The Role of Accounting Information in an Era of Fake News

Betty Liu[a]
Kelley School of Business
Indiana University
bettyliu@iu.edu

Austin Moss[b]
Leeds School of Business
University of Colorado Boulder
austin.moss@colorado.edu

December 2024
Forthcoming at the Journal of Accounting and Economics

Abstract

We offer empirical evidence on the role of accounting information in shaping the incentives to produce fake news. We document that fake news authors strategically (1) publish their articles near earnings announcements, leveraging the widespread market attention these events attract, and (2) within the near-announcement window, avoid publishing post-announcement when investors are less susceptible to fake news due to the disclosure of accounting information. In extending our analyses to the broader accounting information environment, we find that fake news authors are less likely to target firms with more robust accounting information and elicit lower market reactions when doing so. These results highlight both ex-ante and ex-post roles that accounting information plays in safeguarding firms from financial disinformation.

JEL Classification: D82, D83, G14, M41

Keywords: Accounting Information, Fake News, Seeking Alpha, Financial Disinformation

As a public entity in a highly digital world, we have been and in the future may be the subject of so-called "fake news," a type of yellow journalism constructed to look legitimate while consisting of intentional misinformation and misrepresentations. ... While utilizing all available tools to defend the Company and its assets against fake news, there is limited regulatory control, making fake news an ongoing concern for any public company.

<div align="right">

– Carvana Co. Prospectus, 5/23/2019

</div>

1. Introduction

Fake news—defined as intentionally misleading information—poses a significant threat to the integrity of capital markets. Kogan, Moskowitz, and Niessner (2023) document that market reactions to fake news are as strong as those to real news, highlighting the difficulty investors have in differentiating the two. To illustrate, in 2018, "Rota Fortunae" penned a Seeking Alpha article about Farmland Partners Inc., alleging that "310% of 2017 earnings could be made-up" and that the firm bears "significant risk of insolvency." Despite refuting these claims as "false and materially misleading," Farmland Partners suffered a 40% drop in stock price from the ensuing panic selling (Farmland Partners Inc., 2018).[1] Concerned about potential market consequences, managers have discussed fake news during conference calls (e.g., Plymouth Industrial REIT, 2019), issued press releases to counteract misleading information (e.g., Regen BioPharma, 2019), and disclosed fake news as a material risk factor (e.g., Carvana, 2019). Amid growing concerns over the proliferation of fake news, this study investigates how accounting information influences the incentives to disseminate fake news in financial markets.

Fake news authors are incentivized to spread disinformation for a variety of reasons. Some want to manipulate stock prices to profit from short-term positions, much like classic pump-and-dump schemes (e.g., SEC, 2022). Others create content for online platforms that offer

---

[1] Farmland Partners later sued Rota Fortunae and his co-conspirators, who had taken a short position in the firm prior to article publication, for manipulating the stock price for profit. After three years of court proceedings, Farmland Partners won the case, attesting to the difficulty of recouping the costs from a single fake article, even if the firm takes legal action.

compensation based on views and therefore sensationalize their articles to generate more views (i.e., they create "clickbait"), akin to a modern-day form of yellow journalism (e.g., Mourao and Robertson, 2019). Still others generate fake news not for monetary compensation but rather for ideological or political gain or for the satisfaction of "trolling" market participants (e.g., American Bar Association, 2019). Despite these different motivations, fake news authors have one general objective: to enhance the plausibility and visibility of their fake news content.

We examine attention-based and information-based effects through which accounting information interacts with this overarching objective. First, the release of accounting information garners significant attention and prompts market participants to search for information about the firm (e.g., Beaver, 1968; Drake et al., 2012; Drake, Roulstone, and Thornock, 2015). By disseminating fake news around these events, fake news authors may increase the likelihood that investors engage with their articles, thereby elevating the incentives to produce them around these information releases. Second, theory about strategic communications in asset markets suggests that false price signals become less effective when a larger proportion of investors are informed (Schmidt, 2020). Accounting information, as a verifiable source of private information, helps investors evaluate the fundamental value of the firm (i.e., the valuation role of accounting information). Consequently, the disclosure of accounting information may reduce investor susceptibility to fake news, thereby disincentivizing its production within a brief period after the disclosure relative to the immediate pre-disclosure period.

We first examine the textual content of fake financial news and its relevance to accounting information. Using Seeking Alpha as our setting, we collect "fake" and "non-fake" crowdsourced financial news articles from 2006 to 2018 following the methodology of Kogan et al. (2023). Our sample comprises 125,475 articles, of which 2.5% are classified as fake. We then

identify the topics discussed in these articles using the Latent Dirichlet Allocation (LDA) machine learning algorithm. Notably, we find that 57% of fake articles contain accounting content—a substantial proportion, yet significantly less than the 88% observed in non-fake articles.

Our next set of analyses explores how accounting information interacts with the incentives to produce fake news by examining the publication of fake articles around earnings announcements. To do so, we use bunching, a methodology conceptually similar to those used to study discontinuities in earnings distributions, which ascribe distortions in behavior to sharp changes in incentives (e.g., Burgstahler and Dichev, 1997; Kleven, 2016). Earnings announcements have three properties that we exploit. First, the widespread attention they attract enables us to examine how increased investor attention affects the incentives to produce fake news. Second, they endow market participants with significant accounting information, allowing us to assess how the disclosure of this information influences the incentives to write fake news. Lastly, because earnings announcements are often scheduled weeks or months in advance, fake news authors can anticipate these disclosure dates, facilitating our ability to examine the potential strategic considerations on when to publish fake news around these significant accounting information events.

By analyzing the distribution of fake articles published around earnings announcements, we document two stylized facts about the strategic timing of fake news around these events: (1) Fake news authors publish more fake articles near earnings announcements when market attention is high, relative to other times during the quarter. (2) Within the near-announcement window, they tend to avoid publishing post-announcement, after the release of accounting information, relative to pre-announcement. Overall, our findings suggest that the disclosure of

3

accounting information influences the strategic publication of fake news by increasing incentives for its creation through heightened visibility while reducing such incentives by improving the precision of investor beliefs about fundamental value.

Our last set of analyses explores how the broader accounting information environment influences the publication of fake news and its subsequent market impact. We examine two dimensions of the accounting information environment likely to be salient to fake news authors: the frequency of management forecasts and the readability of annual reports. Consistent with our prior results that fake news authors refrain from publishing when investors are relatively more informed, we find that these authors write fewer fake articles about firms that issue more frequent management forecasts or more easily readable annual reports.

We then investigate whether the accounting information environment influences the market reaction to fake news. We find lower volume-based and return-based market reactions to fake articles published about firms that issue more management forecasts or more easily readable annual reports. These results are consistent with two potential interpretations. First, investors informed by robust accounting information are less susceptible to disinformation. Second, cognizant of the dissemination of accounting information, fake news authors are constrained by what they believe informed investors will find plausible, leading them to curtail excessively misleading content.

This study advances our understanding about the role of accounting information in shaping the incentives to publish fake news. Using earnings announcements, we find that the incentives to publish fake news around these events increase due to heightened capital market attention but subsequently decrease after these accounting disclosures provide investors with information that facilitates valuation. Extending our analyses to the broader accounting

4

information environment, we find that a stronger accounting information environment disincentivizes the production of fake news and mitigates its market impact, providing evidence of the ex-ante and ex-post roles accounting information plays in safeguarding firms from financial disinformation.

Furthermore, our study provides insights into disinformation in the stock market. Empirical studies on stock market manipulations remain limited due to challenges in identifying and prosecuting such activities (e.g., De Franco, Lu, and Vasvari, 2007; Leuz, Meyer, Muhn, Soltes, and Hackethal, 2017; Weiner, Weber, and Hsu, 2017). In more recent years, researchers have extended this literature by investigating exploitative behaviors on websites without traditional oversight, such as Seeking Alpha (e.g., Kogan et al., 2023) and Twitter (e.g., Jia, Shu, and Zhao, 2020), and by proposing strategies to curb their proliferation (e.g., Grant, Hodge, and Seto, 2023). We contribute to this literature by documenting the content in articles written by fake news authors and the influence of accounting information on their incentives to publish. Lastly, we contribute to the relative scarcity of research on the propagation and social impact of fake news (Lazer et al., 2018). We leave evaluations on the generalizability of our results to other sources of information or to venues beyond financial markets to future research.

2. Data, Sample Selection, and Fake News Identification

We use Seeking Alpha, an independent investor research website, as our setting. Seeking Alpha articles attract 15.2 million monthly readers and generate sizeable market reactions (e.g., Seeking Alpha, 2020; Kogan et al., 2023). Because many authors hide their identities behind pseudonyms, self-interested authors have the opportunity to manipulate market opinions through

fake news while minimizing reputational risks.[2] Seeking Alpha also offers easy access to filings with the Securities and Exchange Commission (SEC), earnings call transcripts, and press releases. The prominence and availability of accounting information to both authors and readers on Seeking Alpha facilitates our ability to detect the impact of accounting information on the publication behavior of fake news authors. Furthermore, Seeking Alpha covers a comprehensive range of public firms, allowing us to analyze a diverse cross-section of firms and increasing the external validity of our conclusions.

We obtain data from Seeking Alpha for all articles published between 2006 and 2018. For each article, we collect the text, author name, publication date, and the primary stock tickers associated with the firm(s) discussed. If an article lists multiple primary stock tickers, the article appears as multiple observations in our sample, with one observation linked to each ticker. We discard articles that lack a primary stock ticker and those authored by Seeking Alpha employees. These exclusions remove articles related to Seeking Alpha news updates, conference call transcripts, and broader topics such as the general economy that are not directly linked to a specific firm.

We follow the fake news classification methodology detailed by Kogan et al. (2023) to categorize articles as "fake" or "non-fake" using the Linguistic Inquiry Word Count (LIWC2015) model developed by Pennebaker, Booth, Boyd, and Francis (2015).[3] To ensure that the linguistic software has sufficient textual content for classification, we require each article to

---

[2] Interestingly, Rota Fortunae (from the Farmland Partners case discussed in a prior footnote) remained anonymous for almost two years of court proceedings and was found to be the subject of another lawsuit with similar allegations of promoting a "short-and-distort" scheme for a different firm, attesting to the difficulty of imposing reputational costs on authors who publish fake Seeking Alpha articles under a pseudonym.

[3] The linguistics literature documents that individuals who are being dishonest use fewer self-reference words, shorter sentences, less specific information about time and space, fewer insight words (e.g., know, consider, etc.), and more discrepancy words (e.g., could, should, etc.) (Pennebaker, 2011).

contain at least 100 words. We exclude articles that receive an ambiguous classification as neither fake nor non-fake. In addition, we require non-missing financial data from Compustat, CRSP, and IBES for the firm(s) matched to the articles. Our final sample includes 125,475 articles across 37,864 firm-quarters, with fake articles representing 2.5% of the total—a proportion that aligns closely with the 2.8% identified by Kogan et al. (2023). Table 1 provides a summary of our sample selection procedure.

3. The Content and Timing of Fake News

3.1   Content of Fake News Articles

We first provide content analysis and other broad-sample descriptive evidence on fake news.[4] We use Latent Dirichlet Allocation (LDA), a linguistic machine learning algorithm used to identify latent topics within a corpus of text, to characterize the content in our sample of articles.[5] We find that articles cover topics such as accounting information and forecasts, industry news, legal matters, and macroeconomic conditions, among others. Moreover, an individual article may span multiple topics (e.g., an article discussing both accounting forecasts and the pharmaceutical industry). Table 2, Panel A presents the list of our 30 identified topics. For each topic, we report the number of articles containing content for that topic in Column 1 and the percentage of articles classified as fake within all articles assigned to that topic in Column 2.

---

[4] In IA1 of the internet appendix, we discuss two examples of Seeking Alpha articles. The first is a fake bullish article about Galena Biopharma that helped prop up its stock price. The second is a non-fake article that disputed the unsubstantiated claims about this firm by referencing accounting information from 10-Qs, 10-Ks, and press releases; after the release of this second article, Galena Biopharma's stock price fell by 20%, partially offset the mispricing from the fake news. The author of the first article was subsequently investigated and penalized by the SEC for fraud.
[5] See IA2 and IA3 for implementation details of LDA.

We find that a substantial number of Seeking Alpha articles discuss accounting content. Specifically, the two topics pertaining to accounting information—Topics 5 and 25 (henceforth "accounting topics")—are among the top three most popular topics. In untabulated analyses, we find that 86% of all articles contain accounting content and that 32% of articles feature accounting information as their most prominent topic. To validate our LDA classification, we compute the percentage of words identified as "accounting words" within each article using the dictionary outlined by Lerman (2020) and tabulate the average percentage for articles under each topic in Column 3. We find that the percentage of "accounting words" is among the highest in accounting topics, validating our LDA approach in identifying articles with accounting content.

In Table 2, Panel B, we provide comparative statistics on the characteristics of fake and non-fake articles. Generally, our evidence suggests that fake articles use fewer words per article but more words per sentence. We also find that both the percentage of articles with accounting content and the percentage of "accounting words" used are lower for fake articles than for non-fake articles. We then investigate the proportions of fake and non-fake articles that convey positive or negative news. We identify the sentiment of the news associated with these articles using a return-based approach across multiple return thresholds. Specifically, we classify an article as positive if the firm's daily return on the article publication date is greater than or equal to 0.5%, 1%, or 2% and as negative if the return is less than or equal to -0.5%, -1%, or -2%.[6] Interestingly, we find that both the proportions of fake articles classified as positive and as negative exceed those of non-fake articles across all return thresholds. This evidence is

---

[6] For these and subsequent statistics that measure market reactions to articles, we remove articles where an earnings announcement, management forecast, 10-K, 10-Q, or 8-K, occurs within a t-2 to t+2 trading day window centered on the article publication date, as these events may confound the returns attributable to the articles on those dates.

consistent with the notion that fake news authors may publish sensational content in their articles to gain traction.

Lastly, we follow Kogan et al. (2023) in examining the magnitude of market reactions to the articles using two proxies: *Abnormal Volume* and *Idiosyncratic Return Volatility*. *Abnormal Volume* is the sum of scaled trading volume on the publication date of the Seeking Alpha article and the following two trading days, where scaled trading volume is calculated as the daily trading volume divided by the average trading volume over the prior 20 to 140 trading days. *Idiosyncratic Return Volatility* is the sum of squared abnormal returns on the article publication date and the following two trading days multiplied by 100, where abnormal returns are the daily return minus the return on a 5x5x5 size-, book-to-market-, and momentum-matched portfolio (Daniel, Grinblatt, Titman, and Wermers, 1997). We find that the market reacts more strongly to fake articles than to non-fake articles, attesting to the inability of market participants to distinguish fake news from non-fake news on average.[7]

3.2   *Time Trends of Fake News Articles*

We provide evidence on aggregate trends in fake news production during our sample period by plotting the number of fake articles by calendar year in Figure 1. We find that the number of fake articles exhibits a bimodal pattern over our sample period, with one peak occurring around 2007–2009 and a continuous increase from 2014 onwards. When we partition the data based on whether the fake articles contain accounting content, we observe the same bimodal distribution.

