Banerjee and Kremer, 2010; Cookson et al., 2022; Diether et al., 2002; Giannini et al., 2019; Hong and Stein, 2007; Scheinkman and Xiong, 2003). Cookson and Niessner (2020) examine how much of overall investor disagreement is driven by different information sets versus differential interpretation of information, and conclude that there is an even split between both sources of disagreement. When studying the sources of disagreement, they focus on differences in people's investment

[6] In a recent paper, Pikulina and Ferreira (2023) formalize the concept of subtle discrimination and show theoretically that the form of discrimination differently shapes the implications of discrimination. A related strand of the literature we also contribute to focuses on gender disparities in finance academia and other disciplines (Adams and Lowry, 2022; Aragón et al., 2023; Barber et al., 2021; Dworkin et al., 2020; Huang et al., 2020; Sherman and Tookes, 2022).

philosophies. We contribute to their results by showing that the gender of an information originator can be a crucial source of disagreement among investors on social networks, consistent with theories on homophily (McPherson et al., 2001).[7] Gender-based disagreement can be due to gender-driven differences in interpreting otherwise similar information as a result of social stereotypes where some individuals consider viewpoints provided by females less informative and less trustworthy. While Gu (2020) shows that the market response to female professional analyst forecast is slower and weaker, we show that bias and gender-based disagreement outside the professional realm has crucial financial market implications for trading and the speed of incorporating information into stock prices.

By studying gender dynamics in a social finance forum, we join a growing literature that employs investment social media to understand important economic issues (Bali et al., 2021; Cassella et al., 2023; Cookson et al., 2023; Cookson and Niessner, 2020; Da et al., 2021; Dim, 2020; Heimer, 2016; Hirshleifer et al., 2023).[8] We contribute to this research by documenting gender-based nuances in how people interact on social forums, which has implications for how ideas spread on social networks. Importantly, we show that signals of objectively similar quality are subjectively perceived to be of different quality in social forums based on the signal originator's gender. In turn, the gender-based perception of signal relevance is a crucial source of disagreement on social forums and has significant financial market implications.

We also contribute to research highlighting the relevance of diverse viewpoints for efficient information aggregation in financial markets (Chhaochharia et al., 2022; Gerken and Painter, 2023; Merkley et al., 2020). While the wisdom-of-the-crowd has been documented on online forums

[7] More broadly, as noted in Bayer and Rouse (2016), perceived group affiliation such as gender operate as heuristics that have powerful effects on judgement and actions.
[8] See Cookson et al. (2024) for a recent review of this literature.

(Chen et al., 2014; Jame et al., 2016), we show new evidence that gender-based diversity in viewpoints is crucial for the informativeness of the consensus aggregated from the online crowd. Hence, the value of gender-based diversity transcends the realm of sell-side analysts and applies to online forums that democratize financial information production.

2. Data and Summary Statistics

This section describes our data sources and the sample used for the analysis. It gives an overview of the construction of our main variables and describes summary statistics. Internet Appendix Table 1 details the construction of the main variables used in our analysis.

2.1. Data Sources and Variable Construction

We use data from a variety of sources. Stock-specific data, such as stock returns, price, market value and firm fundamentals, come from CRSP and Compustat. Opinion articles about stocks' future return performance are obtained directly from Seeking Alpha (SA), a prominent online social finance forum focused on crowd-sourcing investment perspectives from individual investors. Our starting sample consists of 403,860 articles published from January 2005 to February 2021, focusing on a single stock. In addition to the research article's content, we obtained information on the author and other SA users' public comments in response to the articles.[9] As presented in the SA Community Guidelines, the comments are an essential aspect of SA in that:

> *"Commenters contribute different perspectives, extra insights, and often suggest helpful corrections or point out flaws in an author's data or argument. Seeking Alpha users read our site to learn and digest actionable investment ideas but they*

[9] Special thanks to the team at Seeking Alpha for providing the article data.

are responsible for their own investment decisions. Questions and dissenting views in comments are therefore a crucial part of Seeking Alpha." [10]

Comments are the primary way that we measure interactions in the SA environment. The public comments provide an avenue to measure discriminatory interactions that may not be as easily observed in a traditional, in-person workplace setting.

Similar to earlier studies (Bhagwat et al., 2023; Kumar, 2010), we infer an article author's gender using GenderAPI.com, which algorithmically determines gender by first names. Figure 1 (Figure 2) shows a sample female (male) author's bio page, a snippet of an article published by the author, and snippets of some comments posted on the article.

We quantify the *sentiment* of SA articles and comments based on the National Research Council of Canada[11] Word-Emotion Association Lexicon (hereafter, NRC Emotion Lexicon). Using the NRC Emotion Lexicon, we further quantify the level of *trust* and *joy* expressed towards an article's viewpoint in the comment section. The NRC Emotion Lexicon has been widely used to capture emotions across various disciplines. It is well suited for capturing emotions in an online community's comment section where language is less likely to be formal. We also employ the Loughran and Mcdonald (2011), hereafter LM, dictionary commonly used for measuring sentiment in finance and economics.

For each article's sentiment measure, we obtain a corresponding measure of user *disagreement* with the article's viewpoint as the absolute value of the difference between the article's sentiment and the average sentiment of its comments. Finally, we obtain an article

[10] https://about.seekingalpha.com/community-guidelines
[11] https://nrc.canada.ca/en

author's stated or machine learning-implied *bullishness* from Dim (2020), who develop a supervised machine learning model for inferring SA authors' bullishness from their article text.[12]

We apply the following filters to the SA data to reduce noise. We require articles to have at least 20 words to be representative of the typical SA long-form article. We use articles whose authors' gender classification probability score is at least 75%. This results in a final sample of 200,428 articles written by 8,242 contributors, of which 482 are female. We retain comments posted within seven days of an article publication to reduce staleness and remove comments posted on an article by the article's author. These filters reduce our initial sample of 11,703,916 article comments to a final sample of 7,768,748 comments.

2.2. Summary of Main Variables across Gender

Table 1 provides summary statistics for our main variables of interest. Since our analysis focuses on gender-based differences, the summary statistics are separated into subsamples of male and female contributors. Male-authored articles comprise the majority of our sample, with males authoring approximately 95% of the articles. This statistic shows the dramatic gap in female representation and participation in SA, which mirrors the general trend in finance.

[Table 1 – Descriptive Statistics]

Panel A of Table 1 looks at article characteristics, indicating similar article features for male vs. female authors. The average article length for male contributors is approximately 600

[12] In more recent periods, SA articles are accompanied by a bullishness label (Very Bullish, Bullish, Neutral, Bearish or Very Bearish) that summarizes an author's view on the focal stock's future prospects. SA provided us only the article text but not these bullishness labels. Therefore, we obtain these labels from Dim (2020), who retrieved them by scraping the SA website and then trained an ML model to infer the labels for those articles lacking them.

words, while that of female contributors is approximately 520. Bullishness has a mean of 0.624 for male authors and 0.697 for females, indicating that female authors are slightly more bullish in their writing. Sentiment and article readability are not significantly different between male and female-authored articles. Overall, SA articles are slightly positive based on the Sentiment obtained from the NRC Emotion Lexicon and are close to neutral on average based on the LM Sentiment (mean near zero). Panel B depicts contributor characteristics, indicating that male and female contributors are similar in the years they have been on SA, their monthly workload, and the number of firms and industries they cover. Male contributors have significantly higher academic/industry qualifications. This and other author characteristics are controlled for in subsequent analyses.

Panel C of Table 1 provides an introductory investigation of user engagement with articles through comments. Looking at the number of comments, we observe that female contributors get significantly lower levels of engagement, with an average of only 14 comments. In contrast, the number of comments males receive almost doubles at 25. Another notable difference is that female contributors receive comments displaying significantly lower levels of trust and joy and higher levels of disagreement with the author's viewpoint than males.

Lastly, Panel D provides the summary statistics for the characteristics of the stock covered in our sample of SA articles. We observe that the characteristics of the stocks covered by male and female contributors are not significantly different. Focusing on the distribution of the ex-post five trading days abnormal returns following article publications, we observe similar magnitudes for both genders.

The raw summary statistics in Table 1 indicate differences in the engagement received by female vs. male contributors, even though their individual characteristics and the characteristics of the stocks they cover are similar. However, the pattern may be driven by the within-group

heterogeneity in the stock and contributor characteristics of either gender, masked by the unconditional summary statistics. Hence, we next examine the averages of a few variables of interest for each gender, conditional specific stock and author characteristics.

Figure 3 summarizes the conditional average for the number of comments and the level of disagreement by quintiles for stock size, future abnormal return and contributor age on SA, respectively. Across the different quintiles, we again observe lower comments and higher disagreement for females compared to males authors. These results indicate that the less favorable engagement female authors receive relative to males is not primarily driven by these characteristics we condition on.

[Figure 3 – Conditional Averages]

Overall, the summary statistics tend to suggest that female contributors produce articles of similar characteristics as male authors, yet female authors receive relatively worse user engagement.

3. Empirical Results

This section formally analyzes the informativeness of female vs. male-authored articles for future stock abnormal returns. We then examine how SA users engage with male vs. female authors, accounting for several potential confounders. We investigate the possible explanations of the differential treatment the different genders experience. Finally, we explore the financial market implications of gender-based differences in engagement by examining abnormal trading and price efficiency following disagreement with authors and the relevance of female-authored viewpoints in aggregating relevant information into the SA consensus.

3.1. Does Author Gender Matter for Article Informativeness?

SA articles aim to help the platform users make profitable investment decisions. As such, the natural benchmark for judging the usefulness of any publication is to assess how predictive it is about future stock abnormal returns. We incorporate the author's gender as an interaction term with a measure of an article's bullishness to ascertain whether the informativeness of an article's viewpoint depends on the author's gender. It is not clear whether, in the context of social finance forums like SA, gender matters for one's ability to produce useful content since anyone can contribute opinions on such platforms. At the same time, if we find that author gender matters for article informativeness, then in the face of limited attention constraints, SA users may naturally discount the views of the less informative gender, leading to less favorable engagement for the latter. We use the following regression specification for the analysis:

$$Alpha_{i,k,t+h} = \alpha + \beta_1 ArticleSentiment_{i,k,t} + \beta_2\, Female_i + \beta_3\, (ArticleSentiment_{i,k,t} \times Female_i) + \Gamma \boldsymbol{X} + \varepsilon_{i,k,t+h}, \quad (1)$$

where $Alpha_{i,k,t+h}$ is stock k's four-factor abnormal return computed over horizon h trading days starting $t+1$ following article i's publication on day t. We set h equal to 5, 21, and 63 trading days in different specifications. $ArticleSentiment_{i,k,t}$ is a generic variable that captures how bullish article i published on day t is about stock k. It is either the *Bullishness* score based on Dim (2020), the *LM Sentiment* score, or the *Sentiment* score based on the NRC Emotion Lexicon. $Female_i$ is an indicator variable that equals one if article i's author is female and zero otherwise. $\boldsymbol{X}$ is a vector of controls that include past stock returns, volatility, the log of stock price, the log of stock market capitalization, and year-quarter fixed effects.

Table 2 summarizes the estimation results. In columns 1, 4, and 7, abnormal returns are measured over five trading days. In columns 2, 5, and 8, abnormal returns are calculated over 21 trading days, while in columns 3, 6, and 9, they are calculated over 63 trading days. Appendix Table 1 describes all variables used in this specification and the rest of the analyses in this paper. The results in Table 2 indicate that future stock abnormal returns change in the direction of the bullishness of SA articles, meaning that the articles are informative about future stock returns on average. For example, the positive and significant coefficient for *Bullishness* suggests subsequent returns are higher when an article is classified as bullish (bullishness score equals one). A similar result is found for both *LM Sentiment* and *Sentiment*, with more positive sentiment significantly related to higher subsequent returns. On the other hand, the *Female* dummy variable is insignificant at the 5% level in all but one of our nine specifications. This result suggests that stocks covered by females do not have significantly different future abnormal returns from those covered by male contributors.

*[*Table 2 - *Informativeness FF4]*

Our main coefficient estimates of interest are the interaction terms of *Female* and the respective article bullishness measures. Across all but one of the nine specifications, we find that the interaction terms are insignificant. This indicates that it is the view expressed in an article, not the gender of the author, that determines the article's informativeness about future abnormal returns. Therefore, male and female contributors' viewpoints are equally informative, setting the stage for the remainder of our analyses that focus on gender disparities in user engagement.

An alternative way to ascertain whether female vs. male authors contribute informative viewpoints is to assess informativeness in terms of the novelty of the content of an article's text. The idea is to ignore ex-post stock returns and evaluate whether a class of authors is more or less likely to contribute new perspectives on a stock relative to the prevailing wisdom about the stock on the platform. We embark on this exercise as follows. For each female-authored article about stock *k* in our sample, we quantify the article's novelty score, and that of a randomly selected male-authored article published about the stock within the past six-month period. The male-authored article serves as a benchmark for the female-authored article.

To obtain the novelty scores, we first fit a term-frequency inverse document frequency matrix on our entire text corpus, omitting terms that appear in less than 100 documents. Then, for each female article, we compute the average of the cosine similarity of the article's document vector with that of the most recent *n* (equals two or five articles) published about the same stock. We do the same for the benchmark male-authored article. Finally, an article's novelty score is one minus the average cosine similarity score.

Figure 4 shows the box plots for the distribution of the novelty scores for the female- and male-authored articles, indicating a striking similarity in the novelty of both genders' views. The result is unchanged irrespective of whether we quantify novelty based on the most recent two or five articles published about the focal stock.

*[*Figure 4 – *Article Novelty by Gender]*

Overall, the results align with the market-based analysis: both male and female authors on SA contribute viewpoints with similar levels of originality and they are equally similar in their informativeness about future stock abnormal returns.

3.2.Engagement Conditional on Author Gender

We turn to SA users' engagement with an article's viewpoint conditional on the author's gender. Results presented in Table 2 demonstrate that both male and female authors write articles of similar stock return informativeness. Therefore, it is reasonable to assume that both genders would garner similar interactions in the comment sections after controlling for differences in individual and article characteristics that may affect user interest in an article. We explore this gender-based engagement with the regression:

$$Engagement_i = \alpha + \beta_1 Female_i + \Gamma \boldsymbol{X} + \varepsilon_i, \quad (2)$$

where $Engagement_i$is a generic variable that captures different measures of the engagement quality article i received in the comment section from other platform users. The measure of engagement is either *Number of Comments*, the level of disagreement expressed towards the article (*Disagreement*), the level of trust expressed towards the article (*Trust*), the level of joy expressed towards the article (*Joy*), and the intensity of uncertainty expressed towards the article (*LM Uncertainty Ratio*). $Female_i$ is a dummy variable that equals one if the gender of article *i*'s author is female and zero if male. $\boldsymbol{X}$ captures several control variables that account for confounding factors.

Because other author characteristics, besides gender, can potentially impact a user's engagement with an article, we include controls for such characteristics, namely the author's age

on SA, how many articles they publish per month, number of firms and industries they covered on SA, respectively, and the number of graduate academic and professional qualifications they list on their SA profile. We also control for article readability to rule out article complexity or writing style as a confounding factor. Finally, because user interest can strongly depend on the stock covered in an article, we further control for several stock characteristics: past one-month return, past year volatility, stock price, and market capitalization. All variables are defined in Appendix Table 1. In our most stringent specification, we include stock × year-quarter fixed effects such that we compare the engagement received by male vs. female-authored articles published about the same stock in the same quarter.[13]

*[*Table 3 - *Engagement by Gender]*

Table 3 shows the estimation results for *Number of Comments, Trust, Joy,* and *Uncertainty* as the measures of engagement quality. Starting with the number of comments (columns 1 and 2), we obtain a negative and significant coefficient for the *Female* variable. This demonstrates that female authors receive significantly lower interactions on their published articles. The magnitude of the coefficients is sizeable, with female authors getting roughly 3 – 10 fewer comments than their male counterparts. In terms of economic magnitude, this is equivalent to 12% – 40% fewer comments relative to the average number of comments. Importantly, because the financial compensation an author receives from SA is proportional to their readership, it follows that to the

[13] We would ideally use stock × date or stock × year-month fixed effects. However, because for many stocks-days or stock-year-months there are no publications on the same stock by both male and female authors simultaneously. So, we are forced to compare male and female publications about a stock in the same quarter. While restrictive, this approach still yields a robust comparison, given that key information releases about firms, such as earnings announcements, that generate lots of investor interest and trading are quarterly and we control for daily variation in stock characteristics.

extent that female authors' readership closely aligns with the comments they receive, then female authors, on average, likely earn significantly lower than their male counterparts on SA.

Columns 3-8 of Table 3 show the results for the level trust, joy, and uncertainty displayed towards articles in the comments section. Again, we observe negative and significant coefficients for the female dummy variable, indicating that when users engage with female-authored articles, they demonstrate significantly lower levels of trust and joy towards the article than if the author were male. The estimated coefficients imply that trust (joy) is lower for female-authored articles by roughly 5% (6%) of its standard deviation relative to males. The negative and significant coefficient for *Female* in the uncertainty specification (columns 7 and 8) further indicates that when SA users exhibit less trust and joy towards female-authored viewpoints, they are more certain about these emotions.

Having demonstrated that female authors experience lower levels of interactions on their publications than males and face lower levels of trust expressed towards their viewpoints which are as informative as males', we now turn to the disagreement displayed towards the articles. We quantify the intensity of the platform users' disagreement with an article as the absolute value of the difference between an article's sentiment (polarity) and the average for the comments' sentiment (polarity). This measure of disagreement is in line with existing papers that measure disagreement in the context of text data (Chen et al., 2014; Goldman et al., 2023). We quantify sentiment and polarity using the NRC Emotion Lexicon or the LM dictionary. Table 4 summarizes the results, with the NRC sentiment disagreement in columns 1 and 2, NRC polarity disagreement in columns 3 and 4, and the LM dictionary-based disagreement measures in the remaining columns. We use the full set of controls described under Eq. (2) in all specifications.

[Table 4 - Disagreement by Gender]

The results in Table 4 show that across all the disagreement measures, there is significantly higher user disagreement with the author's viewpoint when the author is female than if the author is male. In terms of economic magnitude, the coefficients 0.282 and 0.101 for *Female* reported in columns 1 and 2 of Table 4 indicate that disagreement towards female viewpoints is higher than males' by 5% to 10% relative to the mean. When we consider alternative measures of disagreement shown in the other columns of the table, including those based on the entirely different LM dictionary, we continue to observe significantly higher disagreement of similar magnitude towards female-authored viewpoints. Importantly, this result is not driven by the negativity or positivity of the article itself. For example, when we drop all articles classified as bearish, we continue to find the same higher disagreement with the female authors' viewpoints than with males' (Internet Appendix Table 8). Moreover, other tests that account for alternative explanations discussed in the next section and in the Robustness Section 4 rule out concerns that the higher disagreement and unfavorable engagement expressed towards female-authored viewpoints could be simply due to other considerations unrelated to gender.

Because we have already shown that female authors are, on average, equally informative as males, the less favorable engagement and higher disagreement we document for female authors relative to males is unlikely to be driven by differences in article informativeness. Moreover, the results are unlikely to be driven by other author characteristics, stock characteristics, or the differences in writing style across genders. We explicitly controlled for all these confounders in all our analyses, and yet the results remain robust. Therefore, we attribute the differential treatment of female contributors relative to their male counterparts to the biases of the social forum's users.

3.2.1. Accounting for Informativeness, Author Experience and Qualifications

Thus far, we have independently examined the informativeness of SA articles by gender in Table 2, finding similar levels of article informativeness across genders. However, even though female and male-authored articles are, on average, equally informative, there could be substantial heterogeneity in informativeness across article features that interact with gender. In turn, if investors who consume information on SA hold accurate expectations about the usefulness of each publication for investment decisions, it could potentially drive the different engagements experienced by both genders. More so, it is possible that male authors have a longer and better track record on the platform and, naturally, have more followers, which drives their better engagement experience. It may also be that higher financial industry experience and academic backgrounds for males lead platform users to perceive males as higher-quality contributors relative to females, inducing skewed engagement.

We directly probe each of these potential drivers that could explain our results by introducing an interaction term to a version of Eq. (2). We separately interact *Female* with a measure of an article's informativeness about future abnormal returns. These measures include the average of an author's past abnormal returns before day *t*, the number of articles an author has published on SA as of day *t*, and the number of graduate academic or professional qualifications an author listed on their SA profile. These variables are all described in the Internet Appendix Table 1. We use the following specification:

$$Engagement_i = \alpha + \beta_1 Female_i + \beta_2 V_i + \beta_3 Female_i \times V_i + \Gamma \boldsymbol{X} + \varepsilon_i, \quad (3)$$

where $Engagement_i$, $Female_i$, and $\boldsymbol{X}$ are as described under Eq. (2). V_i captures one of the abovementioned variables that could potentially drive differential engagement across genders.

We start with article informativeness measured as $Abn\ Ret[1,5]$, i.e., the signed ex-post abnormal return one would have earned over the subsequent five trading days if they invested in the direction of an article's *Bullishness*. This variable allows us to ascertain whether the perceived informativeness of a publication about future abnormal returns drive unfavorable engagement toward female authors. If correct beliefs drive the unfavorable engagement, we should see that the interaction term is significant and has an opposite sign as the *Female* variable. This would indicate that when female authors write objectively informative (uninformative) articles about future performance, market participants engage more (less) favorably with such articles because they correctly infer that the article reflects valuable signals.

On the contrary, the results in Table 5 show an insignificant coefficient for the interaction term across all definitions of engagement. At the same time, the *Female* coefficient remains significant and negative, supporting our previous findings that female authors receive less favorable engagement. On the other hand, the coefficient for $Abn\ Ret[1,5]$ is positive and significant when we use either *Trust* or *Joy* as the measure of engagement, indicating that more informative male-authored articles do experience more trust and joy from platform users, but this is not the case for female-authored articles. Overall, the results in Table 5 show that even after accounting for the informativeness of the focal article, we continue to observe that the lower level of interactions and trust female-authored articles experience are due to the author's gender rather than any perceived article informativeness about future returns.

[Table 5- Engagement by Skill and Gender]

Next, we entertain the idea that even though correct beliefs regarding the usefulness of an article's viewpoint for future abnormal returns do not explain female author's less favorable engagement, it could be that social finance platform users learn from authors' past track records and favorably engage with authors they perceive to be more skilled. Bohren et al., (2019) find that with no prior evaluation mechanism, women face more discrimination; however, once females have a history of positive performance their content is preferred over content from male creators. We measure an author's prior performance or skill that other platform users could have observed as of $t-1$ as the average of the one-day abnormal return realized for the day after each of the author's publications. We denote this variable as $Ave.Abn\ Ret_i$ and then use it in place of V_i in Eq. (3). The results are also reported in Table 5 and show that the interaction term is again insignificant for all measures of engagement. Therefore, potential differences in skill observed by platform users do not drive the relatively less favorable engagement female authors receive.

For our final two variables of V_i, we condition on the author's experience with publishing on SA and the author's academic and professional qualifications. We interact *Female* with the author's number of publications as of day t (*Publications*) and the number of academic and professional qualifications listed on their bio page (*Qualifications*). The results in Table 6 show that both interaction terms are insignificant for all measures of engagement, indicating that experience-based considerations or perception of ability based on academic and professional credentials do not drive the less favorable engagement female authors experience relative to males.

[Table 6 - Engagement by Experience and Gender]

We next examine whether the aforementioned potential confounders drive the higher level of disagreement female authors experience towards their viewpoints.[14] Starting with the article's perceived informativeness about future abnormal returns and the author's track record reflected in past abnormal returns, the results presented in Table 7 again show an insignificant interaction term and significant *Female* coefficient estimates. These results suggest that the disagreement expressed towards female-authored articles is driven by gender considerations rather than information or skill-related considerations.

[Table 7 - Disagreement by Skill and Gender]

Lastly, Table 8 follows the analysis of Table 6 but examines the levels of disagreement conditional on experience and academic/professional qualifications interacted with the gender variable, respectively. The results are consistent with our previous findings: neither experience-based considerations nor perception of ability based on academic credentials can explain the higher level of disagreement platform users exhibit towards female-authored viewpoints relative to male contributors.

[Table 8 - Disagreement by Experience and Gender]

[14] In this and subsequent analysis on disagreement, we focus on the disagreement measures based on the NRC Emotion Lexicon for two reasons. First, this lexicon is better suited for the less formal language used in the comments section. Second, our earlier analysis show that our results are robust to defining disagreement based on the LM dictionary. Our subsequent results are also robust to the use of the LM dictionary and such results can be provided upon request. To keep things simple we just report results for the NRC Emotion Lexicon-based disagreement measures.

Overall, the results of this section further strengthen our finding that female authors on the SA platform face significantly different and less favorable engagement than their male counterparts. This difference is most likely attributable to gender bias rather than skill- or information-based explanations.

3.2.2. Accounting for Author Boldness

Although we have demonstrated that the less favorable engagement female authors face from SA users is unexplained by information-, skill-, experience-, or academic qualification-based considerations, it is still possible that the engagement is a rational response to female authors publishing bold analyses that systematically deviate from the prevailing view about a stock on the platform. Since female authors are generally underrepresented in finance, they may publish bold views to attract more attention and recognition. This could result in less favorable engagement in the form of higher disagreement and lower trust and joy expressed towards female-authored views.

To investigate this possibility, we first examine whether female authors publish bolder articles than male authors. We regress article *Boldness*, defined as the absolute value of the difference between an article's *Bullishness* and the average *Bullishness* of articles published about the same stock over the past 90 days, on *Female* and the same set of controls used in Eq. (2). The results presented in columns 1 and 2 of Table 9 show that female authors are at most equally bold as their male counterparts and in one specification are less bold (closer to the consensus). This provides the first bit of evidence that the higher disagreement female authors face is not because their perspectives are more daring.

*[*Table 9 - *Boldness by Gender]*

We further this analysis in columns 3 - 6 of Table 9 using Eq. (3) with the disagreement measure on the left-hand side and the interaction of *Female* and *Boldness* on the right-hand side. We use of all the controls in Eq. (3). We observe significant and positive coefficients for the interaction term but negative coefficients for the *Boldness*, indicating that deviating more from the prevailing consensus only leads to higher disagreement when a female writes the bold article. These results again demonstrate that female contributors are held to a different standard and face higher hurdles than males when serving as financial information intermediaries on social forums.

3.3. Financial Market Implications of Gender-based Differences in Engagement

Having documented a systematic difference in how investors on SA engage with financial information conditional on the gender of the information provider, we now turn to the natural question of whether this differential interpretation of information has relevant implications for financial markets. In particular, we examine the consequences of the observed gender-based disagreement for trading and price efficiency, i.e., the speed of incorporating new information into prices. Finally, we assess the implications of gender-based differences in engagement for the efficient aggregation of information on investment social media.

3.3.1. Gender-based Disagreement and Abnormal Trading

Models of investor disagreement propose two primary sources of disagreement across investors. The first is disagreement due to the different investors' information sets; the second is disagreement due to differential interpretation of the same information (Hong and Stein, 2007). Differential interpretations of information can be due to differences in how investors process information due to, among other things, technological and cognitive capacity constraints and psychological biases such as stereotypes. Since investors who comment on the SA articles are

plausibly responding to the same financial information the author has in mind and outlined in the article text, the disagreement we observe towards an article's author is likely due to the differential interpretation of information. A crucial prediction from theory is that such disagreement can lead to higher trading volume in financial markets. We test whether this prediction is confirmed in our data by asking, when investors disagree with contributor's information on social forums due to the author's gender, is the disagreement associated with higher abnormal trading of the stock? We answer the question using the following specifications.

$$Abn\ Vol_{k,t+1} = \beta_0 + \beta_1 Disag_{i,k,t} + \beta_2 Female_i + \beta_3 Disag_{i,k,t} \times Female_i + \Gamma \boldsymbol{X} + \epsilon_{k,t+1}, \quad (4)$$

where $Abn\ Vol_{k,t+1}$ is stock *k*'s abnormal trading volume on the next trading day following article *i*'s publication on day *t*. It is computed as the difference between the log volume on date $t+1$ and the average daily log volume from $t-140$ to $t-20$ trading days (6-month period, skipping a month). $Disag_{i,k,t}$ is the disagreement expressed by other platform users towards the viewpoint of the author of article *i* published on day *t* about stock *k*. We restrict comments for computing the disagreement measure to those posted between *t* and $t+1$ following article *i*'s publication. As before, $Female_i$ is the dummy variable that denotes whether article *i*'s author is female. $\boldsymbol{X}$ is a vector of control variables that capture other variables that could matter for future abnormal trading volume, namely recent past abnormal returns ($Abn\ Ret[-5,-1], Abn\ Ret[-25,-6]$), recent past volatility ($Volatility[-5,-1], Volatility[-25,-6]$), traditional news media sentiment, log of number of news media articles, article *i's* sentiment, article *i's* number of comments, an indicator variable for whether no comment is posted on the article, the log of stock price, and the log of

stock market value. $\boldsymbol{X}$ also includes stock and day fixed effects. To facilitate interpretation, we standardize the disagreement measure and all continuous control variables to unit variance.

Table 10 summarizes the estimation results. In columns 1 and 2, abnormal volume is estimated for $t+1$, while in columns 3 and 4 it is averaged over $t+1$ to $t+3$ for robustness. Across all variations, we observe a significant and positive coefficient estimate for the disagreement measures, indicating that higher disagreement with an author is associated with higher abnormal trading volume on the focal stock. The estimates imply that for a one-standard-deviation increase in disagreement with an author's viewpoint, abnormal trading volume increases by between 0.36 – 0.85 percentage points. The interaction term for disagreement and female is positive but insignificant, suggesting that female-authored articles do not generate incremental abnormal trading beyond that generated by users' disagreement with the author. However, since female authors receive significantly more disagreement than males, gender-based disagreement on social forums is associated with higher trading volume in the stock market, consistent with models of differential interpretation of information. Here, the differential interpretation of information seems to arise from gender-based stereotypes that distort information processing.

3.3.2. Gender-based Disagreement and Price Efficiency

Having seen that disagreement within SA articles based on gender is associated with higher abnormal trading volume on the focal stock, we now ask whether this disagreement is subsequently associated with more or less efficient stock prices. It is possible that the higher trading born out of disagreement, even if some of the trading is pure noise, permits more efficient prices by allowing informed traders to hide their informative trades among noise traders (Glosten and Milgrom, 1985; Kyle, 1985). On the other hand, too much uninformative trading due to disagreement unrelated to

fundamentals could dampen the information content of stock prices in line with arguments that there is too much trading in stocks than can be justified by changes in fundamentals (Daniel and Hirshleifer, 2015; Shiller, 1981).

We assess which of these possible scenarios exists in our sample by examining how investors' disagreement with authors' viewpoints on SA relates to the speed with which new information is incorporated into prices around earnings announcements. We focus on price efficiency around earnings announcements because earnings announcements are unambiguous information events that allow a clear assessment of the speed of price discovery. We use the Intraperiod Price Efficiency (IPE) measure that has been used in earlier works (Blankespoor et al., 2020, 2018), computed based on stock returns in excess of the market over window $[t-1, t+3]$ and $[t, t+5]$, respectively, where *t* is the earnings announcement day.[15] Higher IPE values mean a higher speed of incorporating the earnings announcement information into stock prices.

Next, for each earnings announcement on day t we obtain the average disagreement on all articles published over $t-5$ to t. As in the previous section, each article's disagreement is computed using comments posted on the article's publication day and the next day. Finally, we regress the IPE measure on the average disagreement expressed towards authors' viewpoints and interact the latter with the number of female-authored articles included in the average disagreement measure. We include similar controls used in Eq. (4) and standardize IPE, average disagreement and all continuous control variables to unit variance to facilitate interpretation.

[15] For example, for window $[t-1, t+3]$, the $IPE = \sum_{t=-1}^{t=3} 1 - \frac{|Abn\ Ret_3 - Abn\ Ret_t|}{|Abn\ Ret_3|}$, where $Abn\ Ret_t$ is the cumulative abnormal return from $t-1$ to t. In line with the literature mentioned above, we set the IPE measure to missing if the absolute cumulative abnormal return over the announcement window, i.e., $|Abn\ Ret_3|$ in this example, is too small to reduce the impact of very small denominators. We use a threshold of 0.5% and 1% for the $[t-1, t+3]$ and $[t, t+5]$ windows, respectively.

Table 11 summarizes the estimation results, showing that higher disagreement with authors' viewpoints on the social finance forum over the days leading up to an earnings announcement is associated with a slower speed of incorporating the earnings announcement information into stock prices. The estimates in columns 1 and 3 imply that a one-standard-deviation increase in investors' disagreement with the authors' views is associated with roughly 3.4% and 5.4% decline in price efficiency relative to the standard deviation of the price efficiency measures, respectively. The interaction term of disagreement with the number of female-authored articles is insignificant. However, it follows that because female authors, on average, experience more disagreement mainly because of their gender, price efficiency would suffer more when female authors disproportionately cover firms around earnings announcements. Therefore, the gender-based differential interpretation that investors on social finance forums apply to information presented by female vs. male authors can adversely shape price efficiency. This appears to be because informative signals provided by female authors are less likely to be acted upon promptly but rather disagreed with compared to when a male author presents the same signal.

3.3.3. Female Viewpoints and Consensus Cashflow-informativeness?

Next, we examine how informative the SA's consensus view is about a firm's future earnings conditional on aggregating female views into the consensus. We use the following regression specification:

$$Earnings_{k,t} = \alpha + \beta_1 SA\ Concensus_{k,t-2} + \beta_2 Female\ Count_{k,t-2} + \beta_3 SA\ Concensus_{k,t-2} \times Female\ Count_{k,t-2} + \Gamma \boldsymbol{X} + \varepsilon_{k,t}, \quad (4)$$

where k and t index firm and earnings announcement day respectively. $Earnings_{k,t}$ is either firm k's quarterly earnings or earnings surprise (SUE) announced on day t. Following Richardson et al. (2005), we define earnings as operating income after depreciation divided by lagged total assets. Earnings surprise is defined following standard practice as the actual earnings per share minus average analyst earnings per share forecast divided by the standard deviation of earnings per share forecast. The $SA\ Concensus$ is computed as the average bullishness of articles published over the prior 30-day or 60-day horizon ending $t-2$ before earnings announcement on day t. $\boldsymbol{X}$ denotes a vector of control variables that include the lag of the dependent variable and several other firm-level variables that could be informative about future earnings shown in Table 12 and described in the Internet Appendix Table 1.

The estimation results are presented in Table 12. The positive and significant interaction term in columns 1-2 and 5-6 shows that when more female viewpoints are aggregated into the SA consensus computed over the prior 30 days, the consensus can better predict firms' future earnings and earnings surprises (SUE) correctly. This finding indicates that the consensus generated from SA articles is more informative when incorporating more female-authored viewpoints. A more bullish or optimistic firm-specific SA consensus predicts higher earnings and earnings surprise on average. Importantly, the magnitude of this predictability increases significantly when the consensus includes more female viewpoints. The results are less significant when we incorporate older articles in the SA consensus calculation, i.e., for consensus aggregated over the longer 60-day window. This indicates that the cash-flow relevant signals in SA are likely revealed closer to earnings announcements.

[Table 12 - Female Views and Consensus Informativeness]

Overall, the result indicates that female authors on SA do not produce redundant information or just noise. Instead, they provide valuable information that complements those of their male counterparts, resulting in more informative signal aggregation into the consensus. The results, therefore, support the continued participation of female authors on SA and for them to continue contributing valuable perspectives to the platform. The results suggest that if female contributors quit SA due to the less favorable engagement they experience, then the platform's consensus will be less informative. In fact, our subsequent analysis shows that authors who receive highly unfavorable engagement on SA end up quitting the platform.

4. Additional Analysis and Robustness

This section describes additional analysis and robustness tests that reinforce our main results. Overall, the results indicate that our findings are robust. Female contributors on SA provide insights that are as novel and informative as males'. Yet, they receive less favorable engagement from the platform users, which has relevant financial market implications.

4.1. Quitting Seeking Alpha

This section explores the decision to quit participating as an author on the SA platform, conditional on the nature of interactions one experiences. We define an indicator variable, *Quit*, that reflects whether a contributor paused contributions to the SA platform since the end of 2019. We then regress *Quit* on *Female* and its interaction with the average user disagreement with the author over the pre-quit period. The control variables are the same as in Eq. (3).

The estimation results presented in Table 13 show that female authors are generally no more likely to quit SA than males. Looking at the role of disagreement, we observe that authors

are more likely to quit the platform when they experience higher disagreement on average. Across all specifications, we find that the nature of engagement equally impacts female and male authors. However, because prior results demonstrate that female contributors face less favorable engagement, the net result is that women are more likely to quit the platform.