---

[7]   In untabulated analyses, we examine the differences in mean abnormal volume and idiosyncratic return volatility between fake articles with and without accounting content. We find that the market reacts just as strongly to fake articles with accounting content as to fake articles without accounting content.

Next, we examine the production of fake news relative to one of the most prominent accounting disclosure events: earnings announcements. We do so for three primary reasons. First, earnings announcements induce significant attention shocks and stimulate increased information search activity among investors. Second, these events introduce substantial and salient accounting information into the market. Third, earnings announcements are highly anticipated and often scheduled weeks or months in advance. Since Seeking Alpha authors have advance notice of the disclosure date and discretion over when to publish articles, we infer their preferences by examining the timing of article publications relative to earnings announcements.

To study the revealed preferences of fake news authors, we construct frequency distributions of fake article publications around earnings announcement dates. We first match our sample of articles to the earnings announcements of each firm for articles published within 45 days of the announcement date. We populate the variable *Days to EA* for each article by computing the fractional number of 24-hour periods between the article publication timestamp and the earnings announcement timestamp and rounding to the next integer away from zero. For example, *Days to EA* is -2 for an article published 26 hours and 12 minutes prior to an earnings announcement.[8] We then calculate *Fake Articles$_t$*, defined as the sum of all fake articles published on *Days to EA = t* across all earnings announcements.

---

[8] In Sections 3 and 4, we use the term "days" to refer to 24-hour periods relative to the start time of an earnings announcement. For example, the "day before the earnings announcement" for an announcement starting on May 17, 5:00 pm, would be defined as the 24-hour interval from May 16, 5:00 pm, to May 17, 4:59:59 pm, and the "day after the earnings announcement" would span May 17, 5:00 pm, to May 18, 4:59:59 pm. No articles in our data are published on the exact same minute as an earnings announcement. Hence, because fractional days are rounded away from zero, there are no articles classified as being published on day t=0 under this specification, and we do not consider day t=0 in any of our subsequent variable definitions and computations. We adopted this research design instead of calendar day definitions to ensure uniform day lengths and to precisely determine the publication timing of articles relative to earnings announcements, which is central to this analysis. Our main premise is that Seeking Alpha authors are intentional about when to write articles. If, for example, a firm releases earnings after market hours at 5pm, an article published at 11am likely reflects different intent than one published at 8pm. To capture these varying intentions, we use this 24-hour approach to be as precise as possible in determining when articles are published relative to earnings announcements.

Figure 2, Panel A depicts the resulting frequency distribution created from *Fake Articles_t* across *Days to EA*. We observe a general nondescript oscillation in the days outside the immediate vicinity of the earnings announcement. However, there is a marked increase in fake articles directly prior to earnings announcements that reverts quickly to baseline level two days afterward. Interestingly, the increase is asymmetric around earnings announcements, as the peak of the distribution occurs prior to the announcement. For comparison, we also plot the frequency distribution of non-fake articles in Panel B. We find that, while non-fake articles also increase dramatically around earnings announcements, the peak of the distribution occurs the day after the announcement and remains elevated for eight days.

3.3   The Attention and Information Effects of Accounting Information

We propose two aspects of accounting information events that help explain the pattern observed in the frequency distribution of fake news publication around earnings announcements: an attention effect and an information effect. We elaborate on the intuition behind these two effects and how they interact to shape the frequency distribution of fake news as follows.

Accounting information events, particularly highly anticipated ones like earnings announcements, elicit widespread market attention both before the forthcoming information and after its release (e.g., Beaver, 1968; Drake et al., 2012; Noh, So, and Verdi, 2021). Prior literature has documented opportunistic managerial disclosure choices intended to increase stock prices prior to high-attention events, such as seasoned equity offerings (e.g., Lang and Lundholm, 2000), investor conferences (e.g., Bushee, Taylor, and Zhu, 2020), and annual shareholder meetings (e.g., Dimitrov and Jain, 2011). Similarly, we conjecture that fake news authors are incentivized during periods of elevated market attention to publish more fake news; by doing so, they increase the probability of accumulating more article views and influencing

11

investor beliefs or behavior. Hence, we use "the attention effect" to refer to the increase in incentives to publish fake news articles around highly publicized accounting information events.

Recent developments in the theoretical strategic communications literature suggest that false price signals are less effective when a larger proportion of investors are informed (Schmidt, 2020). Furthermore, longstanding theoretical and empirical studies endorse the usefulness of accounting disclosures in increasing the precision of investor beliefs about fundamental value (i.e., the valuation role of accounting information) (e.g., Diamond, 1985; Dye, 1985; Verrecchia, 2001; Beyer, Cohen, Lys, and Walther, 2010). We conjecture that the endowment of accounting information to the market disincentivizes fake news authors from publishing fake news. Specifically, to the extent that the accounting information disclosed during earnings announcements helps investors evaluate the true asset value of the firm, it becomes more difficult for fake news authors to mislead investors. Thus, we use "the information effect" to refer to the reduction in incentives to publish fake news articles when the endowment of accounting information is high and investor susceptibility to false price signals is low.

We propose that the attention and information effects jointly produce the frequency distribution of fake articles observed in Figure 2, Panel A: (1) the attention effect induces a general increase in fake articles around earnings announcements, and (2) the information effect manifests as a relative dearth of fake articles immediately after the accounting disclosure is released, resulting in an asymmetric distribution that peaks prior to the earnings announcement but decreases rapidly afterward. In the remainder of the paper, we test how the attention and information effects impact the incentives of fake news authors to produce fake news.

4. Bunching Analyses of Fake News Publication Timing Preferences

4.1   Examining the Attention and Information Effects

To provide empirical evidence on the attention and information effects of accounting information, we formally test for distortions in fake news publication behavior around earnings announcements using the bunching approach. Bunching estimation is an empirical methodology developed in the economics literature to attribute distortions in behavior around a known threshold to a discontinuous change in incentives (e.g., Sallee, 2011; Kleven, 2016).[9],[10] In the context of our study, we use earnings announcements as salient temporal thresholds at which the incentives for fake news authors to publish change. If these accounting information events create distortions in fake news publication behavior consistent with the attention and information effects, we expect to observe the following in the frequency distribution of fake articles: (1) an excess mass around earnings announcements in general and (2) an excess mass prior to earnings announcements that exceeds the mass afterward.

We use the polynomial bunching approach to empirically test our conjectures about the distribution of fake news published around earnings announcements, as shown in Figure 2.[11] Following prior literature, we first identify the specific time window suspected to be affected by changes in incentives (i.e., the affected region) using visual inspection.[12] The distribution of fake articles in Figure 2, Panel A suggests that potentially abnormal publication behavior starts two

---

[9] This methodology has gained popularity in the public economics and finance literatures to study a diverse range of topics, such as taxpayer responses to tax schedule cutoffs and lenders' supply of credit in response to government loan guarantees (e.g., Saez, 2010; Chetty, Friedman, Olsen, and Pistaferri, 2011; Kleven and Waseem, 2013; Bachas, Kim, and Yannelis, 2021).

[10] Though it has different underlying assumptions, the bunching methodology is conceptually related to the distribution discontinuity methods used to study the effect of salient thresholds on earnings management behavior (e.g., Burgstahler and Dichev, 1997). In the context of earnings management, earnings distributions exhibit excess mass just above salient performance thresholds and missing mass just below.

[11] Additional details on the specification and implementation of the bunching approach we use are in IA4.

[12] We interchangeably use the terms "affected region," "earnings announcement window," and "announcement window."

days prior to earnings announcements and lasts until approximately two days post-announcement. Therefore, we set the affected region equal to t-2 to t+2.

We then model counterfactual fake news publication behavior—that is, how much we expect fake news authors to publish absent sharp changes in incentives. Following Chetty, Friedman, Olsen, and Pistaferri (2011), we fit a seventh-degree polynomial function to the distribution of fake articles outside the affected region. We compute *Abnormal Mass$_t$* as the difference between the observed number of fake articles and the counterfactual polynomial estimates of fake articles on day t. We then construct four different variables of interest: (1) *Pre EA Abnormal Mass$_{t-2,t-1}$* is the sum of *Abnormal Mass$_t$* for days t-2 and t-1; (2) *Post EA Abnormal Mass$_{t+1,t+2}$* is the sum of *Abnormal Mass$_t$* for days t+1 and t+2; (3) *Total Abnormal Mass$_{t-2,t+2}$* is the sum of *Pre EA Abnormal Mass$_{t-2,t-1}$* and *Post EA Abnormal Mass$_{t+1,t+2}$*; and (4) *Differential Abnormal Mass$_{t-2,t+2}$* is the difference between *Pre EA Abnormal Mass$_{t-2,t-1}$* and *Post EA Abnormal Mass$_{t+1,t+2}$*. We follow the bootstrap procedure of Chetty et al. (2011) to compute standard errors for statistical significance.

Table 3, Row 1 presents the results from our polynomial bunching procedure applied to the distribution of fake articles from Figure 2, Panel A. We find estimates that support our conjectures. Specifically, *Pre EA Abnormal Mass$_{t-2,t-1}$*, *Post EA Abnormal Mass$_{t+1,t+2}$*, and *Total Abnormal Mass$_{t-2,t+2}$* are all positive and significant. These results indicate that fake news authors publish more fake articles within the earnings announcement window than expected based on publication trends outside the window, providing statistical evidence consistent with the attention effect. *Differential Abnormal Mass$_{t-2,t+2}$* is also positive and significant, indicating that significantly more fake articles are published directly prior to the earnings announcement than directly afterward, offering prima facie support for the information effect.

To provide more rigorous evidence on the information effect, we use an alternative bunching approach: difference-in-bunching. Analogous to the difference-in-differences research design, difference-in-bunching isolates the proposed effect of an event on the observations of interest by using an alternative set of observations as the counterfactual. As noted for Figure 2, the distributions of fake articles and non-fake articles both exhibit sharp increases around earnings announcements, likely due to the fact that the broad incentives for Seeking Alpha authors to publish are linked to readership metrics (e.g., payment per view, internet clout, etc.) (Dyer and Kim, 2021). Therefore, using the distribution of non-fake articles as the counterfactual, we implement difference-in-bunching to isolate the information effect of earnings announcements, conditional on changes in publication behavior due to heightened market attention.[13]

Before comparing the fake and non-fake distributions, we briefly reexamine the distribution of non-fake articles in Figure 2, Panel B and present the corresponding polynomial bunching statistical estimates in Table 3, Row 2. We note that a visual inspection of the non-fake article distribution yields different days of elevated publication behavior relative to earnings announcements compared to that of fake articles; accordingly, we adjust the affected region to the t-2 to t+8 window for non-fake articles. We find that, similar to the distribution of fake articles, *Pre EA Abnormal Mass$_{t-2,t-1}$*, *Post EA Abnormal Mass$_{t+1,t+8}$*, and *Total Abnormal Mass$_{t-2,t+8}$* are all positive and significant, consistent with heightened market attention increasing the incentive to publish non-fake articles around earnings announcements. In contrast, as indicated

---

[13] Discussion and visual evidence on establishing parallel trends are in the internet appendix. As an additional safeguard against an inappropriate counterfactual, our standard errors derived from Chetty et al. (2011) represent differences in fake and non-fake article publication behavior outside the earnings announcement window. To the extent that these differences exhibit excess variance (i.e., a potential sign that the specified counterfactual is not meaningful), the standard error will be large and result in statistically insignificant estimates.

by a negative and significant *Differential Abnormal Mass$_{t-2,t+8}$,* there are substantially more non-fake articles published after earnings announcements than before.

The difference-in-bunching approach is conducted similarly to the polynomial bunching method, with two key differences. First, rather than using a polynomial estimate, *Abnormal Mass$_t$* is now defined as the difference between the distributions of fake and non-fake articles on day t. Second, due to the large difference in the scale of fake and non-fake articles, we normalize the number of fake articles published on day t by dividing by the total number of fake articles published on days t-45 to t+45 and similarly normalize the number of non-fake articles to facilitate comparison. Figure 3 plots *Abnormal Mass$_t$* over event time. A visually stark contrast in publication behavior pre- and post-announcement emerges: the abnormal density of fake articles bunches immediately prior to earnings announcements and exhibits a missing mass directly afterward. We interpret this evidence as consistent with fake news authors revealing strong preferences to publish prior to the revelation of accounting information during earnings announcements.

Table 3, Row 3 presents the bunching estimates corresponding to Figure 3 using t-2 to t+8 as the affected region. *Pre EA Abnormal Mass$_{t-2,t-1}$* is positive and significant, indicating that the density of fake articles exceeds that of non-fake articles by 5% in the pre-announcement period. *Post EA Abnormal Mass$_{t+1,t+8}$* is negative and significant, indicating that the density of fake articles is 11% lower than that of non-fake articles post-announcement. In addition, the difference between the two, captured by *Differential Abnormal Mass$_{t-2,t+8}$*, is positive and significant. These results statistically support the visual evidence in Figure 3 that the abnormal density of fake articles bunches prior to earnings announcements and exhibits a missing mass afterward. Row 4 performs the same procedure but uses the shortened t-2 to t+2 window used in

Row 1 as the affected region. Our results are robust to this alternative specification. Thus, our difference-in-bunching analyses find evidence consistent with the information effect. Specifically, conditional on publishing around earnings announcements, fake news authors strongly prefer to publish fake articles before earnings announcements and avoid publishing afterward, when market participants are less susceptible to fake news after an earnings release.

4.2   Partitioning by Investor Attention

To provide additional support for the attention effect, we compare the distributions of fake articles published surrounding earnings announcements with high and low investor attention—two distributions with known differences in attention-driven incentives. Specifically, we partition our sample of fake articles into high and low attention subsamples based on the Investor Search Volume Index (ISVI) (Da, Engelberg, and Gao, 2012; deHaan, Lawrence, and Litjens, 2021).[14] The high attention subsample comprises articles matched to firms that received a positive ISVI on the day of the earnings announcement in the prior quarter. If the attention effect influences the incentives of fake new authors to publish, we anticipate that more fake articles will be published around earnings announcements with high expected investor attention. Conversely, if investor attention does not impact the publication preferences of fake news authors, we should observe minimal differences in the distributions between the two subsamples.

Figure 4 presents the distributions of fake articles partitioned by investor attention. Polynomial bunching estimates for the high and low attention subsamples are shown in Table 3, Rows 5 and 6, respectively. First, we note that within each subsample, the estimates are generally consistent with the attention and information effects documented in the overall sample (Table 3, Row 1). We then compare the two distributions. Visual examination of Figure 4

---

[14] Analyses with ISVI use a reduced sample of articles from 2010 onwards due to data availability constraints.

suggests that substantially more fake articles are published around earnings announcements with high investor attention than with low investor attention. Statistical estimates of the differences between the two distributions are presented in Table 3, Row 7. We find that significantly more fake articles are published in the high attention subsample than in the low attention subsample during the pre-announcement, post-announcement, and combined announcement windows, as shown in Columns 1, 2, and 3, respectively.[15] Hence, our evidence from the investor attention subsample analyses is consistent with the attention effect: fake news authors publish more fake articles during periods when they expect greater investor attention.