4.2. Trolling Conditional on Gender

With the rise of social interactions online comes the rise of internet trolls. The Merriam-Webster dictionary defines this term as "to antagonize (others) online by deliberately posting inflammatory, irrelevant, or offensive comments or other disruptive content". One demographic that is more commonly subjected to this type of online behavior is females.[16] To explore whether this behavior exists on SA, we construct a trolling measure, denoted *Troll,* and look at how it varies across author gender. *Troll* captures the number of troll users who commented on an article. A troll user is a commenter who has made multiple comments on the SA platform, and the average tone of all of their comments is in the bottom 10% of all users' distribution, i.e., among the top (bottom) 10% in negativity (positivity). Article tone is measured based on either sentiment or polarity using the NRC Emotion Lexicon or the LM dictionary.

Table 14 summarizes the results of regressing *Troll* on the *Female* dummy variable and other controls and provides some support that female authors are subject to significantly more trolling than male authors. Our LM-based trolling measures are insignificant, likely because the language used in these comments may not reflect the kind of formal text for which the LM dictionary is designed. On the other hand, the measure based on the NRC Emotion Lexicon is intended to capture sentiment and emotions on the internet and social media environments, similar

[16] https://www.reuters.com/technology/trolling-safety-fears-plague-many-young-women-online-uk-study-finds-2022-06-01/.

to the informal SA comment section. The positive and significant coefficient for *Female* in columns 5 and 7 is consistent with female authors on SA facing significantly more trolls in their comments, indicating a more hostile and less welcoming environment for female contributors.

4.3. Direct Engagement

A potential concern with our analysis of differential engagement across genders is that comments posted on an article may not necessarily be directed at the article's author but to other commenters. Fortunately, on SA, one can differentiate replies to other commenters from comments directed at the article author using a flag in the comment indicating who the comment is responding to. Although comments not aimed directly at an article's author can still indirectly be referring to the author by buttressing the point of another commenter, we drop all comments not aimed directly at the article author to ensure robustness.

After applying the above filter, we redo the engagement analysis. The results reported in Internet Appendix Tables 2 and 3 confirm that our results on lower comments, lower trust, lower joy, higher certainty, and higher disagreement towards female-authored relative to male-authored viewpoints are not driven by the abovementioned concern. The estimated coefficients are similar both in their economic magnitude and statistical significance. For instance, column 1 of Internet Appendix Table 2 shows that female contributors get three fewer comments than males. Column 3 shows that the trust expressed towards females' views is lower by roughly 5.3% relative to the standard deviation of trust. Column 1 of Table 3 shows that disagreement towards female-authored views is higher than that of males by 10% relative to the standard deviation of disagreement.

Furthermore, Internet Appendix Tables 4 and 5 confirm earlier results that article informativeness, reflected in the ex-post abnormal return following article publication, does not

moderate the skewed and less favorable engagement for female contributors. Overall, our results are robust to capturing engagement through direct comments or including indirect comments.

4.4. Exclusion of Tail Contributors

Another potential concern is that the distribution of engagement may differ across genders, which could drive our results. For instance, male authors may have superstars compared to females, driving the average numbers we observe. It may also be that a few female authors attract very negative engagement due to some other reasons unrelated to gender, again distorting the average effects we observe. To rule out the concern that the tails of the engagement distribution drive our results, we exclude contributors with a total number of comments over the full sample in the top and bottom 1% of the distribution and then redo the engagement analysis.

Internet Appendix Tables 6 and 7 summarize the results, once more underlining the lower number of comments, lower trust, lower joy, higher certainty, and higher disagreement towards female-authored relative to male-authored viewpoints. More so, the results are qualitatively similar to those reported earlier in magnitude and statistical significance. Overall, the results are not driven by the tails of the engagement distribution.

4.5. Exclusion of Bearish Views

There is the potential concern that since articles on SA are generally bullish, female authors' bearish articles could drive the less favorable engagement they experience. Although the analysis of section 3.2.2 on author boldness indicates that this is unlikely, we conduct further analysis to alleviate such concern by dropping all articles for which the *Bullishness* measure is bearish from our analysis. Internet Appendix Tables 8 and 9 repeat the engagement analysis using the restricted sample, again indicating much less favorable engagement for female authors than males.

4.6. #MeToo

The #MeToo movement brought public attention to sexual harassment and gender discrimination in the workplace. This movement serves as an exogenous shock to the engagement and interactions that occur on Seeking Alpha. We therefore examine if and how gender-based interactions were impacted by the #MeToo movement. Examining this shock also allows us to examine the more general question of whether higher attention to equality impacts a non-traditional setting, where users likely have little concern about negative repercussions from negative interactions towards female contributors.

To explore how Seeking Alpha users behaved in response to the #MeToo movement, we create an indicator variable for observations taking place during or after October 2017, the month that #MeToo gained popularity, and interact that with our female contributor variable. We present the findings in Internet Appendix Table 10 and 11 and the results show a mixed impact of #MeToo on the Seeking Alpha environment. Looking at engagement, we observe that female contributors experienced lower engagement, with a significantly lower number of comments and larger magnitude. While users have lower engagement with female contributors after the #MeToo movement, we do find that *Trust* and *Joy* are marginally positive. Internet Appendix Table 11 shows that female contributors after the #MeToo movement experienced greater levels of disagreement with their article comments. Overall, these results suggest that female contributors on Seeking Alpha where somewhat adversely impacted by the #MeToo movement.

4.7. Random Genders

We explore the possibility that our findings are not truly about gender but some statistical artifact of the data. To address this concern, we take advantage of any ambiguous names in our sample and reexamine our main findings. Our primary sample explores all contributors with an assigned gender which requires a gender identification accuracy above 75%. For this test, we retain only observations for contributors that contain no assigned gender and therefore were not included in our original sample. We then randomly assign gender to each contributor and maintain a 94% male and a 6% female split (results are consistent if we assign a 50%/50% male to female split). We present these findings in Internet Appendix Table 12 and 13. The results show that for both our engagement and disagreement measures the variable of interest, *Random Female*, is no longer significant. This means that our results are truly about the perceived authors' gender and supports the conclusions made in our prior findings.

5. Conclusion

This study analyzes the nature of engagement male and female non-professional financial information intermediaries experience on the Seeking Alpha (SA) platform and its financial market implications in terms of trading, price efficiency, and information aggregation. We endeavor to rule out skill-, information-based, and other alternative explanations to demonstrate that female and male contributors' observed differences in engagement quality are driven primarily by gender considerations. We establish that both male and female-authored articles on SA are equally informative about stocks' future abnormal returns, indicating that both genders have similar abilities to produce informative signals. Nonetheless, female-authored articles experience less favorable engagement with fewer comments and lower trust from platform users. The unfavorable

treatment goes beyond the level of engagement and trust, as users disagree significantly more with female-authored viewpoints than males'.

Building on theories on the sources and consequences of disagreement in financial markets, we link the higher disagreement towards female-authored viewpoints on SA to the differential interpretation of information due to the gender of the information provider. We then test whether, as theory predicts, higher abnormal trading volume follows such disagreement. We find that, indeed, higher disagreement with authors' perspectives on SA is associated with higher abnormal trading on the focal stock. More so, the higher trading volume does not seem to improve price efficiency, as we also find that a higher level of disagreement with authors just before earnings announcements is associated with lower price efficiency following earnings announcements. Crucially, since female authors experience significantly higher levels of disagreement from the platform users, our results imply that disagreement due to gender-based stereotypes can impact stock trading and impair the incorporation of valuable signals into stock prices. Finally, we document that incorporating female perspectives into the SA consensus makes the consensus more informative about firms' future earnings. Hence, female contributors bring novel and diverse perspectives that are useful for information aggregation, and losing such perspectives means less informative platform consensus.

Overall, female contributors face a less favorable environment on the SA platform. After ruling out non-gender related explanations, our findings suggest that the females' unfavorable treatment is primarily due to their gender rather than other article, user, or stock characteristics. That such gender-based hostility manifests in a widely used public platform such as SA, where a contributor's track record is observable, indicates that females likely face even worse experiences in more opaque environments.

Our results suggest that the unfavorable attitudes towards females in finance, as documented in earlier works, are not restricted to the professional, corporate, or academic domains where biases may be attributed to formal and institutional structures. Instead, gender bias in finance is deep-rooted, manifesting even among the ordinary, young people on investment social media. Therefore, addressing gender bias in finance requires measures that transcend eliminating barriers females face in formal settings. There is a need for sensitization and dialogue at different educational and social levels to address gender stereotypes on financial matters.

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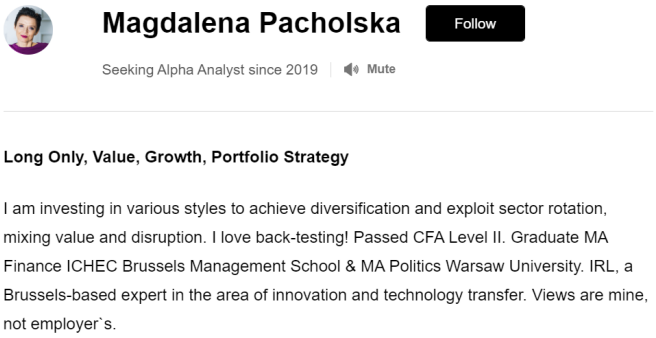
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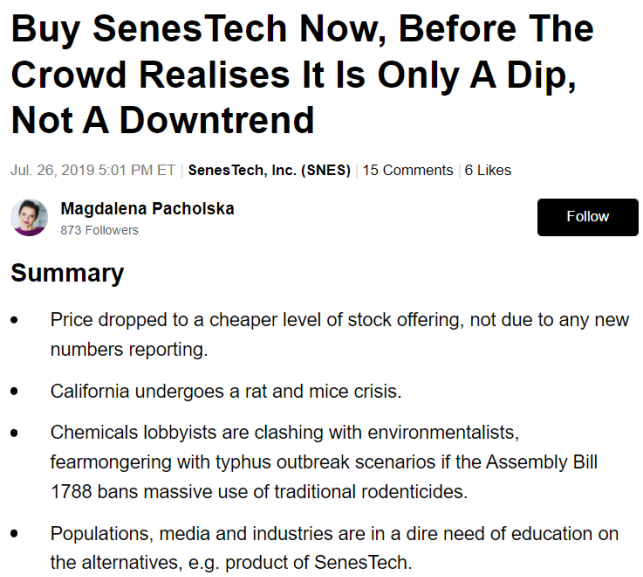
Figure 1: Sample Female Author Bio, Article and Comments Snippets

The figure shows a sample female author's bio page (Panel A), a snippet of an article by the author (Panel B) and a snippet of comments on the article by other platform users (Panel C).

Panel A: Author Bio



Panel B: Article Snippet



Panel C: Comments Snippet

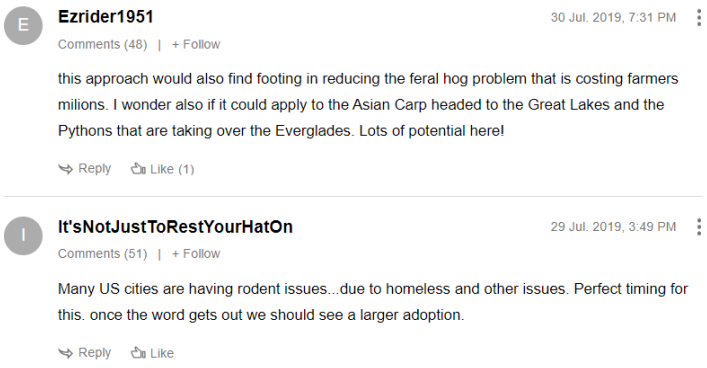
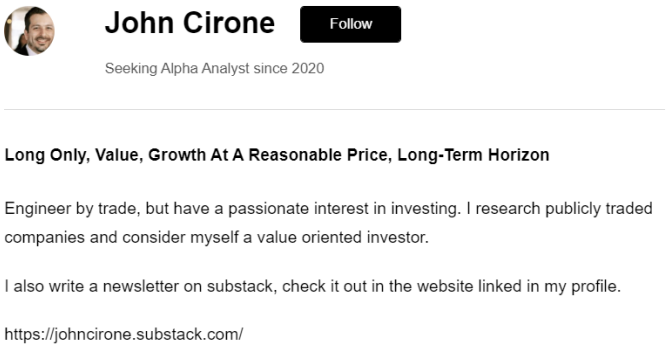


Figure 2: Sample Male Author Bio, Article and Comments Snippets

The figure shows a sample male author's bio page (Panel A), a snippet of an article by the author (Panel B) and a snippet of comments on the article by other platform users (Panel C).

Panel A: Author Bio



Panel B: Article Snippet



Panel C: Comments Snippet

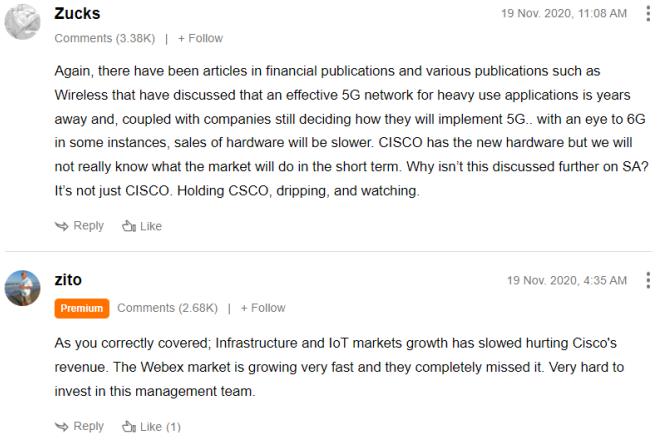


Figure 3: Engagement by Gender Across Characteristics Quintiles

The figures show the nature of engagement received by female- vs. male-authored articles across author age, stock size and post-publication abnormal return quintiles, respectively. In Panel A-C, engagement is measured by the number of comments the article received within one-week of publication. In Panel D-F, engagement is measured by the intensity of platform users' disagreement with the author.

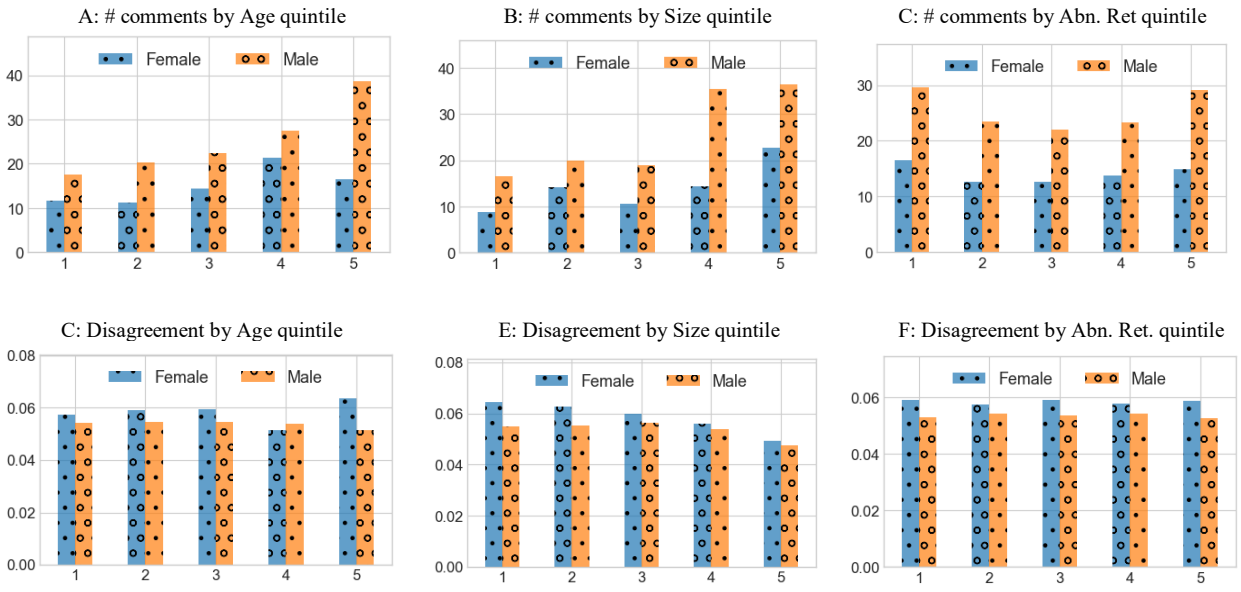


Figure 4: Novelty of Viewpoints by Gender

The figure shows the distribution of the novelty score by contributor gender relative to the *n* most recent articles previously published on the same stock by other contributors. The novelty score for article *i* is computed as one minus the average cosine similarity score of the article with the *n* most recent articles published by other authors on the same stock as article *i*. Appendix Table 1 provides further details on the construction of the novelty score for each article. For each female-authored article about a given stock on day *t*, we randomly select one male-authored article about the same stock published within the past six months of *t* and compute novelty scores. We then plot the distribution of novelty scores of the female-authored and male-authored articles. In Panel A (B), *n* equals two (Five) articles. The bottom and top edges of the boxes indicate the 25th and 75th percentiles, respectively. The solid (dotted) green line indicates the median (mean) of the distribution.

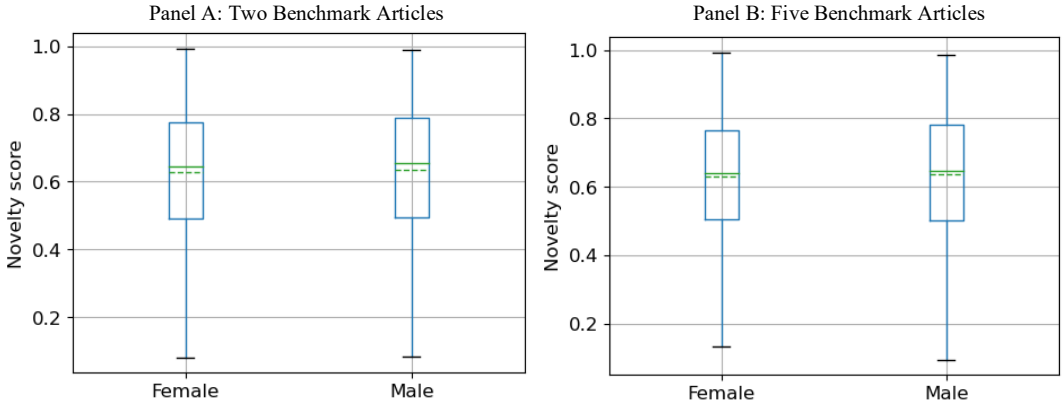


Table 1: Summary Statistics

This table shows summary statistics of our data and main variables by SA author gender. Panel A summarizes variables constructed from the articles. Panel B summarizes the contributor characteristics. Panel C summarizes the variables that capture the quality of engagement the articles received from other platform users. Panel D summarizes the features of the stocks on which the contributions are focused. The last column shows the *t*-statistics for the difference in the mean of the variables for females and males. The construction of the variables is described in Appendix Table 1.

	Male Contributors						Female Contributors						Mean Diff.
	Obs.	Mean	SD	25%	50%	75%	Obs.	Mean	SD	25%	50%	75%	*t*-statistic
Panel A: Article Characteristics													
Number of Words	190,387	604.359	431.014	347.000	512.000	742.000	10,041	519.847	348.397	286.000	452.000	645.000	-2.074
Bullishness	190,387	0.624	0.746	1.000	1.000	1.000	10,041	0.697	0.691	1.000	1.000	1.000	2.244
LM Sentiment	190,387	-0.003	0.023	-0.016	-0.001	0.011	10,041	-0.002	0.023	-0.015	0.000	0.013	0.779
Sentiment	190,387	0.085	0.044	0.058	0.086	0.113	10,041	0.090	0.047	0.059	0.089	0.121	0.932
Article Readability	190,346	11.694	3.300	9.973	11.414	13.033	10,040	11.642	2.627	9.987	11.464	13.094	-0.140
Panel B: Contributor Characteristics													
SA Age in Years	190,387	2.644	2.599	0.584	1.816	3.989	10,041	2.289	2.823	0.373	1.104	3.266	-0.754
Monthly Workload	190,387	13.482	16.883	3.000	7.000	18.000	10,041	11.201	10.939	3.000	8.000	16.000	-0.977
Number of Firms	190,387	120.193	173.337	21.000	63.000	153.000	10,041	82.843	73.609	16.000	61.000	124.000	-1.414
Number of Industries	190,387	55.444	67.263	13.000	32.000	69.000	10,041	41.876	32.616	10.000	41.000	58.000	-1.320
Qualifications	190,387	0.316	0.599	0.000	0.000	1.000	10,041	0.164	0.418	0.000	0.000	0.000	-2.537
Panel C: Engagement by Platform Users													
Number of Comments	190,387	25.324	56.561	2.000	8.000	24.000	10,041	14.035	30.182	1.000	5.000	14.000	-4.972
Ratio of Trust Words	164,561	0.079	0.042	0.058	0.075	0.095	8,166	0.077	0.043	0.053	0.072	0.094	-2.808
Ratio of Uncertainty Words	164,561	0.019	0.017	0.009	0.016	0.024	8,166	0.017	0.018	0.006	0.015	0.023	-3.747
Ratio of Joy Words	164,561	0.047	0.036	0.029	0.042	0.059	8,166	0.045	0.036	0.024	0.039	0.057	-2.715
LM Sentiment Disagreement	164,561	0.028	0.035	0.009	0.019	0.035	8,166	0.031	0.037	0.009	0.020	0.038	1.986
Sentiment Disagreement	164,561	0.054	0.053	0.019	0.041	0.072	8,166	0.058	0.056	0.021	0.045	0.080	1.455
Panel D: Stock Characteristics													
Abn Ret[1, 5]	187,175	-0.001	0.076	-0.022	-0.000	0.020	9,898	-0.000	0.057	-0.020	-0.000	0.020	0.487
Abn Ret[1, 21]	186,950	-0.002	0.134	-0.050	-0.002	0.041	9,892	0.001	0.119	-0.045	-0.002	0.041	1.677
Abn Ret[1, 63]	186,864	-0.003	0.244	-0.095	-0.006	0.075	9,889	-0.002	0.213	-0.094	-0.008	0.074	0.235
1 Month Prior Ret	188,919	0.014	0.248	-0.055	0.008	0.066	9,998	0.011	0.186	-0.050	0.008	0.065	-1.057
Price	188,987	282.893	5739.582	16.900	39.520	87.300	10,004	291.560	5436.168	19.475	41.900	87.038	0.107
Market Cap. (ml)	188,987	69,893	145,464	2,134	13,160	74,834	10,004	61,221	114,853	2,195	13,636	70,200	-0.919

Table 2: Informativeness of Viewpoints by Gender

This table examines whether the informativeness of viewpoints published on Seeking Alpha is different for male vs female contributors. For each publication about a stock on day *t,* we compute the stock's 4-factor abnormal return over horizons *h* ranging from 5 to 63 trading days (as indicated in the column headers) starting from $t + 1$. We then regress the panel of stocks' abnormal returns in percent for a given horizon on an indicator variable for whether the contributor is female interacted with a measure that summarizes the contributor's bullishness about the stock as revealed in the publication. Bullishness is measured in three different ways. First, we use *Bullishness,* which equals 1 for bullish views, -1 for bearish views and 0 for neutral views. Second, we use *LM Sentiment,* which quantifies bullishness as the fraction of positive words minus the fraction of negative Words in the publication using the LM dictionary. Alternatively, we quantify bullishness as *Sentiment* measured based on the NRC Emotion Lexicon. Both *LM Sentiment and* Sentiment are normalized to unit variance. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter fixed effects.

	h=5	h=21	h=63	h=5	h=21	h=63	h=5	h=21	h=63
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Female x Bullishness	-0.151	-0.440**	-0.311						
	(0.117)	(0.222)	(0.425)						
Bullishness	0.209***	0.195***	0.153						
	(0.042)	(0.072)	(0.199)						
Female x LM Sentiment				-0.004	-0.136	-0.127			
				(0.068)	(0.144)	(0.315)			
LM Sentiment				0.132***	0.186***	0.393***			
				(0.029)	(0.064)	(0.122)			
Female x Sentiment							0.047	-0.078	-0.217
							(0.072)	(0.159)	(0.327)
Sentiment							0.091***	0.145**	0.254*
							(0.024)	(0.066)	(0.143)
Female	0.098	0.572**	0.340	-0.001	0.255*	0.103	-0.100	0.420	0.549
	(0.128)	(0.248)	(0.516)	(0.067)	(0.151)	(0.381)	(0.164)	(0.358)	(0.801)
1 Month Prior Ret	-1.984***	-1.624**	-1.892	-2.016***	-1.675**	-2.017	-1.990***	-1.643**	-1.935
	(0.517)	(0.727)	(1.456)	(0.513)	(0.718)	(1.445)	(0.519)	(0.728)	(1.448)
1 Year Prior Vol	-14.204**	-14.585	-1.698	-14.944**	-14.966	-1.054	-15.269**	-15.366	-1.998
	(7.164)	(17.362)	(36.221)	(7.266)	(17.365)	(36.565)	(7.258)	(17.405)	(36.549)
Ln(Price)	0.041	0.081	0.390	0.027	0.069	0.379	0.030	0.073	0.387
	(0.044)	(0.142)	(0.361)	(0.043)	(0.140)	(0.360)	(0.043)	(0.140)	(0.359)
Ln(Market Value)	-0.044**	-0.021	0.038	-0.042**	-0.020	0.036	-0.041**	-0.019	0.039
	(0.018)	(0.065)	(0.134)	(0.018)	(0.066)	(0.136)	(0.018)	(0.066)	(0.136)
Constant	0.774*	0.126	-2.326	0.954**	0.310	-2.107	0.741	-0.018	-2.710
	(0.462)	(1.155)	(2.361)	(0.477)	(1.168)	(2.362)	(0.470)	(1.118)	(2.314)
Year/Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared Adj.	0.008	0.009	0.012	0.007	0.009	0.012	0.007	0.009	0.012
Obs.	197,070	196,840	196,751	197,070	196,840	196,751	197,070	196,840	196,751

Table 3: Engagement by Gender

This table examines how Seeking Alpha users engage with male- vs female-authored articles. We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Trust, Joy, Uncertainty. We regress these measures on a dummy variable, *Female,* while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	-9.710***	-2.710***	-0.237***	-0.181***	-0.221***	-0.199***	-0.129***	-0.087***
	(3.122)	(0.700)	(0.060)	(0.052)	(0.053)	(0.047)	(0.021)	(0.024)
SA Age in Years	1.848***	0.721***	-0.018***	-0.022***	-0.021***	-0.018***	-0.002	-0.006***
	(0.492)	(0.093)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
Monthly Workload	-0.039	-0.055***	-0.005***	-0.005***	-0.003***	-0.003***	-0.001***	-0.001
	(0.040)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	-0.470	0.705	-0.084***	-0.052**	-0.119***	-0.035	0.028**	-0.001
	(0.866)	(0.753)	(0.031)	(0.026)	(0.033)	(0.029)	(0.013)	(0.014)
Number of Industries	-7.307**	-3.562	0.412***	0.297***	0.480***	0.206***	-0.062*	0.036
	(3.073)	(2.272)	(0.091)	(0.073)	(0.092)	(0.078)	(0.036)	(0.035)
Qualifications	-0.911	0.236	0.035	0.017	-0.032*	-0.012	0.021***	0.019***
	(0.914)	(0.316)	(0.021)	(0.017)	(0.017)	(0.018)	(0.006)	(0.007)
Article Readability	-0.614***	-0.400***	0.016***	0.008**	0.008**	0.002	0.001	0.001
	(0.150)	(0.124)	(0.005)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
1 Month Prior Ret	-2.880	-2.089*	-0.001	-0.002	0.158***	0.057	-0.049**	-0.019
	(1.925)	(1.247)	(0.043)	(0.041)	(0.044)	(0.036)	(0.020)	(0.020)
1 Year Prior Vol	606.368**	-171.690***	-7.207***	3.420	-6.216***	0.157	0.521	3.002*
	(274.901)	(56.638)	(2.226)	(3.833)	(1.973)	(2.697)	(0.562)	(1.640)
Ln(Price)	1.909	-2.066	-0.149***	-0.130	-0.126***	-0.024	-0.011	0.043
	(5.437)	(3.159)	(0.049)	(0.117)	(0.040)	(0.107)	(0.009)	(0.060)
Ln(Market Value)	4.743***	3.267	0.004	0.077	0.028*	0.005	-0.020***	-0.075
	(0.830)	(2.556)	(0.031)	(0.117)	(0.017)	(0.113)	(0.005)	(0.074)
Constant	-65.988***	-11.581	8.374***	6.963***	4.762***	4.718***	2.224***	2.835***
	(22.621)	(30.786)	(0.399)	(1.609)	(0.219)	(1.536)	(0.083)	(1.037)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.113	0.505	0.004	0.115	0.005	0.106	0.003	0.097
Obs.	197,578	197,578	165,740	165,740	165,740	165,740	165,740	165,740
Avg Dependent var.	24.933	24.933	7.895	7.895	4.710	4.710	1.850	1.850
SD Dependent var.	55.812	55.812	4.106	4.106	3.511	3.511	1.710	1.710

Table 4: Disagreement by Gender

This table examines whether users disagree more or less with an article's viewpoint when the contributor is male vs. female. Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed based on the NRC Emotion Lexicon or the LM dictionary. Standard errors are clustered by firm and year-quarter, and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement		LM Sentiment Disagreement		LM Polarity Disagreement	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	0.539***	0.250**	2.262***	1.336**	0.282***	0.101**	2.197***	1.539***
	(0.124)	(0.114)	(0.494)	(0.526)	(0.064)	(0.043)	(0.525)	(0.546)
SA Age in Years	-0.051***	-0.022***	0.001	0.066*	-0.041***	-0.019***	0.009	0.083**
	(0.010)	(0.009)	(0.043)	(0.039)	(0.006)	(0.004)	(0.039)	(0.040)
Monthly Workload	0.010***	0.006***	0.040***	0.032***	0.004***	0.003**	0.069***	0.056***
	(0.002)	(0.001)	(0.008)	(0.008)	(0.001)	(0.001)	(0.012)	(0.011)
Number of Firms	0.048	0.086	-0.514*	-0.561*	0.010	0.052*	-0.451*	-0.380
	(0.067)	(0.057)	(0.285)	(0.292)	(0.042)	(0.030)	(0.266)	(0.257)
Number of Industries	0.389**	0.004	2.208***	1.635**	0.243**	-0.040	1.203	0.485
	(0.179)	(0.151)	(0.754)	(0.777)	(0.115)	(0.081)	(0.747)	(0.661)
Qualifications	0.016	0.026	-0.185	-0.044	0.041**	0.019	0.357**	0.213
	(0.033)	(0.031)	(0.132)	(0.121)	(0.020)	(0.016)	(0.167)	(0.167)
Article Readability	0.056***	0.044***	0.249***	0.226***	0.022***	0.013***	0.123***	0.098**
	(0.014)	(0.011)	(0.058)	(0.054)	(0.006)	(0.004)	(0.044)	(0.043)
1 Month Prior Ret	0.175***	0.165***	1.457***	1.115***	0.042	-0.006	0.071	-0.082
	(0.062)	(0.061)	(0.396)	(0.319)	(0.039)	(0.036)	(0.244)	(0.250)
1 Year Prior Vol	-13.837***	-6.741	-14.166	-47.281*	-11.203***	-0.816	-38.878***	7.946
	(3.067)	(5.404)	(8.749)	(26.396)	(2.197)	(2.565)	(9.655)	(24.427)
Ln(Price)	0.185***	-0.115	0.193	0.399	0.111**	-0.081	0.472***	-0.602
	(0.061)	(0.154)	(0.178)	(0.522)	(0.044)	(0.102)	(0.153)	(0.568)
Ln(Market Value)	-0.227***	0.111	-0.017	-0.629	-0.170***	0.162	-0.570***	1.478**
	(0.033)	(0.180)	(0.090)	(0.595)	(0.020)	(0.104)	(0.075)	(0.734)
Constant	7.803***	3.441	21.163***	31.808***	5.062***	0.222	36.627***	6.413
	(0.572)	(2.590)	(1.592)	(9.052)	(0.335)	(1.482)	(1.414)	(10.824)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.019	0.120	0.010	0.089	0.018	0.132	0.016	0.061
Obs.	165,740	165,740	165,740	165,740	165,740	165,740	165,740	165,740
Avg Dependent var.	5.317	5.317	25.252	25.252	2.749	2.749	30.663	30.663
SD Dependent var.	5.182	5.182	18.482	18.482	3.360	3.360	22.990	22.990

Table 5: Engagement by Gender Conditional on Opinion Informativeness and Past Author Performance

This table examines the nature of engagement received by male vs female-authored articles depends on (i) the underlying informativeness of the viewpoint expressed in the article and (ii) the author's past performance reflected in the historical average abnormal return following the author's prior publications. The specification is identical to that of Table 3 except that we now interact the *Female* dummy variable with a measure of the current article's informativeness measured as $Abn\ Ret[1,5]$, i.e., the signed 4-factor abnormal return computed over the five trading days starting $t+1$ following article publication on day *t*. We also interact *Female* with the author's past performance, i.e., the average of signed 4-factor one-day abnormal returns following all articles published by the author prior to day *t*, denoted *Ave Abn Ret*. Each abnormal return is multiplied by 1 (-1) for an article whose *Bullishness* measure is bullish (bearish) to capture the return that would result from taking a long (short) position based on the author's viewpoint. Hence, the abnormal returns capture the extent to which the contributor's current or prior viewpoints turned out to be correct. When computing these abnormal returns, we drop articles whose *Bullishness* equals zero, i.e., neutral articles, as those have no clear investment signal. The outcome variables that measure engagement denoted in the column headers are described in Table 3. In all specifications, we cluster standard errors by firm and year-quarter, and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female x Abn Ret[1, 5]	-9.429	1.184	0.730	0.213	0.669	-0.231	-0.024	-0.076
	(10.227)	(4.275)	(0.615)	(1.016)	(0.743)	(0.863)	(0.346)	(0.385)
Female x Ave. Abn Ret	1.564	-38.527	0.523	-3.534	5.931	4.873	-2.116	-1.605
	(48.687)	(47.497)	(4.397)	(5.206)	(4.317)	(5.216)	(1.559)	(1.798)
Female	-9.262***	-2.539***	-0.231***	-0.174***	-0.206***	-0.188***	-0.122***	-0.082***
	(2.998)	(0.718)	(0.063)	(0.053)	(0.057)	(0.047)	(0.021)	(0.025)
Abn Ret[1, 5]	4.166	1.093	0.153	0.265**	0.325***	0.162	0.022	0.148*
	(6.477)	(2.230)	(0.122)	(0.122)	(0.116)	(0.104)	(0.059)	(0.082)
Ave. Abn Ret	22.027	-3.193	-0.071	1.009	0.873	1.279**	0.526	0.719
	(23.074)	(10.566)	(1.115)	(0.837)	(0.746)	(0.560)	(0.501)	(0.460)
SA Age in Years	1.826***	0.799***	-0.021***	-0.024***	-0.024***	-0.021***	-0.003	-0.007***
	(0.462)	(0.105)	(0.006)	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)
Monthly Workload	-0.043	-0.056***	-0.005***	-0.005***	-0.003***	-0.003***	-0.001***	-0.001
	(0.036)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	0.087	0.864	-0.089***	-0.051*	-0.132***	-0.044	0.028**	-0.001
	(0.833)	(0.699)	(0.032)	(0.027)	(0.033)	(0.030)	(0.014)	(0.015)
Number of Industries	-8.362**	-3.852*	0.432***	0.295***	0.536***	0.235***	-0.061*	0.037
	(3.337)	(2.127)	(0.093)	(0.073)	(0.095)	(0.081)	(0.037)	(0.037)
Qualifications	-0.881	0.171	0.044**	0.027	-0.021	-0.003	0.020***	0.019***
	(0.877)	(0.323)	(0.022)	(0.018)	(0.017)	(0.018)	(0.006)	(0.007)
Article Readability	-0.594***	-0.362***	0.016***	0.007**	0.008**	0.002	0.001	0.000
	(0.150)	(0.116)	(0.005)	(0.003)	(0.004)	(0.004)	(0.001)	(0.001)
1 Month Prior Ret	-3.132	-2.306*	-0.001	0.016	0.162***	0.070*	-0.046**	-0.003
	(2.080)	(1.340)	(0.045)	(0.042)	(0.045)	(0.036)	(0.020)	(0.022)