4.3   Partitioning by Accounting Content

We next investigate whether our results on the attention and information effects are most pronounced in the subsample of fake articles with accounting content.[16] We expect the attention effect to manifest primarily in this subsample for the following reason. Because earnings announcements disclose important accounting information related to firm performance, such as earnings and revenues, investors engage in increased information search and acquisition about these accounting metrics (e.g., Chapman, 2018). Hence, consistent with the objective of maximizing the plausibility or visibility of their fake articles, fake news authors are more inclined to produce content with accounting themes that align with investors' heightened interests during this period.

We also expect the information effect to manifest in the subsample of fake articles specifically about accounting content. The information effect implies that fake articles containing

---

[15] While we tabulate Row 7, Column 4 for completeness, the interpretation of a difference in bunching (or lack thereof) between earnings announcements with high attention and those with low attention is unclear. We caution readers about drawing inferences based on the estimates of this cell.

[16] We use the same LDA methodology described in Section 3.1 to determine whether the fake article contains accounting content.

accounting content are more likely to be disproven once verifiable accounting information is released. As a result, we expect fake news authors to avoid publishing accounting-related articles after earnings announcements, when investors have access to reliable accounting disclosures.

To test these expectations, we conduct subsample bunching analyses by partitioning the fake articles based on whether they contain accounting content. Figure 5, Panel A displays the distribution of fake articles with accounting content around earnings announcements, with corresponding estimates from the polynomial bunching approach presented in Table 3, Row 8. Our inferences remain consistent with those from the full sample, showing a clear bunching pattern around earnings announcements. Figure 5, Panel B depicts the distribution of fake articles with no accounting content, with corresponding polynomial bunching estimates in Table 3, Row 9. A striking difference emerges between these two subsamples. Specifically, while the familiar bunching pattern is present in the distribution of fake articles containing accounting content, there is no meaningful publication pattern for fake articles with no accounting content.[17]

These results show that the attention and information effect are more prominent in the subsample of fake articles with accounting content. In addition, the absence of distributional patterns in the subsample of fake articles without accounting content suggests that our results are specifically tied to the disclosure of accounting information and not the general information environment.

Overall, we document evidence from our bunching analyses consistent with both the attention and information effects of accounting information events on fake news production. Specifically, we find that fake news authors publish more fake articles on the days surrounding earnings announcements, with relatively more fake articles published before the announcement

---

[17] For completeness, we tabulate the difference between these two distributions in Table 3, Row 10.

than afterward. These findings are consistent with fake news authors strategically choosing to publish more fake articles when investor attention is elevated but avoiding publication in periods characterized by a robust accounting information environment. Furthermore, consistent with the attention effect, we show that more fake articles are published around earnings announcements with higher investor attention than those with lower investor attention. We validate our main results by demonstrating that the bunching behavior manifests in a restricted subsample of articles containing accounting content but not within the subsample of articles without accounting content. This pair of findings provides reassurance that our proposed effects manifest in the subsample of articles where accounting information is particularly relevant and that the behavioral patterns we document are not artifacts of fake articles lacking accounting content.

5. Regression Analyses of Accounting Information and the Incentives to Publish Fake News

We further our investigation by exploring the interactions between the broader accounting information environment and the incentives to publish fake news. Specifically, we examine (1) the likelihood of fake news authors targeting firms with more robust accounting information environments and (2) the subsequent market impact of fake news that targets these firms. We use two proxies based on accounting information that are particularly salient to fake news authors: management forecast frequency and 10-K readability.[18]

---

[18] We note that we do not study other measures related to the accounting information environment, as they often require explicit estimation using statistical analyses (e.g., earnings persistence, abnormal accruals, conservatism, etc.). We view these measures as being less accessible and less prominent to fake news authors and therefore less likely to affect the publication of fake news articles.

5.1   Measures of Accounting Information

5.1.1   Management Forecast Frequency

Management forecasts are prominent voluntary disclosures that reduce information asymmetry in the market (e.g., Verrecchia, 2001; Healy and Palepu, 2001; Beyer et al., 2010). In addition, prior literature documents several ways in which management forecasts inform investors, including projecting key line items in financial statements (Lansford, Lev, and Tucker, 2013), clarifying complexities in business transactions (Guay, Samuels, and Taylor, 2016), and reducing uncertainty in the business environment (Billings, Jennings, and Lev, 2015).

Given that management forecasts provide detailed forward-looking information about earnings, sales, and growth opportunities, fake news authors may be less inclined to target firms that issue frequent forecasts. The availability of such information makes it more difficult for misleading portrayals of future firm prospects to sway investors. We measure *Management Forecast Frequency* as the natural logarithm of one plus the number of management forecasts a firm has issued within the past year relative to the Seeking Alpha article publication date.

5.1.2   10-K Readability

Our second proxy, the linguistic readability of the firm's 10-Ks, captures a prominent element of accounting information quality. Despite the fact that 10-Ks contain mandatory disclosures crafted to follow standards set forth by the Financial Accounting Standards Board and vetted by legal and audit teams, there is considerable variation in their writing style and length (e.g., Li, 2008; Bonsall, Leone, Miller, and Rennekamp, 2017). Clearer textual disclosures reduce information acquisition and integration costs, allowing investors to incorporate more information from the disclosures into their valuations and investment decisions (e.g., Blankespoor, deHaan, and Marinovic, 2020). If investors can more easily glean narrative

21

information from a firm's annual reports about its operating environment, such as product line synergies, peer competition, and risk factors, fake news authors may be less likely to target this firm. We measure *10-K Readability* using the Bog Index from Bonsall et al. (2017) of the firm's most recent 10-K as of the article publication date, multiplied by -1 for ease of interpretation so that higher values indicate greater readability.

5.2   The Role of Accounting Information in Disincentivizing Fake News Production

We examine whether accounting information is associated with the conditional probability that an article about a firm is fake. We expect that an increase in *Management Forecast Frequency* or *10-K Readability* corresponds to a decrease in the probability that a fake article is written. We estimate the following model at the article level:

$$Pr(Fake\ Article) = \beta_1\ Accounting\ Information + \sum Controls + \sum Fixed\ Effects + \varepsilon. \qquad (1)$$

Fake Article is an indicator variable equal to one when the article is classified as fake and zero when non-fake. *Accounting Information* is either *Management Forecast Frequency* or *10-K Readability*, as defined in Section 5.1. In all our specifications, we include a vector of control variables that reflect the firm's external information environment or operating environment: adjusted ROA, analyst coverage, number of business segments, institutional ownership, market-to-book ratio, media coverage, past returns, and size. Appendix A contains definitions for our variables. We also include industry and year fixed effects to control for unobserved heterogeneity along these two dimensions that could be correlated with both our accounting information variables and our dependent variables. Table 4 contains descriptive statistics for our primary regression variables.

Table 5, Panel A presents the results of estimating Equation (1) using logistic regression. To interpret the coefficients as percentage changes, we present them as marginal effect estimates

multiplied by 100 and discuss economic magnitudes relative to the unconditional probability that an article is fake. In Column 1, we find a negative and significant coefficient for *Management Forecast Frequency*, indicating that a one-standard-deviation increase in *Management Forecast Frequency* reduces the probability that the article is fake by 8%. Column 2 shows a negative and significant coefficient for *10-K Readability*, which suggests that a one-standard-deviation increase in *10-K Readability* decreases the probability of a fake article by 10%. In Column 3, we include both accounting information variables to examine whether each has an incremental effect on the production of fake news. The coefficient estimates for both variables remain significant in the expected directions without notable decreases in magnitude. Thus, our evidence suggests that the main independent variables capture distinct aspects of accounting information and offer convergent validity for our results that fake news authors are less likely to target firms with more robust accounting information environments.[19]

We briefly note the coefficient estimates on a few control variables. There is some evidence that *Analyst Coverage* is negatively associated with fake news publication, consistent with analysts improving the information environment of firms and reducing investor susceptibility to fake news. *Institutional Ownership* is insignificant, suggesting that fake news authors do not incrementally consider the shareholder base in their decisions to publish fake news. *Media Coverage* is positive and significant, with an economic magnitude of 13%, comparable to our effect estimates for the accounting information variables of 8%–10%. This result indicates that more media attention is associated with a higher probability of a fake article.

---

[19] Our results in Column 3 are robust to a number of sensitivity analyses, which are tabulated in IA5. Specifically, our results are robust to using time period subsamples, shortening the window for measuring management forecast frequency to 180 or 90 days, and dropping industry-years with less than 50 observations. Additionally, see IA6 for a visual analysis of Equation (1) using ordinary least squares estimation and binned scatterplots.

These results are consistent with some professional information intermediaries or firm monitors influencing the incentives to produce fake news.

One potential concern with using non-fake news as a benchmark in our model is that our results are subject to an alternative explanation that accounting information increases the incentives to produce non-fake news rather than decreasing the incentives to produce fake news. To mitigate this concern, we use an alternative specification using observations at the firm-quarter level. The dependent variable is *Fake Article (Quarter)*, an indicator variable equal to one when there is one or more fake articles published about the firm in the quarter and zero otherwise. We note in Table 4 that 7.4% of firm-quarters have at least one fake article, demonstrating the relative prominence of fake news on a quarterly basis despite constituting 2.5% of the total number of articles written. Table 5, Panel B presents the results of estimating this alternative specification. We continue to find negative and significant coefficients for *Management Forecast Frequency* and *10-K Readability*, suggesting that a more robust accounting information environment reduces the likelihood of fake articles being written about a firm during a given quarter.

We address a few other concerns about potential biases in our Table 5 results by conducting a series of additional tests presented in Table 6. These additional tests use the same specification as Table 5, Panel A, Column 3, unless noted otherwise, but for parsimony, we only report the coefficients for our accounting information variables. We first address the concern that our results are contaminated by the publication of fake non-accounting articles that accounting information is less likely to influence. Rows 1 and 2 of Table 6 present our main specification partitioning by whether the article contains accounting content. In Row 1, both accounting information coefficients remain statistically significant in the expected direction within articles

24

that contain accounting content. However, within articles that contain no accounting content (Row 2), we find statistically insignificant coefficients for both accounting information variables, providing falsification evidence against correlated omitted variables that affect the publication of fake articles that do not pertain to accounting information. This pair of analyses provides assurance that our results are driven by articles for which accounting information is relevant.

Next, we address the concern that firm performance determines both accounting disclosure policy and the incentives to publish fake news. Prior literature documents that poor performance is associated with decreased voluntary disclosure or 10-K readability (e.g., Li, 2008; Chen, Matsumoto, and Rajgopal, 2011). We currently use return on assets, short-run past returns, and long-run past returns as control variables to account for the possibility of performance as a correlated omitted variable. As additional tests, we estimate our model within subsamples partitioned by the sign of the earnings surprise in the most recent earnings announcement and tabulate the results in Table 6, Rows 3 and 4. We continue to find statistically significant results for both accounting information variables in each partition, reducing the concern of firm performance as an omitted variable.

We next conduct a host of subsample analyses to mitigate the concern that our independent variables of interest capture the quality of the general information environment around the firm rather than accounting information disclosed by the firm. To the extent that firms providing management forecasts or readable 10-Ks systematically have better general information environments, fake news authors may be considering the broader information environment in their publication decisions rather than accounting disclosures in particular. To alleviate this concern, we conduct our main test on subsamples partitioned by whether the firm provided at least one management forecast in the prior year as well as by median analyst

coverage, institutional ownership, and size, as prior literature shows these characteristics to be important in determining a firm's general information environment (e.g., Beyer et al., 2010). We tabulate these results in Table 6, Rows 5–12 and find statistically significant and economically meaningful coefficients within each subsample, with the exception of insignificant coefficients on *Management Forecast Frequency* in the low analyst coverage and small size groups. Overall, even when we estimate our model within subsamples of firms with similar characteristics to limit the amount of unobserved variation, we continue to find evidence largely supporting our main inferences that fake news authors strategically avoid targeting firms with relatively more robust accounting information environments.

5.3   The Role of Accounting Information in Reducing the Market Reaction to Fake News

Lastly, we examine whether accounting information impacts the market reaction to the fake news ultimately published. In accordance with the information effect, we expect investors to react less to fake articles about firms with strong accounting information environments for two primary reasons. First, investors may use accounting information to cast doubt on or disprove disinformation, resulting in decreased investor reaction to the fake news. Two, anticipating this possibility, fake news authors may limit the extent of their embellished or unsubstantiated claims to still elicit a market response. To test our prediction, we estimate the following model using ordinary least squares regression at the article level:

$$Market\ Reaction_{t,t+2} = \beta_1\ Accounting\ Information + \sum Controls + \sum Fixed\ Effects + \varepsilon. \quad (2)$$

Following Kogan et al. (2023), our dependent variable *Market Reaction* is one of two variables used to measure the market response to fake Seeking Alpha articles from day *t* to *t+2*: *Abnormal Volume*, which is based on trading activity, and *Idiosyncratic Return Volatility*, which

is based on price movement.[20] We use both trade-based and price-based reaction variables to present a more holistic view of the market's response to fake news and to mitigate concerns that excess trading can occur without impacting prices (e.g., Fama, 1970) or that substantial price movements can occur without corresponding trade volume (e.g., Milgrom and Stokey, 1982).

In addition, we exclude articles from these analyses if an earnings announcement, management forecast, 10-K, 10-Q, or 8-K occurs within a t-2 to t+2 trading day window centered on the article publication date because we cannot disentangle the market reaction to these events from the reaction to the Seeking Alpha articles. We continue to use the control variables and fixed effects described in Section 5.2. To control for other potential unobserved events, we also include single-day measurements of our two market reaction variables for each of the three trading days before the article publication date as additional variables in our model.

Table 7 presents the results examining whether accounting information affects the market reaction to fake news. Panel A estimates Equation (2) with *Abnormal Volume* as the dependent variable. In Column 1, we estimate a negative and significant coefficient on *Management Forecast Frequency*. Specifically, we find that a one-standard-deviation increase in *Management Forecast Frequency* is associated with a 3% decrease in *Abnormal Volume*. In Column 2, we again obtain a negative and significant coefficient for *10-K Readability.* A one-standard-deviation increase in *10-K Readability* is associated with a 7% decrease in *Abnormal Volume*. Column 3 estimates Equation (2) with the inclusion of both accounting information variables,

---

[20] We note that our definition of "days" in these tests differ from that in the bunching analyses in Sections 3 and 4. To match articles to their corresponding market reactions, we define "days" following conventions in the literature for studying market responses to information releases, such as earnings announcements. Specifically, we define t as the publication date of the article but adjust t to be the first trading day following the publication date for articles published after market close or on non-trading days (e.g., weekends).

and we find that both coefficient estimates remain significant in the expected directions without notable decreases in magnitude.

Table 7, Panel B reports the results from estimating Equation (2) using *Idiosyncratic Return Volatility* as the dependent variable. In Column 1, we find that a one-standard-deviation increase in the number of management forecasts is associated with a 13% decrease in return volatility. In Column 2, a one-standard-deviation increase in *10-K Readability* is associated with a 21% lower *Idiosyncratic Return Volatility*. Again, our estimates in Column 3, which includes both accounting information variables, are consistent with those from Columns 1 and 2. Overall, our findings suggest that the market reaction to fake news is attenuated when the targeted firm has a strong accounting information environment.

6. Conclusion

This study explores the intersection of accounting information and the strategic incentives to disseminate fake news in financial markets. Specifically, we investigate two main research questions: (1) How do fake news authors strategically time their articles around significant accounting information events, such as earnings announcements? (2) How does the broader accounting information environment affect the likelihood of fake news publication and its market reaction?

With respect to significant accounting information events, such as earnings announcements, we show both attention- and information-based effects on the strategic publication decisions of fake news authors. Specifically, they publish during periods of elevated market attention around these events to enhance the visibility of their articles. However, within

28

the near-announcement window, they avoid publishing fake news post-announcement when the disclosure of accounting information reduces investor susceptibility to disinformation.

We extend our analysis to the broader accounting information environment, finding that firms with more frequent management forecasts or more readable annual reports attract fewer fake news articles and experience lower market reactions when such articles are published. These results provide evidence of both ex-ante and ex-post roles of accounting information in safeguarding firms from financial disinformation. Ex-ante, robust accounting disclosures dissuade fake news authors from targeting firms with well-informed investors. Ex-post, when fake news is published, the market reaction is attenuated for firms with strong accounting environments.

Our results carry important implications for both market participants and policymakers. For firms, the findings suggest that strengthening accounting disclosures can reduce their vulnerability to disinformation. For investors, our study highlights the benefits of using accounting information during the information search process to counteract the adverse effects of fake news on their decision-making. For regulators, our evidence underscores the importance of transparent and accessible financial reporting as a mechanism for protecting market integrity. Nevertheless, stakeholders should be cognizant of the increased risk of fake news around highly anticipated accounting information events.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used ChatGPT in order to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

References

American Bar Association, 2019. Misinformation poses threat to business, political process. Available at: https://www.americanbar.org/news/abanews/aba-news-archives/2019/12/misinformation-poses-threat.

Bachas, N., Kim, O.S., Yannelis, C., 2021. Loan guarantees and credit supply. *Journal of Financial Economics 139* (3), 872–894. https://doi.org/10.1016/j.jfineco.2020.08.008.

Backus, M., Conlon, C., Sinkinson, M., 2021. Common Ownership in America: 1980–2017. *American Economic Journal: Microeconomics 13* (3), 273-308. https://doi.org/10.1257/mic.20190389.

Beaver, W. H., 1968. The Information Content of Annual Earnings Announcements. *Journal of Accounting Research 6*, 67–92. https://doi.org/10.2307/2490070.

Beyer, A., Cohen, D.A., Lys, T.Z., Walther, B.R., 2010. The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics 50* (2-3), 296-343. https://doi.org/10.1016/j.jacceco.2010.10.003.

Billings, M.B., Jennings, R. Lev, B., 2015. On guidance and volatility. *Journal of Accounting and Economics 60* (2-3), pp.161-180. https://doi.org/10.1016/j.jacceco.2015.07.008.

Blankespoor, E., deHaan, E., Marinovic, I., 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics 70* (2-3), 101344. https://doi.org/10.1016/j.jacceco.2020.101344.

Bonsall, S.B., Leone, A.J., Miller, B.P., Rennekamp, K., 2017. A plain English measure of financial reporting readability. *Journal of Accounting and Economics 63* (2-3), 329-357. https://doi.org/10.1016/j.jacceco.2017.03.002.

Burgstahler, D., Dichev, I., 1997. Earnings management to avoid earnings decreases and losses. *Journal of Accounting and Economics 24* (1), 99-126. https://doi.org/10.1016/S0165-4101(97)00017-7.

Bushee, B.J., Taylor, D.J., Zhu, C., 2023. The dark side of investor conferences: Evidence of managerial opportunism. *The Accounting Review 98* (4), 33-54. https://doi.org/10.2308/TAR-2020-0624.

Carvana. 2019. Prospectus Supplement. Available from: sec.gov/Archives/edgar/data/1690820/000119312519155493/d746066d424b2.htm.

Chapman, K., 2018. Earnings notifications, investor attention, and the earnings announcement premium. *Journal of Accounting and Economics 66* (1), 222-243. https://doi.org/10.1016/j.jacceco.2018.05.002.

Chen, S., Matsumoto, D., Rajgopal, S., 2011. Is silence golden? An empirical analysis of firms that stop giving quarterly earnings guidance. *Journal of Accounting and Economics 51* (1-2), 134-150. https://doi.org/10.1016/j.jacceco.2010.10.006.

Chetty, R., Friedman, J.N., Olsen, T., Pistaferri, L., 2011. Adjustment costs, firm responses, and micro vs. macro labor supply elasticities: evidence from Danish tax records. *Quarterly Journal of Economics 126* (2), 749–804. http://dx.doi.org/10.1093/qje/qjr013.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. *The Journal of Finance 66* (5), 1461-1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance 52* (3), 1035-1058. https://doi.org/10.1111/j.1540-6261.1997.tb02724.x.

De Franco, G., Lu, H., Vasvari, F.P., 2007. Wealth transfer effects of analysts' misleading behavior. *Journal of Accounting Research 45* (1), 71-110. https://doi.org/10.1111/j.1475-679X.2007.00228.x.

deHaan, E., Lawrence, A., Litjens, R., 2021. Measurement error in Google ticker search. *Working Paper.* http://dx.doi.org/10.2139/ssrn.3398287.

Diamond, D.W., 1985. Optimal Release of Information by Firms. *The Journal of Finance 40* (4), 1071-1094. https://doi.org/10.2307/2328395.

Dimitrov, V., Jain, P.C., 2011. It's showtime: Do managers report better news before annual shareholder meetings? *Journal of Accounting Research 49* (5), 1193-1221. https://doi.org/10.1111/j.1475-679X.2011.00419.x.

Drake, M.S., Roulstone, D.T., Thornock, J.R., 2012. Investor Information Demand: Evidence from Google Searches Around Earnings Announcements. *Journal of Accounting Research 50*, 1001-1040. https://doi.org/10.1111/j.1475-679X.2012.00443.x.

Drake, M.S., Roulstone, D.T., Thornock, J.R., 2015. The determinants and consequences of information acquisition via EDGAR. *Contemporary Accounting Research 32* (3), 1128-1161. https://doi.org/10.1111/1911-3846.12119.

Dye, R.A., 1985. Disclosure of Nonproprietary Information. *Journal of Accounting Research 23* (1), 123-145. https://doi.org/10.2307/2490910.

Dyer, T., Kim, E., 2021. Anonymous Equity Research. *Journal of Accounting Research 59* (2), 575-611. https://doi.org/10.1111/1475-679X.12359.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance 25* (2), 383-417. https://doi.org/10.2307/2325486.

Farmland Partners, Inc., 2018. Farmland Partners Inc. Responds to Unfounded Allegations. Available from: http://ir.farmlandpartners.com/file/Index?KeyFile=394184917.

Grant, S.M., Hodge, F.D., Seto, S.C., 2024. The Value of Investors Being in a Deliberative Mindset When Reading News Later Revealed to Be Fake. *Journal of Financial Reporting 9* (1), 73-94. https://doi.org/10.2308/JFR-2022-016.

Guay, W., Samuels, D., Taylor, D., 2016. Guiding through the Fog: Financial statement complexity and voluntary disclosure. *Journal of Accounting and Economics 62* (2-3), 234-269. https://doi.org/10.1016/j.jacceco.2016.09.001.

Healy, P.M., Palepu, K.G., 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics 31* (1-3), 405-440. https://doi.org/10.1016/S0165-4101(01)00018-0.

Jia, W., Redigolo, G., Shu, S., Zhao, J., 2020. Can social media distort price discovery? Evidence from merger rumors. *Journal of Accounting and Economics 70* (1), 101334. https://doi.org/10.1016/j.jacceco.2020.101334.

Kleven, H.J., 2016. Bunching. *Annual Review of Economics 8*, 435-64. https://doi.org/10.1146/annurev-economics-080315-015234.

Kleven, H., Waseem, M., 2013. Using notches to uncover optimization frictions and structural elasticities: theory and evidence from Pakistan. *Quarterly Journal of Economics 128* (2), 669-723. https://doi.org/10.1093/qje/qjt004.

Kogan, S., Moskowitz, T.J., Niessner, M., 2023. Social media and financial news manipulation. *Review of Finance 27* (4), 1229-1268. https://doi.org/10.1093/rof/rfac058.

Landsman, W., Maydew, E., 2002. Has the Information Content of Quarterly Earnings Announcements Declined in the Past Three Decades? *Journal of Accounting Research 40* (3), 797-808. https://doi.org/10.1111/1475-679X.00071.

Lang, M.H., Lundholm, R.J., 2000. Voluntary disclosure and equity offerings: reducing information asymmetry or hyping the stock? *Contemporary Accounting Research 17* (4), 623-662. https://doi.org/10.1506/9N45-F0JX-AXVW-LBWJ.

Lansford, B., Lev, B., Tucker, J.W., 2013. Causes and Consequences of Disaggregating Earnings Guidance. *Journal of Business Finance & Accounting 40* (1-2), 26-54. https://doi.org/10.1111/jbfa.12002.

Lazer, D., Baum, M., Benkler, J., Berinsky, A., Greenhill, K., Menczer, F., Metzger, M., Nyhan, B., Pennycook, G., Rothschild, D., Sloman, S., Sunstein, C., Thorson, E., Watts, D., Zittrain, J., 2018. The science of fake news. *Science 359* (6380): 1094-1096. https://doi.org/10.1126/science.aao2998.

Lerman, A., 2020. Individual investors' attention to accounting information: evidence from online financial communities. *Contemporary Accounting Research 37* (4), 2020-2057. https://doi.org/10.1111/1911-3846.12603.

Leuz, C., Meyer, S., Muhn, M., Soltes, E., Hackethal, A., 2017. Who Falls Prey to the Wolf of Wall Street? Investor Participation in Market Manipulation. In *National Bureau of Economic Research Working Paper Series*. https://doi.org/10.3386/w24083.

Li, F., 2008. Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics 45* (2-3), 221-247. https://doi.org/10.1016/j.jacceco.2008.02.003.

Milgrom, P., Stokey, N., 1982. Information, trade and common knowledge. *Journal of Economic Theory 26* (1), 17-27. https://doi.org/10.1016/0022-0531(82)90046-1.

Mourão, R.R., Robertson, C.T., 2019. Fake news as discursive integration: An analysis of sites that publish false, misleading, hyperpartisan and sensational information. *Journalism Studies 20* (14), 2077-2095. https://doi.org/10.1080/1461670X.2019.1566871.

Noh, S., So, E.C., Verdi, R.S., 2021. Calendar rotations: A new approach for studying the impact of timing using earnings announcements. *Journal of Financial Economics 140* (3), 865-893. https://doi.org/10.1016/j.jfineco.2021.01.009.

Plymouth Industrial REIT, 2019. *Q3 2019 Earnings Conference Call.* Available from: sec.gov/Archives/edgar/data/1515816/000117152019000338/ex99-1.htm.

Pennebaker, J., Booth, R., Boyd, R., Francis, M., 2015. *Linguistic inquiry and word count: LIWC 2015 operator's manual*.

Pennebaker, J.W., 2011. *The Secret Life of Pronouns: What Our Words Say About Us.* Chapter 6. New York: Bloomsbury Press.

Regen BioPharma, 2019. *Regen BioPharma, Inc. Responds to Fake News Release.* Available from: sec.gov/Archives/edgar/data/1589150/000160706219000195/ex99_1.htm.

Saez, E., 2010. Do taxpayers bunch at kink points? *American Economic Journal: Economic Policy 2* (3),180–212. https://doi.org/10.1257/pol.2.3.180.

Sallee, J.M., 2011. The Surprising Incidence of Tax Credits for the Toyota Prius. *American Economic Journal: Economic Policy 3* (2), 189-219. https://doi.org/10.1257/pol.3.2.189.

Schmidt, D., 2020. Stock market rumors and credibility. *Review of Financial Studies 33* (8), 3804-3853. https://doi.org/10.1093/rfs/hhz120.

Securities and Exchange Commission, 2014. SEC vs. Lidingo Holdings LLC et al. Available from: https://www.sec.gov/litigation/complaints/2017/comp23802-lidingo.pdf.

Securities and Exchange Commission, 2017. SEC: Payments for Bullish Articles on Stocks Must Be Disclosed to Investors. Available at: https://www.sec.gov/news/press-release/2017-79.

Securities and Exchange Commission, 2022. SEC Charges Eight Social Media Influencers in $100 Million Stock Manipulation Scheme Promoted on Discord and Twitter. Available at: https://www.sec.gov/newsroom/press-releases/2022-221.

Securities Class Action Clearinghouse, 2014. Cho et al. vs. Galena Biopharma, Inc. et al. Available from: https://securities.stanford.edu/filings-documents/1051/GBI00_01/20141031_r01c_14CV00367.pdf.

Seeking Alpha, 2020. Who Reads Seeking Alpha. Available from: https://seekingalpha.com/page/who_reads_sa.

Verrecchia, R.E., 2001. Essays on disclosure. *Journal of Accounting and Economics 32* (1-3), 97-180. https://doi.org/10.1016/S0165-4101(01)00025-8.

Weiner, B.P.M., Weber, R.D., Hsu, K., 2017. The growing menace of 'short and distort' campaigns. *Westlaw Journal Securities Litigation & Regulation*.