1 Year Prior Vol	633.105**	-154.554***	-6.845***	2.554	-5.682***	-0.462	0.529	2.875*
	(282.529)	(52.571)	(2.393)	(4.674)	(2.076)	(3.252)	(0.596)	(1.650)
Ln(Price)	2.218	-1.846	-0.149***	-0.137	-0.126***	-0.011	-0.010	0.054
	(5.372)	(3.413)	(0.051)	(0.118)	(0.041)	(0.107)	(0.009)	(0.060)
Ln(Market Value)	4.629***	2.927	0.003	0.099	0.030*	0.010	-0.020***	-0.081
	(0.826)	(2.439)	(0.032)	(0.121)	(0.017)	(0.115)	(0.005)	(0.076)
Constant	-65.907***	-8.064	8.373***	6.658***	4.706***	4.598***	2.216***	2.910***
	(22.554)	(28.384)	(0.410)	(1.686)	(0.224)	(1.595)	(0.083)	(1.078)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.118	0.509	0.004	0.113	0.006	0.105	0.003	0.096
Obs.	184,537	184,537	154,054	154,054	154,054	154,054	154,054	154,054
Avg Dependent var.	24.823	24.823	7.898	7.898	4.701	4.701	1.851	1.851
SD Dependent var.	55.826	55.826	4.098	4.098	3.507	3.507	1.711	1.711

Table 6: Engagement by Gender Conditional on Academic/Professional Qualifications

This table examines whether the nature of engagement received by male vs female-authored articles depends on an author's number of prior publications or whether they specify possessing a graduate-level academic degree, a CFA qualification or a financial analyst experience in their Seeking Alpha bio. The specification is identical to that of Table 3 except that we now interact the *Female* dummy variable with the number of academic or professional qualifications an author declared in their bio. We also separately interact *Female* with the number of publications the author has made on SA before day *t*. The outcome variables that measure engagement denoted in the column headers are as described under Table 3. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female x Publications	-0.543	0.192	-0.007	-0.008	-0.008	-0.018	-0.011	0.007
	(0.654)	(0.285)	(0.024)	(0.020)	(0.021)	(0.015)	(0.008)	(0.007)
Female x Qualifications	0.042	-0.424	0.122	0.080	0.139	0.123	-0.002	0.041
	(1.304)	(1.055)	(0.125)	(0.154)	(0.116)	(0.131)	(0.050)	(0.049)
Female	-8.588***	-2.942***	-0.246***	-0.180***	-0.228***	-0.187***	-0.110***	-0.106***
	(2.340)	(0.715)	(0.052)	(0.061)	(0.047)	(0.053)	(0.027)	(0.025)
Publications	0.924**	0.098	-0.008	-0.007	0.002	-0.004	-0.002	-0.001
	(0.407)	(0.089)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)	(0.001)
Qualifications	-0.505	0.290	0.028	0.012	-0.034**	-0.017	0.020***	0.018**
	(0.749)	(0.325)	(0.022)	(0.017)	(0.017)	(0.018)	(0.006)	(0.007)
SA Age in Years	1.317***	0.661***	-0.013**	-0.019***	-0.022***	-0.016***	-0.001	-0.005***
	(0.300)	(0.107)	(0.006)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
Monthly Workload	-0.075**	-0.059***	-0.005***	-0.005***	-0.003***	-0.003**	-0.001***	-0.000
	(0.036)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	-1.864	0.548	-0.071**	-0.040	-0.122***	-0.029	0.031**	0.001
	(1.241)	(0.834)	(0.032)	(0.029)	(0.034)	(0.031)	(0.014)	(0.014)
Number of Industries	-6.976**	-3.521	0.407***	0.293***	0.481***	0.204***	-0.064*	0.035
	(3.006)	(2.298)	(0.090)	(0.073)	(0.091)	(0.078)	(0.036)	(0.035)
Article Readability	-0.579***	-0.396***	0.015***	0.007**	0.008**	0.002	0.001	0.001
	(0.138)	(0.124)	(0.005)	(0.003)	(0.004)	(0.004)	(0.001)	(0.002)
1 Month Prior Ret	-2.753	-2.090*	-0.002	-0.002	0.159***	0.057	-0.050**	-0.019
	(1.920)	(1.243)	(0.043)	(0.041)	(0.044)	(0.036)	(0.020)	(0.020)
1 Year Prior Vol	602.165**	-171.605***	-7.172***	3.423	-6.237***	0.157	0.533	3.001*

	(271.911)	(56.570)	(2.216)	(3.828)	(1.969)	(2.694)	(0.562)	(1.641)
Ln(Price)	2.035	-2.045	-0.151***	-0.132	-0.126***	-0.025	-0.011	0.042
	(5.463)	(3.167)	(0.049)	(0.117)	(0.040)	(0.107)	(0.009)	(0.060)
Ln(Market Value)	4.681***	3.244	0.004	0.078	0.028*	0.006	-0.020***	-0.074
	(0.812)	(2.555)	(0.031)	(0.117)	(0.017)	(0.112)	(0.005)	(0.074)
Constant	-65.005***	-11.244	8.362***	6.944***	4.765***	4.707***	2.221***	2.833***
	(21.976)	(30.735)	(0.396)	(1.607)	(0.217)	(1.535)	(0.083)	(1.036)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.115	0.505	0.004	0.115	0.005	0.106	0.003	0.097
Obs.	197,578	197,578	165,740	165,740	165,740	165,740	165,740	165,740
Avg Dependent var.	24.933	24.933	7.895	7.895	4.710	4.710	1.850	1.850
SD Dependent var.	55.812	55.812	4.106	4.106	3.511	3.511	1.710	1.710

Table 7: Disagreement by Gender Conditional on Opinion Informativeness

This table examines whether users' disagreement with an article's viewpoint depends on (i) the underlying informativeness of the viewpoint expressed in the article and (ii) the author's past performance reflected in the historical average abnormal return following the author's prior publications. The specification is identical to that of Table 4 except that we now interact the *Female* dummy variable with a measure of the current article's informativeness measured as $Abn\ Ret[1,5]$, i.e., the signed 4-factor abnormal return computed over the five trading days starting $t+1$ following article publication on day *t*. We also interact *Female* with the author's past performance, i.e., the average of signed 4-factor one-day abnormal returns following all articles published by the author prior to day *t*, denoted *Ave Abn Ret*. Each abnormal return is multiplied by 1 (-1) for an article whose *Bullishness* measure is bullish (bearish) to capture the return that would result from taking a long (short) position based on the author's viewpoint. Hence, the abnormal returns capture the extent to which the contributor's current or pior viewpoints turned out to be true. When computing these abnormal returns, we drop articles whose *Bullishness* equals zero, i.e., neutral articles, as those have no clear investment signal. The outcome variables that measure engagement denoted in the column headers are described in Table 4. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
	[1]	[2]	[3]	[4]
Female x Abn Ret[1, 5]	-1.035	-1.055	-3.232	-2.607
	(1.107)	(1.098)	(3.855)	(4.146)
Female x Ave. Abn Ret	11.830	3.049	43.036	32.998
	(7.396)	(6.558)	(33.767)	(29.314)
Female	0.468***	0.211*	1.941***	1.134**
	(0.119)	(0.113)	(0.499)	(0.538)
Abn Ret[1, 5]	0.009	-0.005	-0.575	-1.266
	(0.190)	(0.222)	(0.619)	(0.789)
Ave. Abn Ret	-0.309	1.243	0.498	0.298
	(1.242)	(1.249)	(4.846)	(5.210)
SA Age in Years	-0.053***	-0.027***	-0.005	0.059
	(0.011)	(0.009)	(0.044)	(0.043)
Monthly Workload	0.010***	0.007***	0.042***	0.036***
	(0.002)	(0.002)	(0.008)	(0.008)
Number of Firms	0.017	0.062	-0.681**	-0.733**
	(0.069)	(0.060)	(0.298)	(0.312)
Number of Industries	0.473**	0.057	2.656***	2.040**
	(0.185)	(0.159)	(0.787)	(0.816)
Qualifications	0.025	0.024	-0.139	-0.083
	(0.033)	(0.032)	(0.136)	(0.126)
Article Readability	0.057***	0.044***	0.258***	0.233***
	(0.014)	(0.012)	(0.062)	(0.057)
1 Month Prior Ret	0.174***	0.153**	1.426***	0.985***
	(0.062)	(0.063)	(0.414)	(0.300)
1 Year Prior Vol	-14.690***	-9.995*	-21.133**	-51.682*
	(3.218)	(5.681)	(9.111)	(28.276)
Ln(Price)	0.168***	-0.131	0.156	0.263
	(0.061)	(0.154)	(0.180)	(0.544)
Ln(Market Value)	-0.223***	0.125	-0.025	-0.632

	(0.033)	(0.179)	(0.091)	(0.596)
Constant	7.805***	3.359	21.513***	32.429***
	(0.587)	(2.578)	(1.644)	(8.960)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.019	0.118	0.010	0.089
Obs.	154,054	154,054	154,054	154,054
Avg Dependent var.	5.319	5.319	25.331	25.331
SD Dependent var.	5.176	5.176	18.534	18.534

Table 8: Disagreement by Gender Conditional on Academic/Professional Qualifications

This table examines whether user disagreement with an article's viewpoint depends on how many articles an author has published on SA or whether an author specifies possessing a graduate-level academic degree, a CFA qualification or financial analyst experience in their Seeking Alpha bio. The specification is identical to that of Table 4 except that we now interact the *Female* dummy variable with the number of academic or professional qualifications an author declared in their bio. We also interact *Female* with the number of articles an author has published on SA before day *t*. The outcome variables that measure disagreement denoted in the column headers are described in Table 4. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
	[1]	[2]	[3]	[4]
Female x Publications	-0.002	-0.060	0.015	-0.250
	(0.067)	(0.049)	(0.278)	(0.228)
Female x Qualifications	-0.272	-0.041	-1.355*	-0.506
	(0.181)	(0.200)	(0.777)	(0.841)
Female	0.576***	0.361**	2.431***	1.849***
	(0.149)	(0.141)	(0.630)	(0.650)
Publications	-0.045***	-0.021***	-0.084**	-0.058
	(0.008)	(0.008)	(0.034)	(0.037)
Qualifications	-0.000	0.016	-0.198	-0.063
	(0.033)	(0.032)	(0.134)	(0.126)
SA Age in Years	-0.026***	-0.009	0.049	0.104***
	(0.009)	(0.008)	(0.046)	(0.037)
Monthly Workload	0.013***	0.008***	0.045***	0.035***
	(0.002)	(0.001)	(0.008)	(0.008)
Number of Firms	0.116*	0.121**	-0.389	-0.464
	(0.069)	(0.060)	(0.304)	(0.321)
Number of Industries	0.371**	-0.006	2.179***	1.609**
	(0.176)	(0.151)	(0.754)	(0.785)
Article Readability	0.054***	0.043***	0.245***	0.223***
	(0.013)	(0.011)	(0.057)	(0.053)
1 Month Prior Ret	0.168***	0.165***	1.444***	1.114***
	(0.062)	(0.061)	(0.395)	(0.319)
1 Year Prior Vol	-13.586***	-6.717	-13.639	-47.188*
	(2.981)	(5.417)	(8.647)	(26.443)
Ln(Price)	0.179***	-0.118	0.184	0.391
	(0.060)	(0.154)	(0.177)	(0.521)
Ln(Market Value)	-0.224***	0.115	-0.012	-0.619
	(0.032)	(0.180)	(0.089)	(0.593)
Constant	7.745***	3.376	21.055***	31.615***
	(0.550)	(2.587)	(1.569)	(9.049)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.019	0.120	0.010	0.089
Obs.	165,740	165,740	165,740	165,740
Avg Dependent var.	5.317	5.317	25.252	25.252
SD Dependent var.	5.182	5.182	18.482	18.482

Table 9: Disagreement by Gender Conditional on Opinion Boldness

This table examines whether differences in boldness expressed in articles drive the differences in disagreement expressed towards female vs male-authored articles. In the first two columns, we regress the article *Boldness* on the *Female* dummy variable. In the remaining columns, we regress the article engagement measures used previously on *Female* and its interaction with the article *Boldness*. *Boldness* is measured as the absolute difference between how bullish an author is and the consensus bullishness of other articles published over the prior 90 days ending the day before an article's publication date. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Boldness		Sentiment Disagreement		Polarity Disagreement	
	[1]	[2]	[3]	[4]	[5]	[6]
Female x Boldness			0.410*	0.524**	1.877**	2.515***
			(0.217)	(0.215)	(0.764)	(0.842)
Female	-0.011	-0.017**	0.345**	0.001	1.387**	0.169
	(0.008)	(0.007)	(0.159)	(0.139)	(0.601)	(0.610)
Boldness			0.016	-0.099**	-0.809***	-0.942***
			(0.041)	(0.043)	(0.208)	(0.193)
SA Age in Years	-0.005***	-0.002*	-0.048***	-0.021**	0.004	0.069*
	(0.001)	(0.001)	(0.011)	(0.009)	(0.044)	(0.040)
Monthly Workload	-0.001***	-0.001***	0.010***	0.007***	0.040***	0.032***
	(0.000)	(0.000)	(0.002)	(0.002)	(0.008)	(0.008)
Number of Firms	-0.044***	-0.029***	0.028	0.072	-0.625**	-0.678**
	(0.005)	(0.006)	(0.066)	(0.056)	(0.293)	(0.291)
Number of Industries	0.153***	0.093***	0.433**	0.035	2.507***	1.931**
	(0.014)	(0.014)	(0.181)	(0.156)	(0.791)	(0.794)
Qualifications	0.003	0.003	0.032	0.037	-0.140	-0.010
	(0.003)	(0.003)	(0.035)	(0.033)	(0.140)	(0.124)
Article Readability	-0.001**	-0.001**	0.059***	0.045***	0.263***	0.230***
	(0.000)	(0.000)	(0.013)	(0.011)	(0.056)	(0.054)
1 Month Prior Ret	-0.003	0.003	0.192***	0.191***	1.486***	1.229***
	(0.005)	(0.006)	(0.073)	(0.068)	(0.466)	(0.350)
1 Year Prior Vol	0.755***	-0.427	-14.913***	-9.212*	-16.849*	-52.683*
	(0.227)	(0.337)	(3.336)	(5.430)	(9.546)	(29.180)
Ln(Price)	0.014***	0.014	0.176***	-0.157	0.176	0.262
	(0.004)	(0.011)	(0.062)	(0.161)	(0.184)	(0.554)
Ln(Market Value)	-0.007***	0.004	-0.226***	0.172	-0.032	-0.322
	(0.002)	(0.012)	(0.035)	(0.180)	(0.095)	(0.541)
Constant	0.542***	0.387**	7.755***	2.620	21.701***	27.796***
	(0.031)	(0.190)	(0.613)	(2.587)	(1.658)	(8.248)
Year-Quarter FE	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.022	0.152	0.019	0.114	0.010	0.088
Obs.	187,405	187,405	155,233	155,233	155,233	155,233
Avg Dependent var.	0.488	0.488	5.270	5.270	25.253	25.253
SD Dependent var.	0.404	0.404	5.113	5.113	18.409	18.409

Table 10: Gender-based Disagreement and Abnormal Trading Volume

This table examines how investors' disagreement with authors' viewpoints on SA relates to stocks' abnormal trading volume, denoted $Abn.Volume$. We regress stock k's abnormal trading volume on the disagreement expressed towards an SA article about that stock interacted with *Female*, an indicator variable that equals one if the article's author is female. In columns 1 and 2, abnormal trading volume is measured as of $t+1$ for an article published on day t. In columns 3 and 4, abnormal trading volume is averaged over $t+1$ to $t+3$ following article publication on day t. For each article published on t, we use comments posted on the day of the article publication and the next day to compute the disagreement measure. We multiply the abnormal volume by 100 and standardize the disagreement measure and other continuous right-hand-side variables to unit variance. Media Sentiment measures the traditional news media sentiment on day t and Ln((# News) is the log of the number of news media articles published about the focal stock on day t. Other control variables included in the regressions are the recent past abnormal returns ($Abn\ Ret[-5,-1]$ and $Abn\ Ret[-25,-6]$), recent past volatility ($Volatility[-5,-1]$ and $Volatility[-25,-6]$), the SA article's sentiment, the SA article's number of comments, an indicator variable for whether no comment was posted on the article, the log of stock price and the log of stock market capitalization. All the regressions also include stock and day fixed effects, and we cluster standard errors by stock and year-quarter.

	$Abn.Volume[t+1] \times 100$		$Abn.Volume[t+1,t+3] \times 100$	
	[1]	[2]	[3]	[4]
Sentiment Disagreement	0.443**		0.363**	
	(0.200)		(0.142)	
Sentiment Disagreement x Female	0.511		0.003	
	(0.639)		(0.573)	
Polarity Disagreement		0.847***		0.698***
		(0.166)		(0.158)
Polarity Disagreement x Female		-0.030		0.067
		(0.581)		(0.533)
Female	-2.516**	-2.049*	-1.512	-1.596
	(1.023)	(1.060)	(0.935)	(1.011)
Media Sentiment	-0.743**	-0.742**	-0.514**	-0.514**
	(0.298)	(0.297)	(0.256)	(0.255)
Ln(# News)	18.363***	18.364***	13.397***	13.400***
	(0.662)	(0.662)	(0.534)	(0.534)
Other Controls	Yes	Yes	Yes	Yes
R-squared Adj.	0.333	0.333	0.349	0.350
Obs.	197,252	197,252	197,193	197,193

Table 11: Gender-based Disagreement and Price Efficiency around earnings announcement.

This table examines how investors' disagreement with authors' viewpoints on SA relates to stocks' price efficiency measured as the Intraperiod Price Efficiency (IPE) around quarterly earnings announcements. We regress stock k's IPE computed over a window (denoted in the column headers) relative to earnings announcement on day t on the average disagreement expressed towards SA articles published about that stock over the prior five days ending $t-1$ before earnings announcement on t. We then interact the average disagreement with *Female Count*, which captures the number of female-authored SA articles included in the average disagreement measure. In columns 1 and 2, IPE is computed over window $t-1$ to $t+3$ relative to earnings announcement on day t, while in columns 3 and 4, it is computed over windows t to $t+5$. For each article published on SA over the prior five days ending $t-1$, we use comments posted on the day of the article publication and the next day to compute the disagreement measure. We standardize the IPE, the disagreement measures, and other continuous right-hand-side variables to unit variance. Media Sentiment measures the traditional news media sentiment on day t and Ln((# News) is the log of the number of news media articles published about the focal stock on day t. Other control variables included in the regressions are the recent past abnormal returns ($Abn\ Ret[-5,-1]$ and $Abn\ Ret[-25,-6]$), recent past volatility ($Volatility[-5,-1]$ and $Volatility[-25,-6]$), the average SA articles' sentiment, the SA articles' number of comments, an indicator variable for whether no comment was posted on the articles, the log of stock price and the log of stock market capitalization. All the regressions also include stock and day fixed effects, and we cluster standard errors by stock and year-quarter.