Appendix A: Variable Definitions

Variable	Definition
Dependent Variables:	
Fake Article$_t$	An indicator variable equal to one when the Seeking Alpha article is classified as fake and zero when non-fake using the methodology in Kogan et al. (2023). Source: Seeking Alpha
Fake Article (Quarter)$_q$	An indicator variable equal to one when there is one or more fake articles published about the firm in the quarter and zero otherwise. Source: Seeking Alpha
Abnormal Volume$_{t,t+2}$	The sum of scaled trading volume on the publication date of the Seeking Alpha article and the following two trading days, where scaled trading volume is calculated as the daily trading volume divided by the average trading volume over the prior 20 to 140 trading days. Source: CRSP
Idiosyncratic Return Volatility$_{t,t+2}$ (%)	The sum of squared abnormal returns on the article publication date and the following two trading days multiplied by 100, where abnormal returns are the daily return minus the return on a 5x5x5 size-, book-to-market-, and momentum-matched portfolio. Source: CRSP
Accounting Information Variables:	
Management Forecast Frequency$_{t-365,t}$	The natural logarithm of one plus the number of management forecasts in the past year. Source: IBES
10-K Readability$_{y-1}$	The Bog Index from Bonsall et al. (2017) of the firm's most recent 10-K as of article publication date *t* multiplied by -1. This variable is available for 10-Ks filed on or prior to March 31st, 2018. Source: Sam Bonsall Data Library (https://sites.psu.edu/sambonsall/data/)

(Continued)

Appendix A: Variable Definitions (Continued)

Variable	Definition
Control Variables:	
Adj. ROA$_{q-1}$	Return on assets (i.e., earnings before extraordinary items divided by total assets) less the average return on assets for firms within the same two-digit standard industrial classification code, year, and quarter. Source: Compustat
Analyst Coverage$_{q-1}$	The natural logarithm of one plus the number of analysts who provided an EPS forecast between the prior quarter's earnings announcement and two days before the forecasted earnings announcement. Source: IBES
Business Segments$_{y-1}$	The number of segments with non-zero revenue in the Compustat Segments file as of the prior fiscal year-end. Source: Compustat
Institutional Ownership$_{q-1}$	The sum of shares owned by institutional investors scaled by the number of shares outstanding. This value is set equal to zero if no institutional ownership is reported and set equal to one if reported institutional ownership exceeds shares outstanding. Source: Backus et al. (2021) via Michael Sinkinson Data Library (https://sites.google.com/view/msinkinson/research/common-ownership-data)
M/B$_{q-1}$	Market value of equity scaled by book equity. Source: Compustat
Media Coverage$_{t-180,t}$	The natural logarithm of one plus the number of news articles about the firm within the past 180 days. Source: RavenPack Analytics Dow Jones Edition
Returns$_{m-12,m-1}$	The firm's returns over the 12-month period ending the month prior to the article publication date. Source: CRSP
Returns$_{t-10,t-1}$	The firm's returns over the 10-trading day period ending the day prior to the article publication date. Source: CRSP
Size$_{q-1}$	The natural logarithm of market value of equity. Source: Compustat

(Continued)

Appendix A: Variable Definitions (Continued)

Variable	Definition
Bunching Variables:	
Days to EA_t	The signed number of 24-hour blocks between the time of Seeking Alpha article publication and the earnings announcement rounded away from zero to the next integer. For example, an article published 26 hours prior to (after) an earnings announcement is classified as being two days prior to (after) an earnings announcement.
Fake Articles$_t$	The number of fake articles published on *Days to EA_t* summed across all earnings announcements and scaled by the total number of fake articles in the sample.
Non-Fake Articles$_t$	The number of non-fake articles published on *Days to EA_t* summed across all earnings announcements and scaled by the total number of non-fake articles in the sample.
Abnormal Mass$_t$	The difference between *Fake Articles$_t$* and *Non-Fake Articles$_t$*.
Pre EA Abnormal Mass$_{t-2,t-1}$	The sum of *Abnormal Mass$_t$* for days t-2 and t-1.
Post EA Abnormal Mass$_{t+1,t+2}$	The sum of *Abnormal Mass$_t$* for days t+1 and t+2.
Differential Abnormal Mass$_{t-2,t+2}$	The difference between *Pre EA Abnormal Mass$_{t-2,t-1}$* and *Post EA Abnormal Mass$_{t+1,t+2}$*.
Total Abnormal Mass$_{t-2,t+2}$	The sum of *Abnormal Mass$_t$* for days between t-2 and t+2.

This table presents the definitions for the primary variables used in our analyses. For the dependent variables, accounting information variables, and control variables, the y, q, m, and t subscripts represent year, quarter, month, and day, respectively, and represent when the variable is measured relative to article publication on day t. Unless otherwise noted, our dependent variables and accounting information variables are measured as of the article publication date. Analyst coverage is measured as of the most recent earnings announcement occurring on or before article publication. Accounting data and market values are measured as of the fiscal quarter-end in which the earnings announcement for the quarter occurs on or before article publication. For the bunching variables, t represents the event date relative to the earnings announcement occurring at $t = 0$.

Figure 1: Fake News Publication Over Time for Articles With and Without Accounting Content
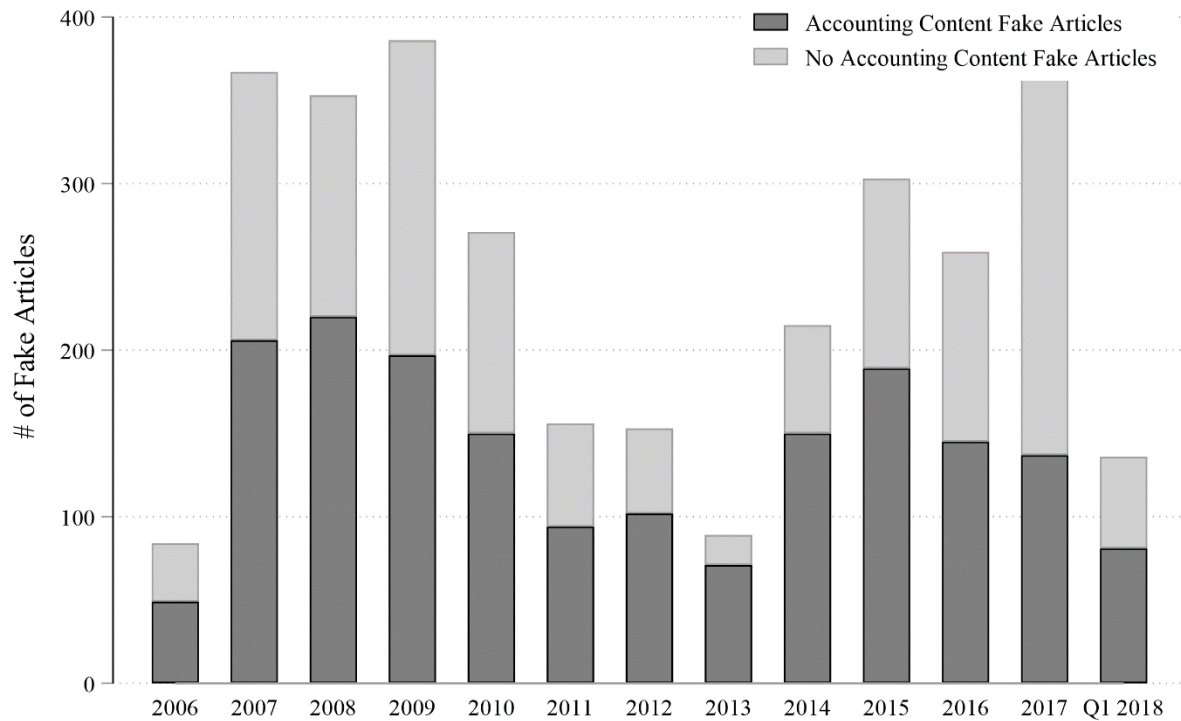
This figure presents the number of articles published on Seeking Alpha that are classified as fake using the methodology in Kogan et al. (2023) for each year during our sample. Within the total number of fake articles published each year, the figure also shows the number of fake articles containing accounting content. Note that our sample only includes the first three months of 2018 due to data availability.

Figure 2: Distributions of Fake and Non-Fake Seeking Alpha Articles Around Earnings Announcements
Panel A: Distribution of Fake Articles Around Earnings Announcements
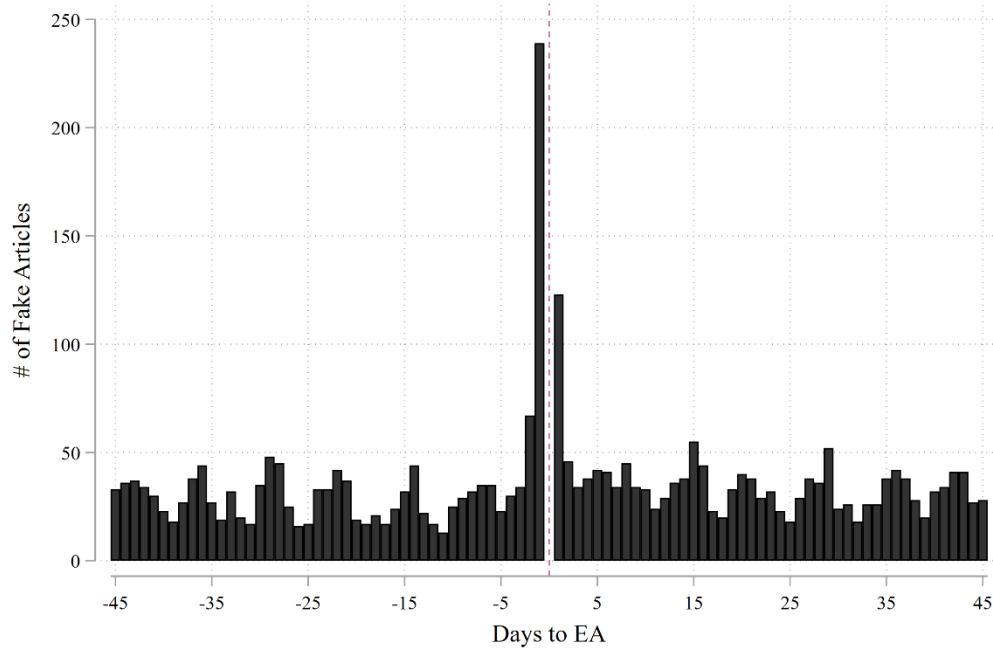
Panel B: Distribution of Non-Fake Articles Around Earnings Announcements
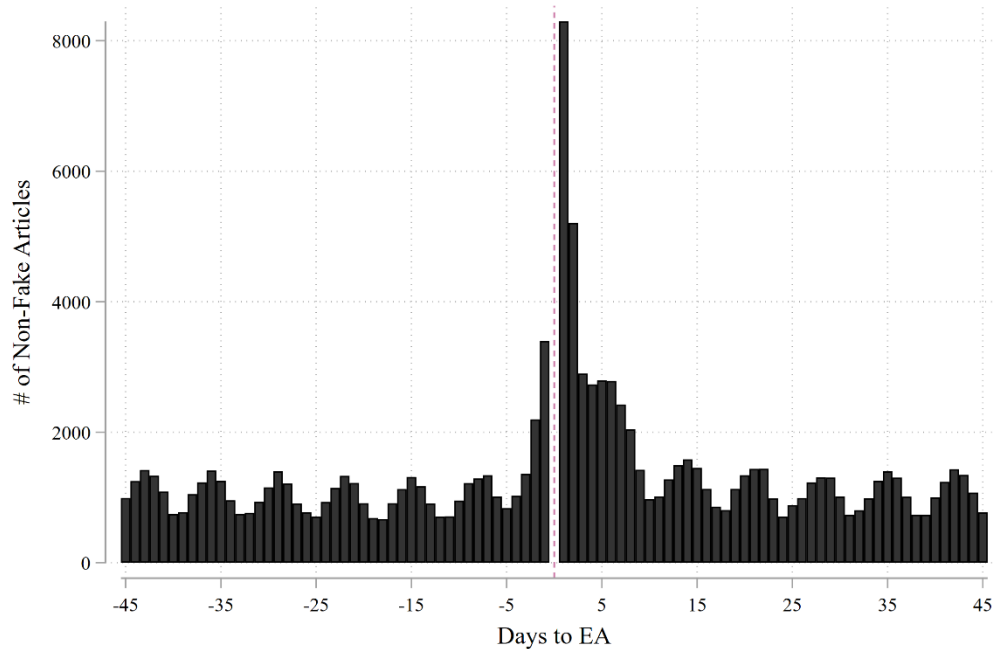
This figure presents graphical evidence on the publication timing of fake and non-fake articles relative to earnings announcements. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles.

Figure 3: Differential Abnormal Mass of Fake Articles Around Earnings Announcements
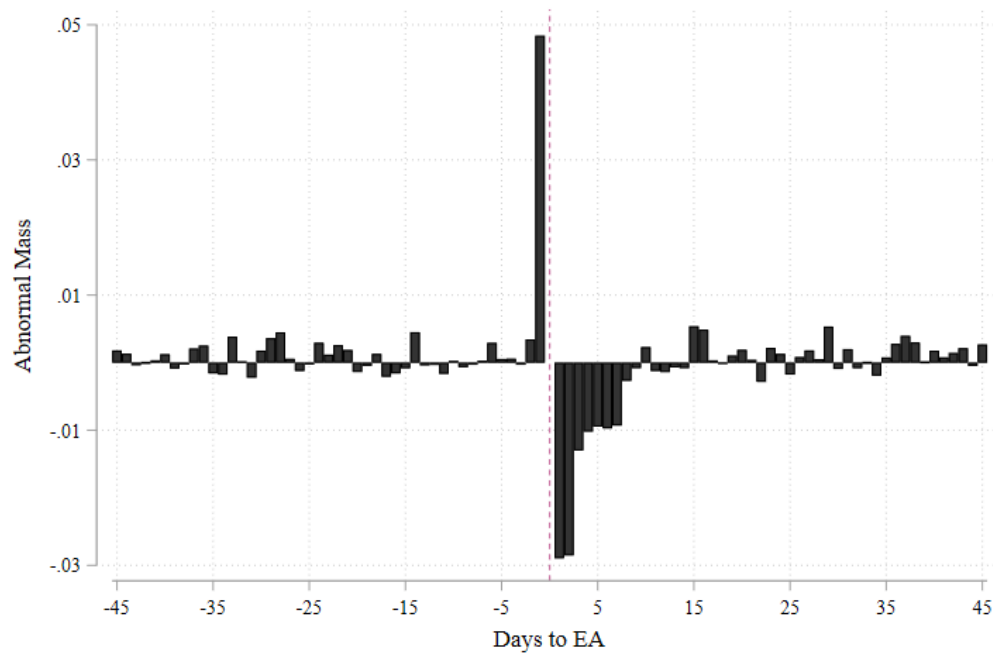
This figure presents a graphical depiction of the main result from the bunching analyses in Table 3, Rows 3 and 4 by plotting the *Abnormal Mass* of fake articles around earnings announcements. In these analyses, *Abnormal Mass* is specified as the difference between fake and non-fake article distributions.

Figure 4: Distributions of Fake Articles Around High and Low Attention Earnings Announcements
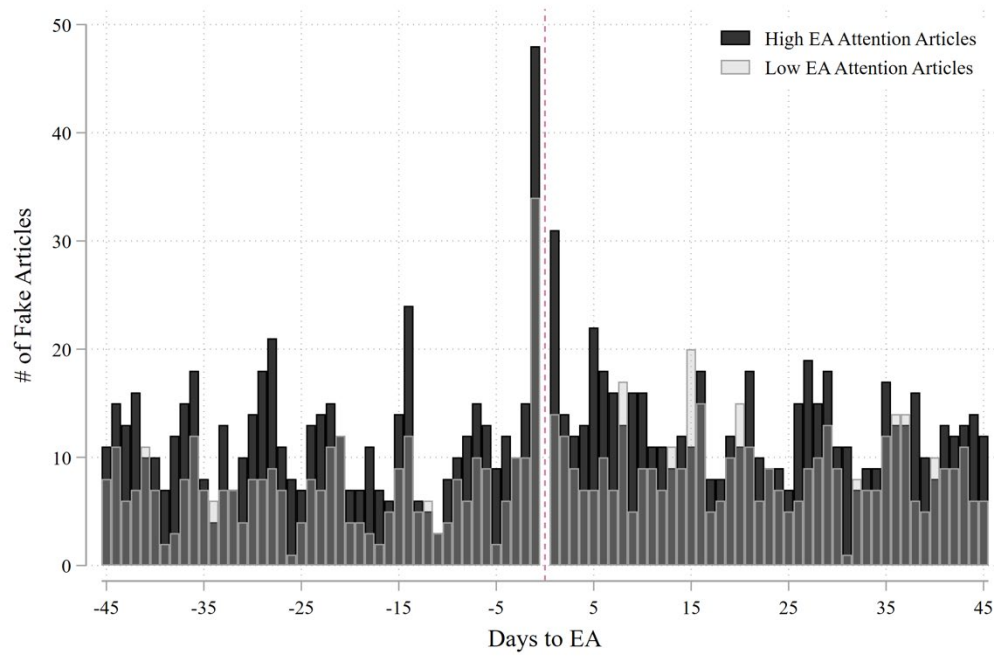
This figure presents a graphical depiction of the main result from the analyses in Table 3, Row 7 by plotting the fake article distributions for high and low attention earnings announcements.

Figure 5: Distributions of Fake Articles With and Without Accounting Content Around Earnings Announcements

Panel A: Accounting Content Fake Articles
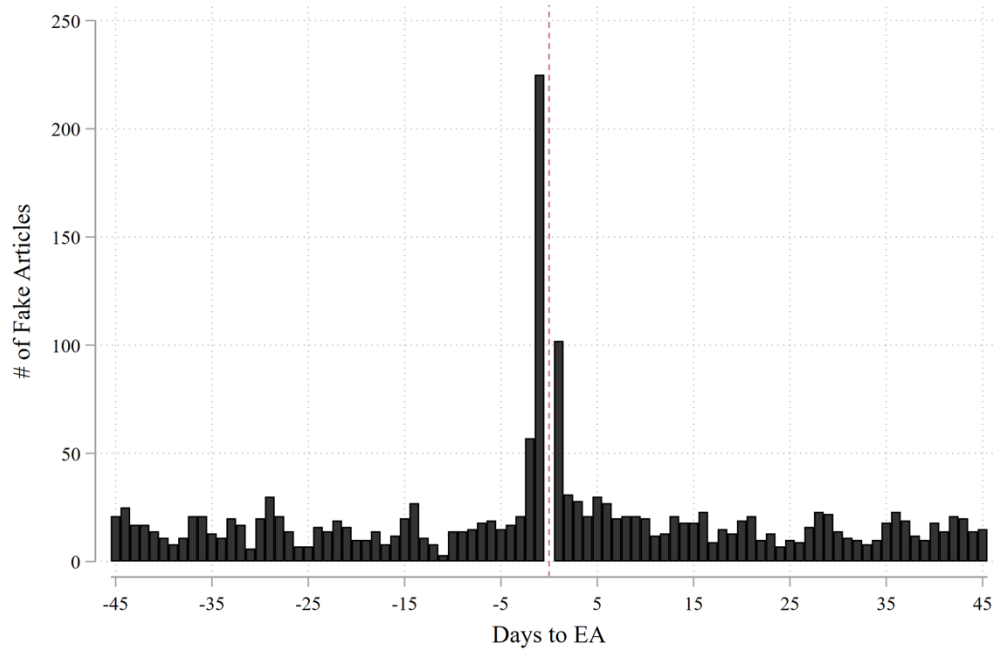
Panel B: No Accounting Content Fake Articles
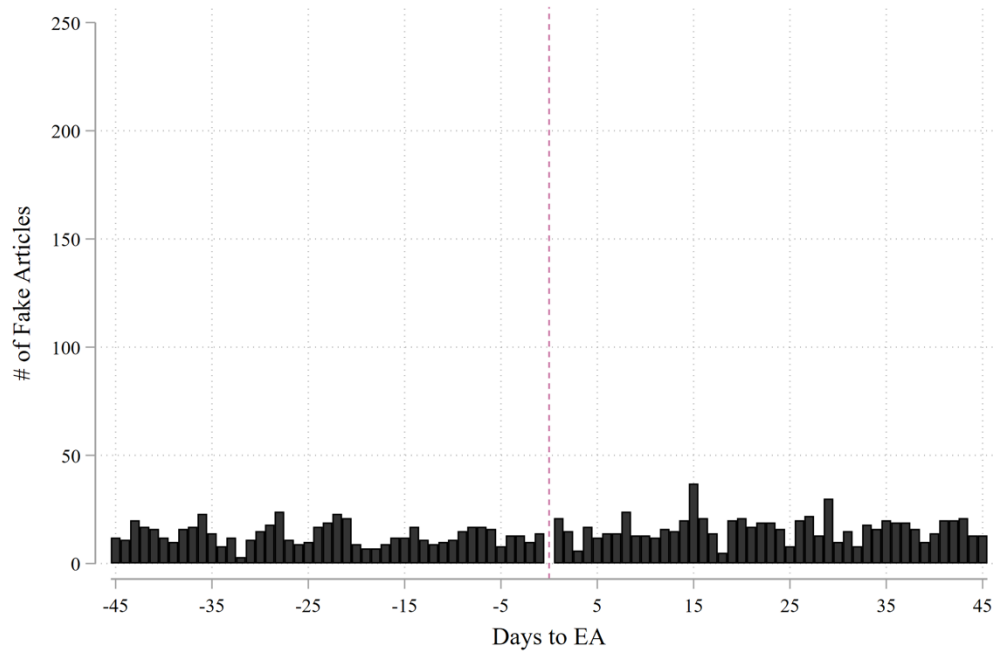
This figure presents a graphical depiction of the main result from the bunching analyses in Table 3, Rows 8 and 9 by plotting the distribution of fake articles around earnings announcements partitioned by whether the article contains accounting content. Panel A plots the distribution of fake articles with accounting content, while Panel B does the same for fake articles without accounting content.

Table 1: Sample Selection

Sample Selection Criteria	# of Articles	# of Firm-quarters
Seeking Alpha articles (January 1st, 2006 – December 31st, 2018)	221,103	
Exclude: Articles without at least 100 words	(2,789)	
Exclude: Articles that cannot be classified as fake or non-fake	(86,205)	
Exclude: Articles missing 10-K Readability (available until March 31st, 2018)	(4,440)	
Exclude: Missing firm-level controls	(2,194)	
Sample	125,475	37,864

This table lists the sample selection criteria for Seeking Alpha articles. We start with all published Seeking Alpha articles from January 1st, 2006 – December 31st, 2018, that match to a CRSP historical stock ticker with a CRSP share code of 10 or 11. To exclude conference call transcripts and other news releases, we require that the article is not written by a Seeking Alpha editor or other staff member. These criteria yield an initial sample of 221,103 articles. We retain articles with more than 100 words and those that we can classify as either fake or non-fake using the methodology in Kogan et al. (2023), excluding 2,789 and 86,205 articles, respectively. The Bog Index from Bonsal et al. (2017) is available for 10-Ks filed on or prior to March 31st, 2018, and requiring this variable eliminates 4,440 articles. Requiring the control variables used in our primary analyses eliminates an additional 2,194 articles. Our final sample comprises of 125,475 articles and 37,864 firm-quarters. The exact number of observations in regression analyses will differ slightly because we drop observations for which the fixed effects perfectly predict the dependent variables from estimation samples as needed across different models.

Table 2: Characteristics of Seeking Alpha Articles
Panel A: Content of Articles Using Latent Dirichlet Allocation Textual Analysis

		(1)	(2)	(3)
Topic #	Topic Label	# of Articles	Fake %	% Accounting Words
Topic 1	Fiscal Policy	23,319	2.6%	2.6%
Topic 2	Green Technology	28,060	2.4%	2.6%
Topic 3	Energy	23,011	2.6%	2.8%
Topic 4	Passive Management	20,647	2.5%	2.9%
Topic 5	Accounting	83,839	1.1%	3.7%
Topic 6	Retail Industry	43,579	1.9%	2.9%
Topic 7	Streaming Services	13,203	3.7%	2.6%
Topic 8	Real Estate	14,514	3.1%	2.9%
Topic 9	Macroeconomy	55,969	1.1%	3.1%
Topic 10	Entertainment Industry	16,582	4.3%	2.7%
Topic 11	Graphical Evidence	57,652	1.2%	2.7%
Topic 12	Precious Metals	5,390	3.1%	2.5%
Topic 13	Mobile Device Technology	19,033	3.4%	2.7%
Topic 14	Unclassified / General	94,952	1.4%	2.9%
Topic 15	Healthcare	17,077	4.8%	2.8%
Topic 16	Risk Modeling	63,853	1.6%	2.7%
Topic 17	General Business	49,823	2.3%	3.0%
Topic 18	Legal	32,776	4.8%	2.4%
Topic 19	Portfolio Management	24,062	3.8%	2.8%
Topic 20	Dividend Investing	41,311	1.0%	4.2%
Topic 21	Bonds	17,203	3.6%	3.2%
Topic 22	Capital Raises	42,410	4.0%	3.0%
Topic 23	Social Media	26,165	3.3%	2.3%
Topic 24	Technology Industry	23,245	2.9%	2.5%
Topic 25	Accounting Forecasts	88,484	1.6%	3.4%
Topic 26	Global Markets	28,128	1.6%	2.8%
Topic 27	Pharmaceutical Industry	11,377	5.7%	2.1%
Topic 28	Financial Services Industry	18,462	4.8%	2.9%
Topic 29	Foreign Currency Exchange	14,421	4.5%	2.6%
Topic 30	E-Commerce	21,329	2.7%	2.7%

(Continued)

Table 2: Characteristics of Seeking Alpha Articles
Panel B: Comparison of Fake and Non-Fake Articles

Characteristic	Fake	Non-Fake	Difference
# of Articles	3,139	122,336	-119,197
Word Count	458.6	620.5	-161.8***
Words Per Sentence	28.4	26.8	1.5***
Accounting Information			
% Articles with Accounting Content	57.1	88.1	-31.0***
% Accounting Words	2.2	3.1	-0.9***
Direction of Article News			
% Positive Articles (Return $\geq$ 0.5%)	40.6	38.5	2.1**
% Negative Articles (Return $\leq$ -0.5%)	38.0	35.9	2.1**
% Positive Articles (Return $\geq$ 1%)	31.3	28.3	3.0***
% Negative Articles (Return $\leq$ -1%)	30.0	26.4	3.6***
% Positive Articles (Return $\geq$ 2%)	18.8	15.4	3.4***
% Negative Articles (Return $\leq$ -2%)	19.1	15.0	4.1***
Market Reaction			
Abnormal Volume	4.0	3.8	0.2***
Idiosyncratic Return Volatility	0.4	0.2	0.2***

This table presents descriptive statistics for our sample of articles. Panel A presents descriptive statistics by topics identified using Latent Dirichlet Allocation (LDA). *Topic #* is the original topic number designated by LDA. *Topic Label* is a descriptive name for the topic based on researcher examination of the most prominent words for the topic. *# of Articles* is the number of articles which contain content in that topic. *Fake %* is the percentage of fake articles within all articles assigned to that topic. *% Accounting Words* is the average percentage of accounting words used in articles assigned to that topic. In some analyses, we use Topic 5 (i.e., Accounting) and Topic 25 (i.e., Accounting Forecasts) to define whether articles contain accounting content. We have highlighted these topics in the table. Panel B presents descriptive statistics by fake and non-fake articles. *Word Count* is the average number of words in the article. *Words Per Sentence* is the average number of words per sentence in the article. *% Articles with Accounting Content* is the percentage of articles that contain accounting content. See Appendix A for details on *Abnormal Volume* and *Idiosyncratic Return Volatility*. For the market reaction characteristics, we remove articles where an earnings announcement, management forecast, 10-K, 10-Q, or 8-K, occurs within a t-2 to t+2 trading day window centered on the article publication date. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 3: Bunching Analyses Examining Fake News Publication Timing Preferences

Window of Interest	(1) Pre EA Abnormal Mass$_{t-2,t-1}$	(2) Post EA Abnormal Mass$_{t+1,t+2}$	(3) Total Abnormal Mass$_{t-2,t+2}$	(4) Differential Abnormal Mass$_{t-2,t+2}$
Fake vs Non-Fake:				
(1) # Fake Articles (Polynomial)	242***	101***	343***	141***
	(7.19)	(3.11)	(7.08)	(3.14)
(2) # Non-Fake Articles(t-2,t+8) (Polynomial)	3,246**	19,182***	22,428***	-15,937***
	(2.25)	(6.91)	(7.16)	(-5.10)
(3) Fake vs Non-Fake(t-2,t+8) (DiB)	0.051***	-0.112***	-0.061***	0.164***
	(5.04)	(-5.38)	(-2.65)	(6.95)
(4) Fake vs Non-Fake(t-2,t+2) (DiB)	0.051***	-0.057***	-0.006	0.109***
	(5.04)	(-5.88)	(-0.43)	(7.67)
High vs Low EA Attention:				
(5) # Fake Articles – High EA Attention (Polynomial)	37***	18**	55***	18*
	(4.76)	(2.45)	(4.88)	(1.80)
(6) # Fake Articles – Low EA Attention (Polynomial)	22***	7	29***	15**
	(4.28)	(1.24)	(3.79)	(2.09)
(7) # Fake Articles – High vs Low EA Attention (DiB)	20***	17**	37***	3
	(2.84)	(2.44)	(3.70)	(0.31)
Accounting vs No Accounting Content:				
(8) # Fake Articles – Accounting Content (Polynomial)	244***	93***	337***	152***
	(7.65)	(3.03)	(7.41)	(3.53)
(9) # Fake Articles – No Accounting Content (Polynomial)	-3	8	5	-11
	(-0.36)	(1.06)	(0.48)	(-1.03)
(10) # Fake Articles – Accounting vs No Accounting Content (DiB)	258***	97***	355***	161***
	(7.75)	(3.06)	(7.60)	(3.56)

This table reports the results from bunching analyses examining the publication timing preferences of fake news authors in an event window around earnings announcements. *Pre EA Abnormal Mass$_{t-2,t-1}$* is the sum of *Abnormal Mass$_t$* for days t-2 and t-1. *Post EA Abnormal Mass$_{t+1,t+2}$* is the sum of *Abnormal Mass$_t$* for days t+1 and t+2. *Total Abnormal Mass$_{t-2,t+2}$* is the sum of *Pre EA Abnormal Mass$_{t-2,t-1}$* and *Post EA Abnormal Mass$_{t+1,t+2}$*. *Differential Abnormal Mass$_{t-2,t+2}$* is the difference between *Pre EA Abnormal Mass$_{t-2,t-1}$* and *Post EA Abnormal Mass$_{t+1,t+2}$*. The sample partitions are described in Section 4. Rows 1, 2, 5, 6, 8, and 9 use the polynomial bunching estimation methodology, while Rows 3, 4, 7, and 10 use the difference-in-bunching (DiB) estimation methodology. The table reports effect estimates and (in parentheses) *t*-statistics based on standard errors calculated using a bootstrap procedure following Chetty et al. (2011). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 4: Descriptive Statistics for Primary Regression Variables

Variable	N	Mean	Std. Dev.	P1	P25	Median	P75	P99
Dependent Variables:								
Fake Article$_t$	125,475	0.025	0.156					
Fake Article (Quarter)$_q$	37,864	0.074	0.261					
Abnormal Volume$_{t,t+2}$	1,380	3.353	2.626	0.669	2.057	2.692	3.694	19.493
Idiosyncratic Return Volatility$_{t,t+2}$ (%)	1,380	0.208	0.504	0.001	0.019	0.054	0.162	3.576
Accounting Information Variables:								
Management Forecast Frequency$_{t-365,t}$	125,475	1.447	0.767	0.000	1.099	1.609	1.946	2.639
10-K Readability$_{y-1}$	125,475	-85.941	6.216	-102	-90	-86	-81	-72
Control Variables:								
Adj. ROA$_{q-1}$	125,475	0.020	0.046	-0.158	-0.000	0.014	0.038	0.170
Analyst Coverage$_{q-1}$	125,475	2.762	0.797	0.000	2.485	2.944	3.296	3.932
Business Segments$_{y-1}$	125,475	1.731	1.785	0.000	1.000	1.000	3.000	8.000
Institutional Ownership$_{q-1}$	125,475	0.680	0.217	0.000	0.582	0.700	0.832	1.000
M/B$_{q-1}$	125,475	4.834	8.128	-24.339	1.534	3.019	5.610	46.692
Media Coverage$_{t-180,t}$	125,475	3.777	1.270	0.000	3.045	3.871	4.682	6.198
Returns$_{m-12,m-1}$	125,475	0.161	0.496	-0.762	-0.111	0.102	0.338	2.506
Returns$_{t-10,t-1}$	125,475	0.004	0.090	-0.288	-0.037	0.004	0.044	0.329
Size$_{q-1}$	125,475	9.575	2.296	3.931	7.903	9.853	11.510	13.348

This table presents descriptive statistics for variables used in the regression analyses. The *y*, *q*, *m*, and *t* subscripts represent year, quarter, month, and day, respectively, and indicate when the variable is measured relative to article publication on day *t*. Our dependent variables are *Fake Article, Fake Article (Quarter)*, *Abnormal Volume,* and *Idiosyncratic Return Volatility*. Our primary independent variables are two distinct measures of accounting information: (1) *Management Forecast Frequency* and (2) *10-K Readability*. Variable definitions are found in Appendix A. Except for variables with natural lower or upper bounds, we winsorize all variables at the 1st and 99th percentiles.