	IPE[-1, 3]		IPE[0, 5]	
	[1]	[2]	[3]	[4]
Sentiment Disagreement	-0.034**		-0.054***	
	(0.015)		(0.016)	
Sentiment Disagreement x Female Count	-0.041		0.085	
	(0.073)		(0.063)	
Polarity Disagreement		-0.027*		-0.028*
		(0.015)		(0.016)
Polarity Disagreement x Female Count		-0.052		0.008
		(0.059)		(0.075)
Female Count	-0.004	0.019	-0.067	0.007
	(0.086)	(0.086)	(0.067)	(0.085)
Media Sentiment	0.008	0.008	-0.021	-0.022
	(0.019)	(0.019)	(0.023)	(0.023)
Ln(# News)	0.008	0.008	0.208***	0.205***
	(0.047)	(0.047)	(0.063)	(0.063)
Other Controls	Yes	Yes	Yes	Yes
R-squared Adj.	0.163	0.162	0.213	0.212
Obs.	8,615	8,615	8,056	8,056

Table 12: Fundamental Relevance of Gender-Diverse Viewpoints

This table examines the informativeness of the Seeking Alpha (SA) consensus view about future firm earnings (denoted *Earnings* or *SUE* in table headers) conditional on the number of female-authored viewpoints (denoted *Female Count*) included in the consensus aggregation. As the Table headers indicate, the *SA Consensus* is calculated as the LM Sentiment (or Sentiment) averaged over the past 30 and 60 days, respectively, ending two days before the earnings announcement day. We require at least two articles to calculate the *SA Consensus;* the latter is standardized to unit variance. SUE is earnings surprise measured as the standardized unexpected earnings. In all specifications, we cluster standard errors by firm and year-quarter and include firm and year-quarter fixed effects.

	LM Sentiment Consensus				Sentiment Consensus			
	30 days		60 days		30 days		60 days	
	Earnings	SUE	Earnings	SUE	Earnings	SUE	Earnings	SUE
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
SA Consensus x Female Count	0.031***	0.038*	0.004	0.021*	0.031***	0.049*	0.003	0.032**
	(0.010)	(0.023)	(0.006)	(0.012)	(0.011)	(0.026)	(0.007)	(0.013)
SA Consensus	0.011**	0.045***	0.011***	0.033**	0.002	0.005	0.008*	0.004
	(0.005)	(0.015)	(0.004)	(0.014)	(0.006)	(0.018)	(0.005)	(0.012)
Female Count	-0.003	-0.015	-0.007	-0.021	-0.093***	-0.155**	-0.016	-0.113***
	(0.009)	(0.021)	(0.005)	(0.014)	(0.032)	(0.075)	(0.019)	(0.040)
Size	0.019	-0.100	0.002	-0.074*	0.017	-0.105*	0.001	-0.076*
	(0.034)	(0.063)	(0.029)	(0.044)	(0.034)	(0.063)	(0.029)	(0.044)
Leverage	-0.468***	0.234	-0.418***	0.232**	-0.474***	0.209	-0.419***	0.217*
	(0.123)	(0.197)	(0.106)	(0.118)	(0.123)	(0.199)	(0.107)	(0.118)
Loss	-0.934***	-0.305***	-0.974***	-0.341***	-0.938***	-0.315***	-0.975***	-0.346***
	(0.063)	(0.060)	(0.048)	(0.053)	(0.063)	(0.060)	(0.048)	(0.053)
Ln(Book-to-market)	0.133***	-0.022	0.110***	-0.048	0.134***	-0.016	0.110***	-0.045
	(0.026)	(0.060)	(0.021)	(0.039)	(0.027)	(0.061)	(0.021)	(0.038)
Ln(Price)	0.057**	0.090	0.062***	0.068*	0.059**	0.098	0.064***	0.077*
	(0.026)	(0.062)	(0.018)	(0.041)	(0.025)	(0.062)	(0.018)	(0.041)
Turnover	0.015*	0.000	0.007	0.002	0.015*	-0.001	0.007	0.001
	(0.009)	(0.015)	(0.007)	(0.011)	(0.009)	(0.015)	(0.007)	(0.011)
Small Size	-0.063	0.199	-0.047	0.052	-0.063	0.203	-0.046	0.052
	(0.074)	(0.153)	(0.045)	(0.102)	(0.074)	(0.153)	(0.045)	(0.102)
Lag(Earnings)	7.745***		7.097***		7.744***		7.113***	
	(1.060)		(0.764)		(1.060)		(0.763)	
Lag(SUE)		0.037***		0.036***		0.038***		0.037***
		(0.007)		(0.006)		(0.007)		(0.006)
Forecast Dispersion		-0.492***		-0.480***		-0.506***		-0.486***
		(0.087)		(0.062)		(0.088)		(0.063)
Number of Analysts		-0.009***		-0.009***		-0.010***		-0.009***
		(0.003)		(0.002)		(0.003)		(0.002)
Constant	-0.060	1.288**	0.127	1.121***	-0.055	1.297**	0.103	1.103***
	(0.311)	(0.517)	(0.259)	(0.362)	(0.310)	(0.524)	(0.259)	(0.364)
R-squared Adj.	0.872	0.256	0.859	0.249	0.871	0.255	0.859	0.249
Obs.	6,709	5,873	12,493	10,591	6,709	5,873	12,493	10,591

Table 13: Quitting by Gender

This table examines whether the propensity of a contributor quiting the Seeking Alpha platform depends on the nature of engagement they receive. We define *Quit* as an author who last posted an article before 2020. We then run a cross-sectional regression of *Quit* on the average disagreement an author experienced from platform users over the pre-quit period and its interaction with the Female dummy variable.

	Quit			
	[1]	[2]	[3]	[4]
Sentiment Disagreement	0.212**			
	(0.087)			
Female x Sentiment Disagreement	-0.334			
	(0.431)			
Polarity Disagreement		0.041		
		(0.025)		
Female x Polarity Disagreement		0.014		
		(0.106)		
LM Sentiment Disagreement			0.275**	
			(0.126)	
Female x LM Sentiment Disagreement			0.037	
			(0.623)	
LM Polarity Disagreement				0.100***
				(0.020)
Female x LM Polarity Disagreement				0.009
				(0.080)
Female	0.032	0.011	0.013	0.011
	(0.027)	(0.029)	(0.022)	(0.028)
Qualifications	-0.017***	-0.017***	-0.017***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.006)
Number of Industries	-0.554***	-0.556***	-0.553***	-0.553***
	(0.066)	(0.066)	(0.066)	(0.066)
Number of Firms	-0.068**	-0.067**	-0.068**	-0.067**
	(0.033)	(0.033)	(0.033)	(0.032)
Monthly Workload	0.010***	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Article Readability	-0.001	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
SA Age in Years	-0.049***	-0.049***	-0.049***	-0.049***
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.964***	0.965***	0.967***	0.944***
	(0.014)	(0.014)	(0.013)	(0.014)
R-squared Adj.	0.151	0.151	0.151	0.153
Obs.	7,579	7,579	7,579	7,579

Table 14: Trolling by Gender

This table examines whether female authors attract more "Trolls" than males. We define *Troll* as a commenter who has made multiple comments on the Seeking Alpha platform and whose comments are very negative – in the bottom 10% of all user comment sentiment (polarity). The column headers indicate whether Troll is measured based on LM Sentiment, LM Polarity, or the Sentiment and Polarity measures based on the NRC Emotion Lexicon. In all specifications, we cluster standard errors by firm and year-quarter, and include year-quarter or stock by year-quarter fixed effects.

	LM Sentiment Troll		LM Polarity Troll		Sentiment Troll		Polarity Troll	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	-0.030	-0.058	0.050	-0.074	0.178**	0.090	0.210**	0.099
	(0.091)	(0.085)	(0.079)	(0.079)	(0.082)	(0.066)	(0.088)	(0.079)
SA Age in Years	-0.010	0.001	-0.013**	-0.004	-0.014**	-0.002	-0.023***	-0.006
	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
Monthly Workload	-0.001	0.000	-0.000	0.000	-0.001	0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of Firms	-0.025	-0.031	-0.050	-0.051	0.006	-0.060	0.008	-0.098**
	(0.052)	(0.054)	(0.037)	(0.039)	(0.043)	(0.046)	(0.045)	(0.047)
Number of Industries	0.068	0.036	0.156*	0.073	-0.017	0.104	-0.025	0.211*
	(0.134)	(0.132)	(0.093)	(0.089)	(0.103)	(0.115)	(0.116)	(0.123)
Qualifications	0.026	0.004	-0.000	-0.018	-0.047*	-0.063**	-0.074***	-0.086***
	(0.030)	(0.027)	(0.024)	(0.023)	(0.026)	(0.026)	(0.026)	(0.023)
Article Readability	0.004	0.001	0.004	-0.001	-0.009**	-0.010**	-0.011**	-0.011**
	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)
1 Month Prior Ret	-0.207**	-0.070	-0.167**	-0.029	-0.080	-0.045	-0.123*	-0.114
	(0.096)	(0.071)	(0.075)	(0.068)	(0.094)	(0.089)	(0.063)	(0.071)
1 Year Prior Vol	13.795***	11.763*	7.441***	-0.954	8.788***	4.777	8.677***	3.258
	(3.165)	(6.505)	(2.546)	(5.741)	(1.950)	(6.141)	(2.126)	(6.820)
Ln(Price)	-0.022	-0.055	-0.004	0.097	-0.017	-0.122	-0.023	-0.029
	(0.047)	(0.183)	(0.038)	(0.170)	(0.034)	(0.264)	(0.036)	(0.269)
Ln(Market Value)	-0.021	-0.271	-0.041**	-0.233	-0.015	-0.302	-0.014	-0.321
	(0.025)	(0.249)	(0.019)	(0.152)	(0.017)	(0.251)	(0.019)	(0.294)
Constant	1.487***	5.775	1.525***	4.609**	1.439***	6.607*	1.692***	6.817*
	(0.373)	(3.870)	(0.298)	(2.184)	(0.253)	(3.481)	(0.283)	(4.112)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.028	0.131	0.046	0.158	0.029	0.128	0.026	0.123
Obs.	165,740	165,740	165,740	165,740	165,740	165,740	165,740	165,740
Avg Dependent var.	1.435	1.435	1.072	1.072	1.207	1.207	1.387	1.387
SD Dependent var.	6.591	6.591	6.076	6.076	5.983	5.983	6.334	6.334

Internet Appendix

for

Gender Bias and Crowd-Sourced Financial Information

Table 1: Variable Definitions

This table describes the variables used in our analysis.

Variable	Definition
	A: Article Characteristics
Article Readability	The readability score of an article based on the Gunning Fog Index.
Bullishness	The bullishness of the viewpoint expressed in an article about a stock. Bullishness is either stated in the article as *Bullish*, *Neutral* or *Bearish* or inferred from the machine learning (ML) framework of Dim (2020). To obtain the author-stated bullishness labels, we use the unique article identifiers to merge our data with that of Dim (2020), which contains author-stated bullishness labels. We then apply the paper's ML model to infer the ML-implied bullishness labels for all articles in our sample without an author-stated bullishness. We convert the qualitative labels to numeric values by mapping bullish to 1, bearish to -1 and neutral to 0.
Boldness	The absolute value of the difference between an article's Bullishness score and the consensus Bullishness, where the consensus is calculated as the average Bullishness score of articles published about the same stock over the 90-day window ending the day before an article is published.
Comment Polarity	The average polarity of an article's comments, excluding any comments made by the article's author. Polarity is calculated as the number of positive words minus the number of negative words divided by the sum of positive and negative in the article. Positive and negative word lists are based on the National Research Council of Canada and their Sentiment and Emotion Lexicons (NRC Emotion Lexicon).
Comment Sentiment	The average of the sentiment of an article's comments, excluding any comments made by the article's author. Sentiment is calculated as the fraction of positive words minus the fraction of negative words in the article. Positive and negative word lists are based on the NRC Emotion Lexicon.
LM Comment Sentiment	Computed similar to Comment Sentiment but uses the Loughran and McDonald (2011) dictionary for positive and negative word lists.
LM Comment Polarity	Computed similar to Comment Polarity but uses the Loughran and McDonald (2011) dictionary for positive and negative word lists.
LM Polarity	The number of positive words minus the number of negative words in an article scaled by the sum of number of positive and negative words plus one. Positive and negative words are defined based on the Loughran and McDonald (2011) word list.
LM Polarity Disagreement	The absolute value of the difference between the LM Polarity of the article and the average LM Polarity of the comments on the article, excluding any comments made by the article's author. For use in regression analysis, we multiply the variable by 100.
LM Sentiment	The number of positive words minus the number of negative words scaled by the number of words in the article. Positive and negative words are defined based on the Loughran and McDonald (2011) word list.
LM Sentiment Disagreement	The absolute value of the difference between the LM Sentiment of the article and the LM Sentiment of the comments on the article, excluding any comments made by the article's author. For use in regression analysis, we multiply the variable by 100.
LM Uncertainty Ratio	Average of the fraction of uncertainty words used in the comments posted on an article. Uncertainty words are based on the Loughran and McDonald (2011) word list. For use in regression analysis, we multiply the variable by 100.
Joy	Average of the fraction of words expressing a joyful emotion used in the comments posted on an article. Joy words are based on the NRC Emotion Lexicon. For use in regression analysis, we multiply the variable by 100.
Number of Comments	The number of comments posted on an article by other users besides the article's author.
Novelty Score	Captures how novel the viewpoints in an article is relative to other recent articles published by other contributors on the same stock. It is calculated as one minus the average cosine similarity score of an article with the n (equals 2 or 5) most recent articles published about the same stock by other contributors besides the article's author. To obtain the cosine similarity score between two articles, we use the term-frequency inverse-frequency vector of the respective articles, where the vectors are fitted based on the entire articles in our sample omitting words that appear less than 100 times in the entire corpus.

Polarity	The number of positive words minus the number of negative words in an article scaled by the sum of the number of positive and negative words plus one, where positive and negative words are based on the NRC Emotion Lexicon.
Polarity Disagreement	The absolute value of the difference between the Polarity of the article and the average Polarity of the comments on the article, excluding any comments made by the article's author. For use in regression analysis, we multiply the variable by 100.
Sentiment	The difference between the fraction of positive words and the fraction of negative words in the article, where positive and negative words are based on the NRC Emotion Lexicon
Sentiment Disagreement	The absolute value of the difference between the Sentiment of the article and the Sentiment of the comments for the article, excluding any comments made by the article's author. For use in regression analysis, we multiply the variable by 100.
Troll	The fraction of troll users that commented on an article. Troll users are individuals who post overly negative comments based on a given sentiment measure. To obtain the measure for a given sentiment measure (e.g., LM sentiment), we calculate the average sentiment of a user across all her comments on the platform. We then classify troll users as those in the bottom 10% of the distribution.
Trust	The average of the fraction of words expressing trust used in the comments posted on an article. Trust words are based on the NRC Emotion Lexicon. For use in regression analysis, we multiply the variable by 100.
B: Contributor Characteristics	
Female	An indicator variable that equals one if a contributor's gender is female and zero if male. Similar to other studies such as Kumar (2010) and Bhagwat et al. (2022), we obtain female and male gender classifications based on an author's first name using GenderAPI.com, which algorithmically determines gender by first names. We drop gender classifications for which the associated accuracy score is below 70%.
Monthly Workload	The count of articles an author has written in a given month.
Number of Firms	The number of unique firms an author wrote about on the platform. For use in regression analysis, we divide the variable by 100.
Number of Industries	The number of unique SIC code industries an author wrote about on the platform. For use in regression analysis, we divide the variable by 100.
Number of Publications	The number of articles an author has published on the platform as of day *t*. For use in regression analysis, we divide the variable by 100.
Qualifications	The number of graduate academic or professional qualifications an author listed in their bio on the platform. We check if an author mentions having an MSc, MBA, PhD, or CFA qualification or whether they have job experience as a financial analyst. To check the mention of these terms in a bio, we use different variants of the terms.
Quit	An indicator variable that equals one if an author did not publish any article since the end of 2019 and zero otherwise.
SA Age in Years	The number of days an author has spent on the SA platform as of day *t* divided by 365.
C: Stock Characteristics	
1 Month Prior Ret	Cumulative stock return over the past 21 trading days ending one day before article publication.
1 Year Prior Vol	Stock volatility computed as the standard deviation of daily returns over the past 252 trading days ending one day before article publication.
Abn Ret[*m*, *n*]	Future *h* trading days cumulative stock abnormal return relative to the four-factor model starting the next day after article publication, i.e., day $m = t+1$, and ending on day $n = t+h$. Betas used for abnormal return calculation are based on 252 trading days data ending 21 days before article publication.
Abn. Volume[*m, n*]	Abnormal trading volume average over the next trading days' *m* to *n* following article *i*'s publication on day *t*. It is computed as the difference between the log volume on date $t + 1$ and the average daily log volume from $t - 140$ to $t - 20$ trading days (6-month period, skipping a month).
Number of Analysts	The number of analysts covering a firm in a given quarter as measured by IBES.
Earnings	The operating income after depreciation (OIADPQ) divided by lagged total assets.

Female Count	The number of female authors whose viewpoints were part of the SA Consensus calculation. SA Consensus is defined below.
Forecast Dispersion	The standard deviation of one quarter ahead analyst forecast of earnings per share.
IPE[m, n]	Intraperiod Price Efficiency (IPE) measure computed based on stock returns in excess of the market over window $[m, n]$. For example for the window $[t-1, t+3]$, the $IPE = \sum_{t=-1}^{t=3} 1 - \frac{\lvert Abn\ Ret_3 - Abn\ Ret_t \rvert}{\lvert Abn\ Ret_3 \rvert}$, where $Abn\ Ret_t$ is the cumulative abnormal return from $t-1$ to t. In line with the literature mentioned above, we set the IPE measure to missing if the absolute cumulative abnormal return over the announcement window, i.e., $\lvert Abn\ Ret_3 \rvert$ in this example, is too small to reduce the impact of very small denominators. We use a threshold of 0.5% and 1% for the $[t-1, t+3]$ and $[t, t+5]$ windows, respectively.
Leverage	The sum of short-term debt (DLCQ) and long-term debt (DLTTQ), divided by total assets (ATQ).
Ln(Market-to-Book)	The natural log of Market-to-Book ratio. Market-to-Book ratio is calculated as the market value of equity (PRCCQ × CSHOQ) divided by the book value of equity. The book value of equity depends on data availability as follows. The shareholders' equity (SEQQ), or commons/ordinary equity (CEQQ). If both items are missing, the shareholders' equity is total assets (ATQ) minus total liabilities (LTQ) and minority interests (MIBQ).
Ln(Market Value)	The natural log of firm market value, calculated as shares outstanding multiplied by share price as of the end of the last calendar month.
Ln(Price)	The natural log of firm price as of the end of the last calendar month.
Loss	Takes on the value of one if operating income after depreciation is a negative number and zero otherwise.
SA Consensus	The average LM sentiment (or Sentiment based on the NRC Emotion Lexicon) of the articles published about a firm over the past k calendar days ending two days before the earnings announcement.
Size	The natural logarithm of total assets (ATQ).
Small Size	A dummy variable that Equals one if firm size is less than the median value for the quarter.
SUE	Earnings surprise measured as the actual reported earnings minus the average of analysts' earnings forecasts, scaled by forecast dispersion (standard deviation of estimates).
Turnover	Volume traded scaled by shares outstanding, then averaged over the past six calendar months before the current month.

Table 2: Direct Engagement by Gender

This table examines how Seeking Alpha users engage with male- vs female-authored articles. The analysis focuses only on comments aimed directly at the article and hence excludes comments made on comments. We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Uncertainty, Joy, and Trust. We regress these measures on a dummy variable *Female,* while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	-3.001***	-0.942***	-0.232***	-0.169***	-0.237***	-0.192***	-0.118***	-0.085***
	(0.580)	(0.201)	(0.063)	(0.056)	(0.054)	(0.051)	(0.021)	(0.022)
SA Age in Years	0.524***	0.229***	-0.020***	-0.027***	-0.022***	-0.021***	-0.003	-0.007***
	(0.087)	(0.037)	(0.006)	(0.006)	(0.005)	(0.005)	(0.002)	(0.002)
Monthly Workload	-0.032***	-0.030***	-0.005***	-0.005***	-0.003***	-0.003***	-0.001**	-0.000
	(0.010)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	-0.056	-0.026	-0.064*	-0.016	-0.104***	-0.009	0.028**	-0.006
	(0.293)	(0.202)	(0.036)	(0.029)	(0.034)	(0.029)	(0.013)	(0.015)
Number of Industries	-2.477***	-0.598	0.358***	0.207***	0.442***	0.151*	-0.063*	0.048
	(0.882)	(0.593)	(0.101)	(0.080)	(0.094)	(0.078)	(0.038)	(0.039)
Qualifications	-0.107	0.158	0.038*	0.020	-0.037**	-0.016	0.022***	0.019**
	(0.188)	(0.127)	(0.022)	(0.017)	(0.017)	(0.016)	(0.008)	(0.008)
Article Readability	-0.227***	-0.147***	0.018***	0.010**	0.010**	0.003	-0.000	-0.000
	(0.052)	(0.036)	(0.005)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
1 Month Prior Ret	-0.955	-0.785*	0.015	-0.017	0.160***	0.036	-0.054***	-0.022
	(0.608)	(0.448)	(0.045)	(0.050)	(0.048)	(0.041)	(0.020)	(0.021)
1 Year Prior Vol	158.882***	-60.020***	-7.717***	4.139	-6.188***	0.557	0.200	2.149
	(49.718)	(20.467)	(2.204)	(4.333)	(1.901)	(2.966)	(0.552)	(2.025)
Ln(Price)	-0.658	-0.686	-0.156***	-0.095	-0.138***	-0.045	-0.003	0.020
	(0.976)	(0.541)	(0.046)	(0.129)	(0.038)	(0.118)	(0.008)	(0.056)
Ln(Market Value)	1.933***	0.963**	0.007	0.025	0.031*	0.056	-0.026***	-0.075
	(0.306)	(0.483)	(0.030)	(0.132)	(0.017)	(0.126)	(0.005)	(0.074)
Constant	-19.117***	0.771	8.378***	7.703***	4.813***	4.008**	2.256***	2.912***
	(5.702)	(7.637)	(0.395)	(1.807)	(0.219)	(1.719)	(0.082)	(1.045)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.156	0.479	0.004	0.110	0.006	0.105	0.003	0.093
Obs.	197,578	197,578	165,724	165,724	165,724	165,724	165,724	165,724
Avg Dependent var.	10.541	10.541	7.929	7.929	4.759	4.759	1.802	1.802
SD Dependent var.	15.092	15.092	4.353	4.353	3.715	3.715	1.812	1.812

Table 3: Direct Disagreement by Gender

This table examines whether users disagree more or less with an article's viewpoint when the contributor is male vs. female. The analysis focuses only on comments aimed directly at the article and hence excludes comments made on comments. Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed using the NRC Emotion Lexicon. Standard errors are clustered by firm and year-quarter and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[1]	[2]	[3]	[4]
Female	0.517***	0.237**	2.277***	1.351***
	(0.121)	(0.115)	(0.484)	(0.511)
SA Age in Years	-0.055***	-0.023***	-0.042	0.044
	(0.010)	(0.008)	(0.043)	(0.040)
Monthly Workload	0.011***	0.006***	0.044***	0.035***
	(0.002)	(0.002)	(0.008)	(0.007)
Number of Firms	0.068	0.116**	-0.474*	-0.476*
	(0.065)	(0.057)	(0.280)	(0.282)
Number of Industries	0.345*	-0.049	2.280***	1.510**
	(0.180)	(0.156)	(0.751)	(0.755)
Qualifications	0.030	0.047	-0.093	0.051
	(0.034)	(0.031)	(0.130)	(0.123)
Article Readability	0.055***	0.044***	0.240***	0.218***
	(0.013)	(0.011)	(0.056)	(0.052)
1 Month Prior Ret	0.157***	0.181***	1.316***	1.030***
	(0.058)	(0.067)	(0.345)	(0.317)
1 Year Prior Vol	-13.998***	-8.461	-16.460*	-46.408*
	(3.256)	(6.086)	(9.611)	(26.531)
Ln(Price)	0.185***	-0.075	0.299	0.220
	(0.067)	(0.204)	(0.193)	(0.662)
Ln(Market Value)	-0.242***	0.122	-0.168*	-0.553
	(0.034)	(0.193)	(0.094)	(0.649)
Constant	8.242***	3.342	23.172***	31.057***
	(0.574)	(2.728)	(1.661)	(9.448)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.017	0.114	0.010	0.086
Obs.	165,724	165,724	165,724	165,724
Avg Dependent var.	5.504	5.504	25.054	25.054
SD Dependent var.	5.368	5.368	18.955	18.955

Table 4: Direct Engagement by Gender Conditional on Opinion Informativeness

This table examines the nature of engagement received by male vs female-authored articles conditional on the underlying informativeness of the viewpoint expressed in the article. The analysis focuses only on comments aimed directly at the article and hence excludes comments made on comments. The specification is identical to that of Table 3 except that we now interact the *Female* dummy variable with the signed 4-factor abnormal return computed over the five trading days starting $t+1$ following article publication on day *t*. The ex-post abnormal return is multiplied by 1 (-1) for an article whose *Bullishness* measure is bullish (bearish) to capture the return that would result from taking a long (short) position based on the author's viewpoint. Hence, the abnormal return captures the extent to which the contributor's viewpoint turned out to be true over the succeeding five trading days. We drop articles whose *Bullishness* equals zero, i.e., neutral articles, as those have no clear investment signal. The outcome variables that measure engagement denoted in the column headers are described in Table 3 in the main text. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female x Abn Ret[1, 5]	1.034	-0.985	-1.131*	-1.231	-0.621	-1.113	-0.098	-0.085
	(2.372)	(1.549)	(0.668)	(0.990)	(0.801)	(0.857)	(0.302)	(0.360)
Female	-2.869***	-0.882***	-0.231***	-0.168***	-0.227***	-0.189***	-0.112***	-0.080***
	(0.558)	(0.203)	(0.066)	(0.055)	(0.058)	(0.051)	(0.021)	(0.023)
Abn Ret[1, 5]	-1.829**	-1.554	0.312**	0.193	0.364***	0.110	0.036	0.154*
	(0.836)	(1.043)	(0.124)	(0.126)	(0.128)	(0.117)	(0.072)	(0.079)
SA Age in Years	0.524***	0.250***	-0.025***	-0.031***	-0.027***	-0.024***	-0.003	-0.008***
	(0.084)	(0.040)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)
Monthly Workload	-0.031***	-0.030***	-0.006***	-0.006***	-0.004***	-0.004***	-0.001**	-0.000
	(0.009)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	0.102	0.041	-0.071*	-0.019	-0.110***	-0.013	0.028**	-0.007
	(0.297)	(0.193)	(0.037)	(0.030)	(0.035)	(0.030)	(0.014)	(0.016)
Number of Industries	-2.830***	-0.738	0.390***	0.226***	0.490***	0.177**	-0.068*	0.047
	(0.921)	(0.569)	(0.103)	(0.082)	(0.100)	(0.081)	(0.039)	(0.041)
Qualifications	-0.119	0.142	0.045*	0.029	-0.025	-0.006	0.022***	0.019**
	(0.190)	(0.127)	(0.024)	(0.018)	(0.018)	(0.017)	(0.008)	(0.009)
Article Readability	-0.223***	-0.137***	0.019***	0.010**	0.010**	0.003	-0.000	-0.000
	(0.052)	(0.035)	(0.005)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)
1 Month Prior Ret	-1.085*	-0.924*	0.008	-0.012	0.151***	0.041	-0.050***	-0.008
	(0.613)	(0.528)	(0.049)	(0.052)	(0.051)	(0.043)	(0.019)	(0.020)
1 Year Prior Vol	168.753***	-55.396***	-7.324***	2.728	-5.674***	-0.162	0.210	1.218
	(51.100)	(21.083)	(2.361)	(5.327)	(1.978)	(3.462)	(0.587)	(1.986)
Ln(Price)	-0.558	-0.598	-0.156***	-0.120	-0.139***	-0.044	-0.003	0.029
	(0.964)	(0.577)	(0.048)	(0.132)	(0.040)	(0.120)	(0.009)	(0.056)
Ln(Market Value)	1.899***	0.752	0.007	0.059	0.034*	0.067	-0.025***	-0.098
	(0.307)	(0.514)	(0.031)	(0.143)	(0.018)	(0.133)	(0.006)	(0.076)
Constant	-19.148***	3.602	8.357***	7.270***	4.739***	3.824**	2.249***	3.286***
	(5.773)	(8.423)	(0.406)	(1.995)	(0.226)	(1.830)	(0.083)	(1.090)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.161	0.483	0.004	0.108	0.006	0.104	0.003	0.091
Obs.	184,537	184,537	154,039	154,039	154,039	154,039	154,039	154,039
Avg Dependent var.	10.540	10.540	7.929	7.929	4.749	4.749	1.803	1.803
SD Dependent var.	15.146	15.146	4.335	4.335	3.702	3.702	1.806	1.806

Table 5: Direct Disagreement by Gender Conditional on Opinion Informativeness

This table examines whether users' disagreement with an article's viewpoint depends on the informativeness of the viewpoint expressed in the article. The analysis focuses only on comments aimed directly at the article and hence excludes comments made on comments. The specification is identical to that of Table 4 in the main text except that we now interact the *Female* dummy variable with the signed 4-factor abnormal return computed over the five trading days starting $t+1$ following article publication on day *t*. The ex-post abnormal return is multiplied by 1 (-1) for an article whose *Bullishness* measure is bullish (bearish) to capture the return that would result from taking a long (short) position based on the author's viewpoint. Hence, the abnormal return captures the extent to which the contributor's viewpoint turned out to be true over the succeeding five trading days. We drop articles whose *Bullishness* equals zero, i.e., neutral articles, as those have no clear investment signal. The outcome variables that measure disagreement denoted in the column headers are described in Table 4. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[1]	[2]	[3]	[4]
Female x Abn Ret[1, 5]	0.415	-0.372	1.049	2.768
	(1.159)	(1.129)	(4.272)	(4.400)
Female	0.444***	0.193*	1.974***	1.133**
	(0.116)	(0.113)	(0.491)	(0.520)
Abn Ret[1, 5]	-0.533***	-0.509***	-2.179***	-2.290***
	(0.181)	(0.179)	(0.756)	(0.801)
SA Age in Years	-0.057***	-0.028***	-0.045	0.042
	(0.010)	(0.008)	(0.044)	(0.043)
Monthly Workload	0.011***	0.007***	0.046***	0.038***
	(0.002)	(0.002)	(0.008)	(0.007)
Number of Firms	0.031	0.086	-0.639**	-0.645**
	(0.068)	(0.059)	(0.295)	(0.299)
Number of Industries	0.447**	0.024	2.709***	1.913**
	(0.187)	(0.161)	(0.788)	(0.785)
Qualifications	0.045	0.054*	-0.042	0.026
	(0.034)	(0.033)	(0.132)	(0.131)
Article Readability	0.056***	0.045***	0.250***	0.225***
	(0.013)	(0.011)	(0.060)	(0.055)
1 Month Prior Ret	0.176***	0.153***	1.333***	0.935***
	(0.053)	(0.059)	(0.353)	(0.293)
1 Year Prior Vol	-14.282***	-8.621	-22.032**	-43.794
	(3.366)	(6.042)	(10.131)	(27.180)
Ln(Price)	0.170**	-0.132	0.261	0.045
	(0.066)	(0.184)	(0.196)	(0.644)
Ln(Market Value)	-0.237***	0.142	-0.171*	-0.460
	(0.034)	(0.185)	(0.096)	(0.642)
Constant	8.192***	3.207	23.377***	30.036***
	(0.585)	(2.673)	(1.725)	(9.455)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.018	0.113	0.011	0.087
Obs.	154,039	154,039	154,039	154,039
Avg Dependent var.	5.495	5.495	25.109	25.109
SD Dependent var.	5.355	5.355	18.986	18.986

Table 6: Engagement by Gender Excluding Tail Authors

This table examines how Seeking Alpha users engage with male- vs female-authored articles. We drop very unpopular and popular authors by focusing only on articles contributed by authors with a total number of comments in the sample outside the top and bottom 1% of the distribution. We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Uncertainty, Joy, and Trust. We regress these measures on a dummy variable *Female,* while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	-5.140***	-2.048***	-0.214***	-0.178***	-0.172***	-0.149***	-0.101***	-0.082***
	(1.254)	(0.457)	(0.051)	(0.057)	(0.051)	(0.049)	(0.023)	(0.025)
SA Age in Years	0.167	0.225**	-0.008	-0.013	-0.020***	-0.012*	0.000	-0.006**
	(0.207)	(0.099)	(0.007)	(0.008)	(0.006)	(0.007)	(0.003)	(0.003)
Monthly Workload	-0.091***	-0.070***	-0.005***	-0.005***	-0.004***	-0.003*	-0.002**	-0.001
	(0.025)	(0.013)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Number of Firms	-0.047	-1.140*	-0.157***	-0.067	-0.199***	-0.086*	0.015	-0.033
	(1.009)	(0.604)	(0.057)	(0.059)	(0.055)	(0.049)	(0.023)	(0.026)
Number of Industries	-4.937**	1.380	0.520***	0.260**	0.669***	0.284***	-0.063	0.075
	(2.318)	(1.473)	(0.122)	(0.124)	(0.130)	(0.109)	(0.051)	(0.057)
Qualifications	-0.493	-0.514	0.049*	0.024	-0.009	0.003	0.025***	0.027**
	(0.430)	(0.313)	(0.026)	(0.025)	(0.022)	(0.026)	(0.007)	(0.011)
Article Readability	-0.327***	-0.253***	0.017***	0.007	0.008	0.000	0.002	0.002
	(0.083)	(0.060)	(0.006)	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)
1 Month Prior Ret	-1.593	-3.087**	-0.019	0.010	0.175***	0.058	-0.048*	-0.016
	(1.992)	(1.278)	(0.062)	(0.052)	(0.050)	(0.048)	(0.027)	(0.029)
1 Year Prior Vol	385.494***	-100.487	-4.616**	7.903	-3.786**	2.679	0.288	3.371
	(140.795)	(67.795)	(2.251)	(5.091)	(1.727)	(3.741)	(0.687)	(2.187)
Ln(Price)	0.005	-4.686	-0.130***	-0.078	-0.101***	0.124	-0.008	0.028
	(2.565)	(4.513)	(0.047)	(0.179)	(0.031)	(0.136)	(0.010)	(0.087)
Ln(Market Value)	3.428***	4.511	0.008	0.106	0.034**	-0.145	-0.020***	-0.077
	(0.588)	(4.265)	(0.030)	(0.174)	(0.014)	(0.143)	(0.006)	(0.108)
Constant	-40.374***	-31.645	8.163***	6.217***	4.483***	6.528***	2.192***	2.900*
	(13.404)	(53.779)	(0.404)	(2.371)	(0.204)	(2.004)	(0.097)	(1.488)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.110	0.471	0.003	0.101	0.005	0.093	0.003	0.085
Obs.	139,799	139,799	111,727	111,727	111,727	111,727	111,727	111,727
Avg Dependent var.	17.747	17.747	7.923	7.923	4.673	4.673	1.846	1.846
SD Dependent var.	39.638	39.638	4.334	4.334	3.689	3.689	1.801	1.801