Table 5: The Role of Accounting Information in Disincentivizing Fake News Production
Panel A: Article Analysis

Fake Article as Dependent Variable	*(1)*	*(2)*	*(3)*
Accounting Information Variables:			
Management Forecast Frequency	-0.279***		-0.285***
	(-4.21)		(-3.85)
10-K Readability		-0.042***	-0.042***
		(-3.82)	(-4.42)
Control Variables:			
Adj. ROA	-2.900***	-2.480**	-1.877*
	(-2.79)	(-2.27)	(-1.75)
Analyst Coverage	-0.126	-0.217**	-0.131
	(-1.23)	(-1.98)	(-1.25)
Business Segments	0.049	0.016	0.031
	(1.12)	(0.37)	(0.71)
Institutional Ownership	0.256	-0.007	0.140
	(0.99)	(-0.03)	(0.56)
M/B	-0.005	-0.004	-0.005
	(-0.86)	(-0.58)	(-0.77)
Media Coverage	0.266***	0.285***	0.260***
	(4.00)	(4.43)	(4.08)
Returns$_{m-12,m-1}$	-0.248***	-0.243***	-0.253***
	(-2.81)	(-2.81)	(-2.91)
Returns$_{t-10,t-1}$	0.578**	0.590**	0.557**
	(2.08)	(2.13)	(2.03)
Size	-0.070	-0.072	-0.067
	(-1.61)	(-1.63)	(-1.55)
Industry & Year Fixed Effects	Included	Included	Included
Mean of *Fake Article* (%)	2.50	2.50	2.50
Economic Magnitude (%)	-8.6	-10.4	-
Pseudo R^2	0.116	0.116	0.118
N	124,602	124,602	124,602
Estimation Method	Logit	Logit	Logit

(Continued)

Table 5: The Role of Accounting Information in Disincentivizing Fake News Production
Panel B: Firm-Quarter Analysis

Fake Article (Quarter) as Dependent Variable	(1)	(2)	(3)
Accounting Information Variables:			
Management Forecast Frequency	-1.089***		-1.028***
	(-4.43)		(-3.86)
10-K Readability		-0.119***	-0.110***
		(-3.95)	(-3.87)
Control Variables:			
Adj. ROA	-13.384***	-13.453***	-11.239***
	(-5.62)	(-5.57)	(-4.73)
Analyst Coverage	0.447*	0.032	0.367
	(1.71)	(0.13)	(1.40)
Business Segments	-0.093	-0.139	-0.114
	(-0.62)	(-0.92)	(-0.77)
Institutional Ownership	-3.142***	-3.770***	-3.350***
	(-5.15)	(-6.09)	(-5.57)
M/B	-0.001	0.007	0.003
	(-0.05)	(0.36)	(0.16)
Media Coverage	1.254***	1.275***	1.252***
	(6.45)	(6.58)	(6.57)
Returns$_{m-12,m-1}$	-1.126***	-1.086***	-1.135***
	(-4.09)	(-3.97)	(-4.19)
Returns$_{t-10,t-1}$	0.384	0.527	0.373
	(0.39)	(0.53)	(0.38)
Size	1.107***	1.071***	1.092***
	(7.92)	(7.43)	(7.80)
Industry & Year Fixed Effects	Included	Included	Included
Mean of *Fake Article* (%)	7.40	7.40	7.40
Economic Magnitude (%)	-12.3	-10.5	-
Pseudo R^2	0.147	0.146	0.149
N	37,690	37,690	37,690
Estimation Method	Logit	Logit	Logit

(Continued)

Table 5 (Continued)

This table reports analyses on the effect of accounting information on the likelihood of being targeted by fake news. The analyses are conducted at the article (quarterly) level in Panel A (Panel B). In Panel A, the dependent variable is *Fake Article*, which is an indicator variable equal to one when the article is classified as fake and equal to zero for non-fake articles using the methodology in Kogan et al. (2023). In Panel B, the dependent variable is *Fake Article (Quarter)*, an indicator variable equal to one when there is one or more fake articles published about the firm in the quarter and equal to zero otherwise. Our primary independent variables of interest are defined as follows: (1) *Management Forecast Frequency* is the natural logarithm of one plus the number of management forecasts in the last year. (2) *10-K Readability* is the Bog Index from Bonsall et al. (2017) of the firm's most recent 10-K as of the article publication date multiplied by -1. In Panel B, all independent variables are measured as of the first article in each firm-quarter. Appendix A contains definitions on the remaining variables. The table reports marginal effect estimates from a logit regression and *z*-statistics (in parentheses) based on robust standard errors clustered by firm. Marginal effect estimates are calculated at the means of the regressors and multiplied by 100 so that they can be interpreted directly as percentage changes. We include industry (two-digit SIC) and year fixed effects in the regressions but do not report the coefficients. Observations for which the fixed effects perfectly predict the dependent variables are dropped from the estimation sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively. The reported economic magnitude is calculated by multiplying the estimated coefficient by the standard deviation of the *Accounting Information* variable and then scaled by the mean of the dependent variable.

Table 6: Subsample Tests of the Role of Accounting Information in Disincentivizing Fake News Production

	Coefficient Estimates for:		
	(1)	*(2)*	*(3)*
Fake Article as	*Management Forecast*	*10-K*	*# of*
Dependent Variable	*Frequency*	*Readability*	*Observations*
Article Content			
(1) Accounting	-0.161***	-0.033***	108,614
	(-2.79)	(-4.94)	
(2) No Accounting	-0.258	-0.013	15,602
	(-0.74)	(-0.24)	
Earnings Surprise$_{q-1}$			
(3) Negative	-0.311***	-0.073***	30,038
	(-3.03)	(-4.87)	
(4) Positive	-0.299***	-0.035***	84,523
	(-3.79)	(-3.58)	
Management Forecast Provision			
(5) None		-0.076***	20,536
		(-2.83)	
(6) One or more		-0.033***	103,036
		(-3.25)	
Analyst Coverage			
(7) Low	-0.053	-0.063***	59,512
	(-0.55)	(-5.31)	
(8) High	-0.348***	-0.029**	63.437
	(-3.69)	(-2.05)	
Institutional Ownership %			
(9) Low	-0.361***	-0.032**	61,655
	(-3.39)	(-2.32)	
(10) High	-0.231**	-0.050***	61,887
	(-2.34)	(-4.52)	
Size			
(11) Small	-0.029	-0.056***	61,869
	(-0.30)	(-4.11)	
(12) Large	-0.405***	-0.038***	62,449
	(-5.46)	(-3.79)	

(Continued)

Table 6 (Continued)

This table reports subsample analyses using the specification presented in Table 5, Panel A, Column 3. The coefficients for the accounting information variables are reported in Columns 1 and 2 corresponding to each subsample analysis. The dependent variable is *Fake Article*. All subsample analyses include the control variables and fixed effects specified in Table 5, Panel A, Column 3, but we do not report the coefficients for brevity. The article content subsamples are partitioned by whether the article contains accounting content. The earnings surprise subsamples are partitioned by whether the firm had a negative or positive earnings surprise in the most recent quarter. The management forecast provision subsamples are partitioned by whether the firm provides at least one management forecast in the past year. Additionally, we exclude *Management Forecast Frequency* as an independent variable from these subsamples to avoid collinearity issues. The analyst coverage, institutional ownership, and size subsamples are created by partitioning at the median for each of these characteristics, respectively. Appendix A contains definitions on the remaining variables. The table reports marginal effect estimates from a logit regression and (in parentheses) *z*-statistics based on robust standard errors clustered by firm. Marginal effect estimates are calculated at the means of the regressors and multiplied by 100 so that they can be interpreted directly as percentage changes. Observations for which the fixed effects perfectly predict *Fake Article* are dropped from the estimation sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 7: The Role of Accounting Information in Mitigating the Market Reaction to Fake News
Panel A: Trade-based Market Reaction

Abnormal Volume$_{t,t+2}$ as Dependent Variable	(1)	(2)	(3)
Accounting Information Variables:			
Management Forecast Frequency	-0.127*		-0.124*
	(-1.81)		(-1.96)
10-K Readability		-0.029***	-0.029***
		(-3.45)	(-3.52)
Control Variables:			
Adj. ROA	-1.855*	-1.599	-1.352
	(-1.80)	(-1.56)	(-1.33)
Analyst Coverage	-0.297**	-0.327**	-0.289**
	(-2.39)	(-2.57)	(-2.32)
Business Segments	-0.006	-0.027	-0.023
	(-0.25)	(-1.09)	(-0.89)
Institutional Ownership	0.292	0.113	0.173
	(0.91)	(0.36)	(0.56)
M/B	0.003	0.003	0.002
	(0.54)	(0.59)	(0.43)
Media Coverage	-0.065	-0.056	-0.059
	(-1.05)	(-0.92)	(-0.97)
Returns$_{m-12,m-1}$	-0.200*	-0.214**	-0.226**
	(-1.87)	(-2.00)	(-2.12)
Returns$_{t-10,t-1}$	-0.371	-0.430	-0.416
	(-0.55)	(-0.64)	(-0.62)
Size	0.094**	0.096**	0.093**
	(2.02)	(2.04)	(1.98)
Lagged Abnormal Volume Variables	Included	Included	Included
Industry & Year Fixed Effects	Included	Included	Included
Economic Magnitude (%)	-3.3	-6.7	-
Adjusted R^2	0.478	0.482	0.483
N	1,371	1,371	1,371
Estimation Method	OLS	OLS	OLS

(Continued)

Table 7: The Role of Accounting Information in Mitigating the Market Reaction to Fake News
Panel B: Price-based Market Reaction

Idiosyncratic Return Volatility$_{t,t+2}$ as Dependent Variable	(1)	(2)	(3)
Accounting Information Variables:			
Management Forecast Frequency	-0.028*		-0.028**
	(-1.87)		(-2.01)
10-K Readability		-0.005***	-0.004***
		(-2.89)	(-2.95)
Control Variables:			
Adj. ROA	-0.860***	-0.839***	-0.785***
	(-3.54)	(-3.48)	(-3.26)
Analyst Coverage	-0.019	-0.026	-0.017
	(-0.64)	(-0.88)	(-0.59)
Business Segments	-0.000	-0.004	-0.003
	(-0.02)	(-0.75)	(-0.55)
Institutional Ownership	0.009	-0.023	-0.010
	(0.15)	(-0.38)	(-0.17)
M/B	-0.002	-0.002	-0.002
	(-1.42)	(-1.31)	(-1.45)
Media Coverage	0.024*	0.025*	0.025*
	(1.70)	(1.89)	(1.85)
Returns$_{m-12,m-1}$	-0.016	-0.018	-0.021
	(-0.66)	(-0.72)	(-0.84)
Returns$_{t-10,t-1}$	-0.230	-0.239*	-0.234*
	(-1.62)	(-1.68)	(-1.66)
Size	-0.021**	-0.021*	-0.022**
	(-1.98)	(-1.94)	(-2.03)
Lagged Idiosyncratic Return Volatility Variables	Included	Included	Included
Industry & Year Fixed Effects	Included	Included	Included
Economic Magnitude (%)	-13.3	-21.1	-
Adjusted R^2	0.292	0.294	0.297
N	1,370	1,370	1,370
Estimation Method	OLS	OLS	OLS

(Continued)

Table 7 (Continued)

This table reports analyses on the effect of accounting information on the market's trading reaction (Panel A) and price reaction (Panel B) to fake news. We remove articles where an earnings announcement, management forecast, 10-K, 10-Q, or 8-K, occurs within a t-2 to t+2 trading day window centered on the article publication date. We also exclude days when both a fake and non-fake article are published. In Panel A, our dependent variable is *Abnormal Volume*, which is the sum of scaled trading volume on the publication date of the Seeking Alpha article and the following two trading days, where scaled trading volume is calculated as the daily trading volume divided by the average trading volume over the prior 20 to 140 trading days. The dependent variable in Panel B is *Idiosyncratic Return Volatility*, which is the sum of squared abnormal returns on the article publication date and the following two trading days multiplied by 100, where abnormal returns are the daily return minus the return on a 5x5x5 size-, book-to-market-, and momentum-matched portfolio. In addition to the *Accounting Information* and control variables described in Table 5, we include lagged one-day measures of our dependent variables to control for serial correlation and unobserved confounding events but do not report the coefficients. Panel A includes *Abnormal Volume$_{t-1}$, Abnormal Volume$_{t-2}$,* and *Abnormal Volume$_{t-3}$*, which are the scaled trading volumes for the three trading days prior to article publication. In Panel B, we include *Idiosyncratic Return Volatility$_{t-1}$, Idiosyncratic Return Volatility$_{t-2}$,* and *Idiosyncratic Return Volatility$_{t-3}$,* which are the squared abnormal returns for the three trading days prior to article publication. Appendix A contains definitions on the remaining variables. The table reports OLS coefficient estimates and (in parentheses) *t*-statistics based on robust standard errors clustered by firm. We include industry (two-digit SIC) and year fixed effects in the regressions as indicated, but do not report the coefficients. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively. The reported economic magnitude is calculated by multiplying the estimated coefficient by the standard deviation of the *Accounting Information* variable and then scaled by the mean of the dependent variable within each sample.

Internet Appendix for
"The Role of Accounting Information in an Era of Fake News"

Betty Liu
Kelley School of Business
Indiana University
bettyliu@iu.edu

Austin Moss
Leeds School of Business
University of Colorado Boulder
austin.moss@colorado.edu

This internet appendix contains additional discussion and analyses referenced in the main paper.