Table 7: Disagreement by Gender Excluding Tail Authors

This table examines whether users disagree more or less with an article's viewpoint when the contributor is male vs. female. We drop very unpopular and popular authors by focusing only on articles contributed by authors with a total number of comments in the sample outside the top and bottom 1% of the distribution. Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed using the NRC Emotion Lexicon. Standard errors are clustered by firm and year-quarter, and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[5]	[6]	[7]	[8]
Female	0.564***	0.372***	2.816***	1.988***
	(0.115)	(0.117)	(0.466)	(0.529)
SA Age in Years	-0.027**	-0.026**	-0.034	0.034
	(0.012)	(0.011)	(0.048)	(0.049)
Monthly Workload	0.021***	0.013***	0.080***	0.066***
	(0.003)	(0.003)	(0.013)	(0.014)
Number of Firms	0.223**	0.200**	-0.491	-0.457
	(0.109)	(0.101)	(0.418)	(0.500)
Number of Industries	0.199	-0.014	3.304***	2.729**
	(0.238)	(0.221)	(0.953)	(1.126)
Qualifications	-0.008	0.024	-0.019	-0.053
	(0.037)	(0.036)	(0.147)	(0.150)
Article Readability	0.049***	0.039***	0.233***	0.232***
	(0.012)	(0.011)	(0.056)	(0.050)
1 Month Prior Ret	0.167**	0.193**	1.449***	1.266***
	(0.079)	(0.076)	(0.451)	(0.410)
1 Year Prior Vol	-13.108***	-8.350	-14.516*	-51.266*
	(2.892)	(6.761)	(8.415)	(26.435)
Ln(Price)	0.190***	0.049	0.402**	0.504
	(0.056)	(0.196)	(0.180)	(0.730)
Ln(Market Value)	-0.197***	0.097	0.015	-0.407
	(0.030)	(0.253)	(0.087)	(0.764)
Constant	7.423***	3.293	19.841***	27.540**
	(0.542)	(3.622)	(1.556)	(10.964)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.020	0.107	0.016	0.086
Obs.	111,727	111,727	111,727	111,727
Avg Dependent var.	5.526	5.526	25.606	25.606
SD Dependent var.	5.427	5.427	19.161	19.161

Table 8: Engagement by Gender Excluding Bearish Views

This table examines how Seeking Alpha users engage with male- vs female-authored articles. The analysis focuses only on articles for which the *Bullishness* measure is not bearish. We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Uncertainty, Joy, and Trust. We regress these measures on a dummy variable *Female,* while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Female	-7.431***	-2.437***	-0.248***	-0.187***	-0.238***	-0.208***	-0.147***	-0.098***
	(1.636)	(0.601)	(0.068)	(0.062)	(0.058)	(0.055)	(0.025)	(0.028)
SA Age in Years	1.324***	0.774***	-0.017***	-0.023***	-0.020***	-0.021***	-0.001	-0.004*
	(0.211)	(0.119)	(0.006)	(0.007)	(0.005)	(0.006)	(0.003)	(0.002)
Monthly Workload	-0.044	-0.033**	-0.006***	-0.004***	-0.003***	-0.003**	-0.001***	-0.001
	(0.033)	(0.014)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	-0.223	0.498	-0.106***	-0.081***	-0.135***	-0.053*	0.021	-0.003
	(0.798)	(0.522)	(0.032)	(0.027)	(0.034)	(0.032)	(0.013)	(0.015)
Number of Industries	-5.603**	-3.349**	0.468***	0.368***	0.504***	0.247***	-0.045	0.039
	(2.307)	(1.696)	(0.098)	(0.076)	(0.100)	(0.088)	(0.037)	(0.039)
Qualifications	-1.437	-0.416	0.038	0.012	-0.031*	-0.014	0.023***	0.024***
	(1.035)	(0.425)	(0.024)	(0.019)	(0.019)	(0.019)	(0.007)	(0.007)
Article Readability	-0.528***	-0.305***	0.016***	0.007*	0.008*	0.000	0.000	0.000
	(0.131)	(0.085)	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
1 Month Prior Ret	-6.424***	-5.040***	0.027	0.032	0.295***	0.165**	-0.077**	-0.016
	(2.340)	(1.568)	(0.075)	(0.087)	(0.070)	(0.079)	(0.032)	(0.038)
1 Year Prior Vol	439.104***	-78.271	-8.537***	3.010	-7.176***	-1.998	1.349**	1.682
	(160.804)	(52.695)	(2.299)	(4.917)	(1.882)	(3.647)	(0.623)	(2.116)
Ln(Price)	-1.923	4.690	-0.143***	0.017	-0.117***	0.094	-0.011	0.031
	(2.704)	(3.331)	(0.048)	(0.222)	(0.037)	(0.177)	(0.009)	(0.083)
Ln(Market Value)	4.840***	-1.873	0.006	-0.137	0.025	-0.159	-0.020***	-0.042
	(0.878)	(2.704)	(0.032)	(0.255)	(0.019)	(0.201)	(0.005)	(0.107)
Constant	-53.404***	40.692	8.335***	9.954***	4.873***	7.120***	2.189***	2.389
	(16.358)	(34.167)	(0.425)	(3.486)	(0.238)	(2.732)	(0.081)	(1.493)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.113	0.488	0.004	0.109	0.005	0.101	0.004	0.089
Obs.	162,795	162,795	135,939	135,939	135,939	135,939	135,939	135,939
Avg Dependent var.	21.648	21.648	7.896	7.896	4.769	4.769	1.842	1.842
SD Dependent var.	44.671	44.671	4.148	4.148	3.545	3.545	1.718	1.718

Table 9: Disagreement by Gender Excluding Bearish Views

This table examines whether users disagree more or less with an article's viewpoint when the contributor is male vs. female. The analysis focuses only on articles for which the *Bullishness* measure is not bearish. Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed using the NRC Emotion Lexicon. Standard errors are clustered by firm and year-quarter, and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[5]	[6]	[7]	[8]
Female	0.559***	0.241*	2.222***	1.164**
	(0.138)	(0.132)	(0.534)	(0.585)
SA Age in Years	-0.050***	-0.020*	-0.008	0.056
	(0.011)	(0.010)	(0.049)	(0.050)
Monthly Workload	0.011***	0.008***	0.043***	0.035***
	(0.002)	(0.002)	(0.009)	(0.008)
Number of Firms	0.009	0.061	-0.838***	-0.756**
	(0.071)	(0.059)	(0.288)	(0.298)
Number of Industries	0.432**	0.023	2.957***	2.111***
	(0.191)	(0.158)	(0.754)	(0.788)
Qualifications	0.034	0.035	-0.214	-0.082
	(0.041)	(0.038)	(0.141)	(0.131)
Article Readability	0.057***	0.046***	0.251***	0.252***
	(0.015)	(0.013)	(0.063)	(0.065)
1 Month Prior Ret	0.298***	0.404***	2.016***	1.993***
	(0.095)	(0.107)	(0.482)	(0.477)
1 Year Prior Vol	-11.011***	-8.812	2.448	-56.484*
	(3.215)	(5.809)	(9.950)	(31.641)
Ln(Price)	0.249***	-0.140	0.399**	-0.248
	(0.061)	(0.211)	(0.187)	(0.599)
Ln(Market Value)	-0.241***	0.115	-0.060	0.109
	(0.037)	(0.199)	(0.102)	(0.719)
Constant	7.850***	3.579	21.582***	22.849**
	(0.655)	(2.795)	(1.856)	(10.718)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.018	0.118	0.010	0.089
Obs.	135,939	135,939	135,939	135,939
Avg Dependent var.	5.442	5.442	26.228	26.228
SD Dependent var.	5.209	5.209	18.762	18.762

Table 10: Engagement by Gender After MeToo

This table examines how Seeking Alpha users engage with male- vs female-authored articles. The analysis includes an indicator variable that denotes the time period after the MeToo movement began (October 2017). We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Uncertainty, Joy, and Trust. We regress these measures on a dummy variable *Female, MeToo,* and their interaction, while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
meToo x female	-13.898***	-2.944***	0.251**	0.212*	0.262**	0.169	0.015	-0.008
	(4.680)	(1.122)	(0.123)	(0.129)	(0.124)	(0.132)	(0.044)	(0.047)
Female	-6.872***	-2.219***	-0.294***	-0.221***	-0.280***	-0.231***	-0.132***	-0.086***
	(2.220)	(0.732)	(0.066)	(0.057)	(0.052)	(0.046)	(0.024)	(0.028)
SA Age in Years	1.860***	0.724***	-0.018***	-0.023***	-0.021***	-0.019***	-0.002	-0.006***
	(0.496)	(0.093)	(0.006)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)
Monthly Workload	-0.038	-0.056***	-0.005***	-0.005***	-0.003***	-0.003***	-0.001***	-0.001
	(0.040)	(0.015)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Firms	-0.442	0.715	-0.084***	-0.053**	-0.119***	-0.036	0.028**	-0.001
	(0.863)	(0.753)	(0.031)	(0.026)	(0.032)	(0.029)	(0.013)	(0.014)
Number of Industries	-7.444**	-3.594	0.414***	0.299***	0.483***	0.208***	-0.062*	0.036
	(3.102)	(2.273)	(0.091)	(0.073)	(0.091)	(0.078)	(0.036)	(0.035)
Qualifications	-0.948	0.232	0.035*	0.017	-0.032*	-0.012	0.021***	0.019***
	(0.924)	(0.316)	(0.021)	(0.017)	(0.017)	(0.018)	(0.006)	(0.007)
Article Readability	-0.606***	-0.399***	0.016***	0.008**	0.008**	0.002	0.001	0.001
	(0.149)	(0.124)	(0.005)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
1 Month Prior Ret	-2.852	-2.089*	-0.002	-0.002	0.158***	0.057	-0.049**	-0.019
	(1.924)	(1.247)	(0.043)	(0.041)	(0.043)	(0.036)	(0.020)	(0.020)
1 Year Prior Vol	603.317**	-171.875***	-7.154***	3.436	-6.160***	0.170	0.524	3.001*
	(273.793)	(56.668)	(2.227)	(3.838)	(1.965)	(2.698)	(0.562)	(1.641)
Ln(Price)	1.918	-2.061	-0.150***	-0.131	-0.126***	-0.025	-0.011	0.043
	(5.438)	(3.159)	(0.049)	(0.117)	(0.040)	(0.107)	(0.009)	(0.060)
Ln(Market Value)	4.718***	3.262	0.004	0.078	0.029*	0.006	-0.020***	-0.075
	(0.830)	(2.556)	(0.031)	(0.117)	(0.017)	(0.113)	(0.005)	(0.074)
Constant	-65.600***	-11.518	8.367***	6.955***	4.755***	4.712***	2.224***	2.835***
	(22.498)	(30.782)	(0.400)	(1.608)	(0.218)	(1.535)	(0.083)	(1.037)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.113	0.505	0.004	0.115	0.006	0.106	0.003	0.097
Obs.	197,578	197,578	165,740	165,740	165,740	165,740	165,740	165,740
Avg Dependent var.	24.933	24.933	7.895	7.895	4.710	4.710	1.850	1.850
SD Dependent var.	55.812	55.812	4.106	4.106	3.511	3.511	1.710	1.710

Table 11: Disagreement by Gender After MeToo

This table examines whether users disagree more or less with an article's viewpoint when the contributor is male vs. female. The analysis includes an indicator variable that denotes the time period after the MeToo movement began (October 2017). Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed using the NRC Emotion Lexicon. Standard errors are clustered by firm and year-quarter, and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[1]	[2]	[3]	[4]
meToo x female	0.730***	0.501*	1.951**	1.537
	(0.254)	(0.270)	(0.848)	(1.005)
Female	0.374***	0.156	1.820***	1.048*
	(0.134)	(0.125)	(0.583)	(0.609)
SA Age in Years	-0.052***	-0.022***	0.000	0.065*
	(0.010)	(0.009)	(0.043)	(0.039)
Monthly Workload	0.010***	0.006***	0.040***	0.032***
	(0.002)	(0.001)	(0.008)	(0.008)
Number of Firms	0.047	0.085	-0.517*	-0.565*
	(0.067)	(0.057)	(0.285)	(0.292)
Number of Industries	0.395**	0.009	2.224***	1.649**
	(0.179)	(0.152)	(0.754)	(0.778)
Qualifications	0.018	0.026	-0.180	-0.043
	(0.033)	(0.031)	(0.131)	(0.121)
Article Readability	0.055***	0.043***	0.248***	0.225***
	(0.014)	(0.011)	(0.058)	(0.054)
1 Month Prior Ret	0.173***	0.165***	1.453***	1.115***
	(0.062)	(0.061)	(0.396)	(0.320)
1 Year Prior Vol	-13.682***	-6.702	-13.750	-47.160*
	(3.059)	(5.396)	(8.717)	(26.373)
Ln(Price)	0.184***	-0.116	0.192	0.395
	(0.061)	(0.155)	(0.178)	(0.522)
Ln(Market Value)	-0.226***	0.113	-0.014	-0.625
	(0.033)	(0.180)	(0.090)	(0.594)
Constant	7.783***	3.423	21.110***	31.752***
	(0.571)	(2.590)	(1.588)	(9.042)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.019	0.120	0.010	0.089
Obs.	165,740	165,740	165,740	165,740
Avg Dependent var.	5.317	5.317	25.252	25.252
SD Dependent var.	5.182	5.182	18.482	18.482

Table 12: Engagement by Random Gender

This table examines how Seeking Alpha users engage with randomly assigned male- vs female-authored articles. We quantify different measures of user engagement from the comments contributed by other users besides the article author: Number of Comments, Uncertainty, Joy, and Trust. We regress these measures on a dummy variable *Female,* while controlling for several contributor and stock characteristics. In all specifications, we cluster standard errors by firm and year-quarter and include year-quarter or stock by year-quarter fixed effects.

	Number of Comments		Trust		Joy		LM Uncertainty Ratio	
variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Random Female	-0.362	-1.060*	-0.055	-0.065	-0.051	-0.045	0.020	0.006
	(0.280)	(0.633)	(0.091)	(0.094)	(0.072)	(0.084)	(0.029)	(0.024)
SA Age in Years	0.093	0.352	-0.061***	-0.032*	-0.058***	-0.048***	-0.002	-0.015**
	(0.497)	(0.369)	(0.017)	(0.019)	(0.014)	(0.016)	(0.006)	(0.006)
Monthly Workload	-0.049*	-0.046***	-0.006*	-0.004*	-0.005**	-0.003**	-0.002***	-0.002***
	(0.028)	(0.016)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Number of Firms	3.514	-3.067*	-0.546**	-0.174	-0.909***	-0.325	0.076	-0.047
	(4.000)	(1.657)	(0.213)	(0.229)	(0.202)	(0.210)	(0.079)	(0.098)
Number of Industries	-18.282*	2.010	1.312***	0.555	1.958***	0.806**	-0.172	0.104
	(9.470)	(2.529)	(0.351)	(0.405)	(0.356)	(0.372)	(0.144)	(0.176)
Article Readability	-0.219	-0.618***	0.026**	0.030**	0.018	0.017	0.002	0.005
	(0.445)	(0.120)	(0.011)	(0.012)	(0.011)	(0.012)	(0.004)	(0.005)
1 Month Prior Ret	0.945	-4.380**	-0.050	0.030	0.096*	0.093	-0.029	-0.037
	(3.729)	(1.884)	(0.059)	(0.080)	(0.054)	(0.065)	(0.028)	(0.031)
1 Year Prior Vol	343.661**	-73.871	0.074	-1.856	-0.613	-6.644	0.216	1.016
	(143.367)	(103.712)	(2.628)	(6.474)	(1.915)	(5.665)	(0.628)	(2.988)
Ln(Price)	0.181	-0.215	-0.146***	0.032	-0.161***	0.045	-0.008	0.017
	(4.407)	(3.543)	(0.043)	(0.168)	(0.044)	(0.146)	(0.011)	(0.092)
Ln(Market Value)	3.997***	-2.673	0.056*	-0.130	0.074***	-0.132	-0.025***	-0.044
	(0.822)	(2.107)	(0.033)	(0.230)	(0.027)	(0.179)	(0.007)	(0.054)
Constant	-44.765***	77.466**	7.071***	9.519***	3.767***	6.650**	2.325***	2.492***
	(16.890)	(37.364)	(0.514)	(3.451)	(0.449)	(2.847)	(0.123)	(0.860)
Year-Quarter FE	Yes	No	Yes	No	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared Adj.	0.128	0.517	0.005	0.106	0.009	0.112	0.003	0.064
Obs.	45,210	45,210	36,731	36,731	36,731	36,731	36,731	36,731
Avg Dependent var.	21.566	21.566	7.746	7.746	4.601	4.601	1.844	1.844
SD Dependent var.	48.340	48.340	4.164	4.164	3.662	3.662	1.795	1.795

Table 13: Disagreement by Random Gender

This table examines whether users disagree more or less with an article's viewpoint when the contributor is randomly assigned gender. Disagreement is measured as the absolute value of the difference between the article's sentiment or polarity score and the corresponding measure averaged across all comments. Sentiment and polarity are computed using the NRC Emotion Lexicon. Standard errors are clustered by firm and year-quarter, and we include year-quarter or stock by year-quarter fixed effects.

	Sentiment Disagreement		Polarity Disagreement	
variables	[1]	[2]	[3]	[4]
Random Female	-0.134	-0.119	-0.250	-0.188
	(0.114)	(0.131)	(0.377)	(0.429)
SA Age in Years	0.007	0.013	0.078	-0.041
	(0.024)	(0.029)	(0.105)	(0.112)
Monthly Workload	0.009***	0.007*	0.041***	0.023
	(0.003)	(0.003)	(0.015)	(0.015)
Number of Firms	-0.776**	-0.335	-6.748***	-5.525***
	(0.345)	(0.353)	(1.279)	(1.492)
Number of Industries	2.524***	1.473**	15.397***	13.290***
	(0.636)	(0.624)	(2.244)	(2.564)
Article Readability	0.123***	0.113***	0.558***	0.489***
	(0.016)	(0.016)	(0.058)	(0.064)
1 Month Prior Ret	0.098	0.002	1.335**	0.664
	(0.111)	(0.096)	(0.626)	(0.435)
1 Year Prior Vol	-7.866**	-1.807	-5.283	-10.593
	(3.823)	(5.572)	(11.714)	(27.013)
Ln(Price)	0.184**	0.232	0.295	0.482
	(0.072)	(0.211)	(0.256)	(0.709)
Ln(Market Value)	-0.168***	0.176	-0.060	0.472
	(0.039)	(0.276)	(0.124)	(0.753)
Constant	5.790***	0.006	17.525***	9.457
	(0.677)	(4.245)	(1.992)	(12.114)
Year-Quarter FE	Yes	No	Yes	No
Stock x Year-Quarter FE	No	Yes	No	Yes
R-squared Adj.	0.025	0.130	0.025	0.104
Obs.	36,731	36,731	36,731	36,731
Avg Dependent var.	5.606	5.606	26.651	26.651
SD Dependent var.	5.517	5.517	19.508	19.508