IA1. Seeking Alpha Article Examples

IA2. Latent Dirichlet Allocation (LDA) implementation details

IA3. LDA Top 10 most prominent words per topic

IA4. Details on Bunching

IA5. Sensitivity analyses

IA6. Binned scatterplots of the role of accounting information in disincentivizing fake news production

IA1: Seeking Alpha Article Examples

For illustrative purposes, we present and discuss examples of a fake and a non-fake Seeking Alpha article. The first example (see: https://web.archive.org/web/20130826052615/http://seekingalpha.com/article/1633692-galena-biopharma-best-and-worst-case-scenario) is a fake article authored by an individual who was penalized by the SEC for fraud in 2014. In this article, the author conducts analyses on the future profitability of Galena Biopharma based on its two major pharmaceutical products. The quantitative approach resembles that of non-fake articles with fundamental analyses. Notably, the author characterizes the management forecast of 10%–15% long-term market share as "conservative" (under the section "Best Case"), arguing that the future market share could potentially escalate to 30%. This deliberate downplaying of the management forecast's validity suggests that fake news authors are not only aware of accounting disclosures but also recognize that investors rely on them to assess the credibility of claims made in Seeking Alpha articles.

The second example (see: https://seekingalpha.com/article/1984371-galena-biopharma-numerous-red-flags-suggest-a-significant-overvaluation) is written by a different author who disputes the claims made in the first article by referencing the company's 10-Qs, 10-Ks, and press releases. Following the publication of this article, the stock price fell by 20%, partially offsetting the inflated price induced by the fake news (SCAC, 2014). In addition to correcting the market, this article demonstrates that the author uses accounting information to disprove the content of other articles and believes that referring to accounting information can help persuade other investors. These examples provide useful insights into the content of fake news and illustrate how market participants evaluate fake news through the lens of accounting information.

IA2: Latent Dirichlet Allocation (LDA) Implementation Details

Latent Dirichlet Allocation (LDA) is a natural language processing technique used to identify latent topics in a collection of documents and assign these documents to the most relevant topics. More specifically, LDA uses unsupervised machine learning to compute statistics about the likelihood of certain words appearing concurrently in a passage of text and imputes groups of words that tend to occur together as topics. By training the LDA algorithm on large repositories of text, LDA can also be used to assign documents (or portions of documents, if multiple topics exist within a document) both inside and outside the training sample to the identified topics. In the context of this paper, we use LDA on Seeking Alpha articles to shed light on the type of topics covered by financial fake articles.

We detail our LDA methodology below, using common benchmarks and thresholds as input to steps within the algorithm. We treat each Seeking Alpha article as an individual document for our analysis.

Preliminary Cleaning

We first compile a dictionary of all words used across documents. We stem each word into its root form (e.g., "education" becomes "educat") and discard any common stop words (e.g., "the", "about", etc.), words fewer than 3 letters, as well as numbers and symbols. We count the number of documents in which each word appears and filter out extremely common and uncommon words by discarding any words that appear in fewer than 15 documents and in more than 50% of the documents. We then identify the 100,000 most frequently used words across documents. For our analyses, we construct a list of words for each document comprising of only words found in this list of 100,000 words.

Estimating the Number of Topics Present

LDA requires researcher input on the number of topics to identify in a corpus. Running LDA for too low or too high a topic number inhibits the model's ability to appropriately assign words into semantically coherent topics. We first generate LDA models for a wide range of potential topic numbers from 10 topics up to 100 topics in multiples of 10 (e.g., 10, 20, 30, etc.). To determine the appropriate number of topics, we compute the *C_v* coherence score for each model to evaluate the coherence of words within topics (3rder, Both, and Hinneburg, 2015; Syed and Spruit, 2017). A high coherence score implies well-defined topics across documents that are unlikely to be statistical artifacts. In Figure IA1, we plot the coherence scores and find that the coherence score peaks at around 30 topics. Thus, we use the model utilizing 30 topics for our LDA analysis.

Identifying Representative Topics

While LDA can detect which words belong to each topic, it is up to the researchers to assign a label or theme to the group of words that comprise a topic. Both authors independently reviewed the most salient words for each topic and agreed on a suitable topic name for each set of words. In IA2, we present the 30 topics as well as the top 10 words predictive of each topic.

Figure IA2: Coherence Scores for LDA Implementation

Coherence Scores for Different Topic Number Inputs
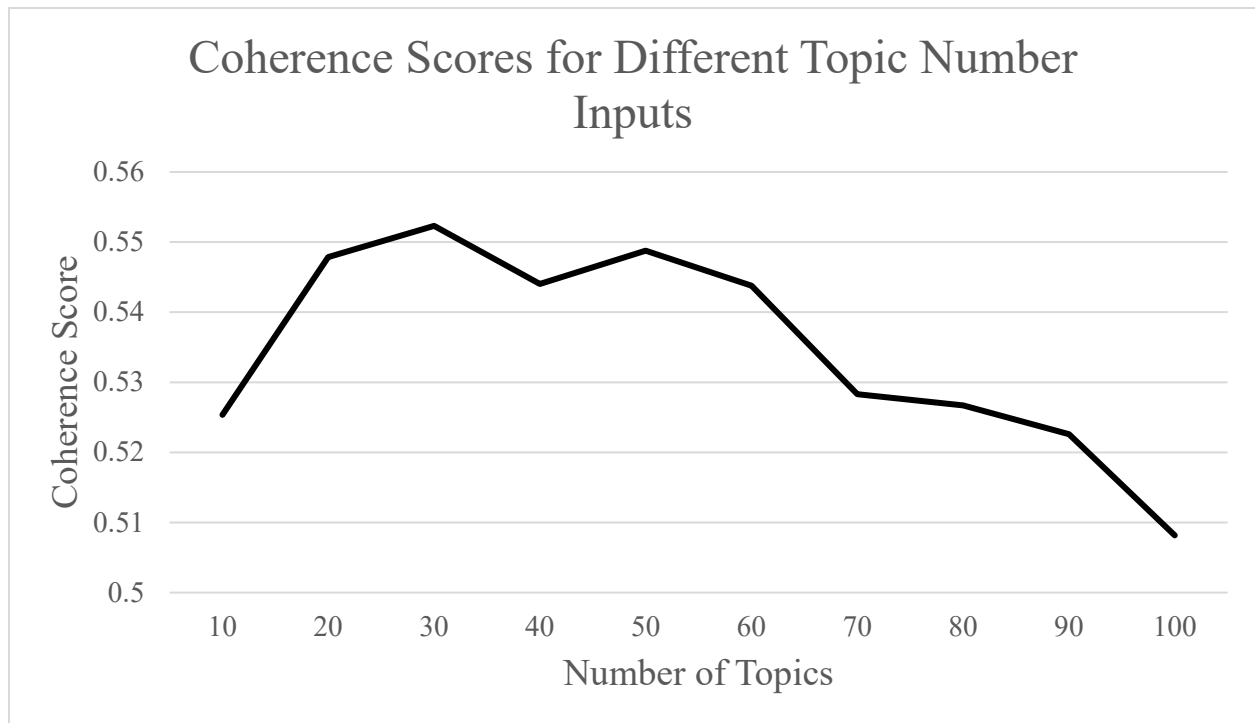
IA3: LDA Top 10 Most Prominent Words Per Topic

Topic 1		Topic 2		Topic 3	
Fiscal Policy		Green Technology		Energy	
polici	1.33%	electr	2.32%	product	3.46%
economi	1.30%	vehicl	2.11%	energi	2.32%
econom	1.19%	power	2.02%	natur	1.53%
trump	1.01%	industri	1.79%	barrel	1.26%
govern	0.98%	model	1.58%	crude	1.14%
inflat	0.89%	energi	1.56%	produc	1.14%
debt	0.73%	cost	1.56%	million	0.94%
money	0.72%	solar	1.45%	drill	0.85%
financi	0.66%	manufactur	1.44%	demand	0.80%
central	0.63%	car	1.30%	suppli	0.77%

Topic 4		Topic 5		Topic 6	
Passive Management		Accounting		Retail Industry	
fund	3.60%	cash	2.97%	sale	3.62%
index	3.10%	valu	2.25%	store	3.27%
sector	2.63%	flow	2.02%	brand	2.26%
return	2.03%	valuat	1.72%	retail	2.19%
perform	1.87%	earn	1.56%	food	1.31%
portfolio	1.60%	debt	1.50%	product	1.27%
volatil	1.37%	margin	1.45%	consum	1.10%
etf	1.24%	oper	1.40%	custom	0.76%
hold	1.21%	ratio	1.18%	ford	0.71%
analyst	1.19%	capit	1.08%	busi	0.70%

Topic 7		Topic 8		Topic 9	
Streaming Services		Real Estate		Macroeconomy	
subscrib	5.16%	reit	5.43%	declin	1.48%
netflix	5.01%	properti	3.10%	percent	1.46%
content	3.57%	real	2.57%	data	1.30%
stream	2.84%	estat	2.42%	rise	1.28%
gilead	2.72%	home	2.16%	rate	1.18%
servic	2.14%	hous	1.68%	remain	1.13%
subscript	1.76%	leas	1.62%	econom	1.11%
nflx	1.58%	mortgag	1.40%	report	1.06%
gild	1.42%	trust	1.03%	demand	1.00%
warner	1.37%	rent	0.97%	economi	0.97%

Topic 10		**Topic 11** Graphical		**Topic 12**	
Entertainment Industry		Evidence		Precious Metals	
game	2.40%	week	3.85%	gold	12.46%
disney	2.10%	chart	2.09%	silver	3.15%
hotel	1.40%	level	1.59%	metal	2.94%
sport	1.13%	short	1.46%	mine	2.65%
movi	1.07%	averag	1.29%	miner	1.91%
entertain	1.03%	click	1.21%	product	1.77%
travel	0.94%	enlarg	1.11%	copper	1.54%
revenu	0.92%	move	1.00%	project	1.47%
million	0.84%	indic	0.98%	ounc	1.45%
film	0.82%	higher	0.91%	resourc	1.19%

Topic 13 Mobile Device		**Topic 14** Unclassified		**Topic 15**	
Technology		/ General		Healthcare	
mobil	3.30%	go	2.01%	product	2.30%
game	2.23%	think	2.00%	boe	2.26%
micron	1.50%	good	1.18%	healthcar	2.24%
verizon	1.35%	thing	1.02%	sale	1.97%
qualcomm	1.21%	sell	0.97%	health	1.90%
wireless	1.17%	right	0.90%	medic	1.83%
network	1.06%	want	0.86%	drug	1.54%
semiconductor	1.04%	know	0.85%	care	1.37%
tencent	1.02%	say	0.83%	order	1.29%
billion	0.91%	point	0.73%	airbus	1.21%

Topic 16		**Topic 17**		**Topic 18**	
Risk Modeling		General Business		Legal	
risk	1.28%	busi	2.42%	report	1.58%
articl	0.76%	servic	2.08%	say	1.27%
valu	0.71%	revenu	1.80%	legal	0.89%
differ	0.71%	custom	1.72%	regul	0.85%
model	0.67%	product	1.71%	claim	0.81%
return	0.59%	technolog	1.70%	state	0.79%
strategi	0.58%	provid	1.03%	street	0.73%
chang	0.56%	manag	1.02%	court	0.71%
import	0.53%	industri	1.00%	case	0.71%
futur	0.52%	data	0.97%	issu	0.67%

Topic 19		**Topic 20**		**Topic 21**	
Portfolio Management		Dividend Investing		Bonds	
fund	4.79%	dividend	14.46%	bond	4.49%
manag	3.70%	yield	4.94%	yield	4.29%
portfolio	3.18%	incom	3.01%	rat	4.26%
asset	2.47%	portfolio	1.97%	rate	3.38%
hedg	1.67%	payout	1.45%	risk	2.24%
capit	1.67%	ratio	1.24%	treasuri	1.72%
hold	1.65%	return	1.19%	fund	1.45%
valu	1.56%	distribut	1.18%	inflat	1.37%
stake	1.34%	pay	1.18%	rise	1.27%
berkshir	1.33%	annual	1.16%	asset	1.23%

Topic 22		**Topic 23**		**Topic 24**	
Capital Raises		Social Media		Technology Industry	
million	3.08%	googl	3.33%	appl	9.39%
cash	1.26%	user	2.57%	intel	3.20%
deal	1.12%	facebook	2.40%	iphon	2.34%
sharehold	1.06%	advertis	1.63%	aapl	2.19%
manag	1.00%	platform	1.34%	nvidia	1.87%
offer	0.94%	media	1.34%	product	1.61%
capit	0.93%	revenu	1.34%	devic	1.28%
sell	0.85%	video	1.01%	sale	1.17%
debt	0.84%	content	0.93%	cola	1.01%
valu	0.83%	social	0.91%	chip	0.98%

Topic 25		**Topic 26**		**Topic 27**	
Accounting Forecasts		Global Markets		Pharmaceutical Industry	
quarter	7.39%	china	5.67%	patient	2.26%
million	5.12%	global	2.53%	drug	1.77%
revenu	4.99%	countri	2.39%	trial	1.73%
earn	3.99%	chines	2.16%	phase	1.52%
billion	2.93%	world	1.73%	approv	1.32%
report	2.37%	currenc	1.70%	studi	1.27%
sale	1.99%	emerg	1.32%	treatment	1.18%
result	1.94%	dollar	0.98%	data	1.05%
estim	1.68%	export	0.97%	develop	0.99%
guidanc	1.38%	foreign	0.96%	clinic	0.97%

Topic 28 Financial Services Industry		**Topic 29** Foreign Currency Exchange		**Topic 30** E-Commerce	
bank	13.26%	dollar	2.96%	amazon	6.59%
loan	4.61%	european	1.70%	microsoft	2.78%
financi	3.16%	euro	1.59%	onlin	2.11%
credit	2.85%	week	1.56%	amzn	1.96%
capit	1.38%	bank	1.25%	alibaba	1.83%
asset	1.30%	europ	1.16%	commerc	1.78%
lend	1.30%	currenc	1.10%	retail	1.74%
billion	1.24%	meet	0.91%	payment	1.43%
insur	1.21%	hike	0.76%	busi	1.29%
deposit	1.14%	itali	0.72%	billion	1.16%

IA4. Details on Bunching

Bunching requires the specification of a counterfactual behavior that approximates what would be observed in the behavior of interest absent the change in incentives at a particular threshold. We describe how we construct the counterfactual for both the polynomial approach and difference-in-bunching, as follows.

Polynomial Approach

The polynomial approach estimates a counterfactual distribution using a polynomial approximation. More specifically, we fit a seventh-degree polynomial function to the frequency distribution of articles published around earnings announcements but exclude the affected region from the estimation, as this region contains publication behavior distorted by the announcement itself. Intuitively, this approach utilizes the distribution of observed outcomes unaffected by the event to estimate a counterfactual for the outcomes otherwise affected by the event.

Difference-in-Bunching

The difference-in-bunching approach follows Sallee (2011) in combining the difference-in-differences and bunching methodology. It uses an alternative distribution of observed outcomes as the counterfactual, analogous to the control group in a difference-in-differences research design. To meet the "parallel trends assumption" for difference-in-bunching, the behavior of interest and the counterfactual behavior must respond similarly to incentives in general but not to the incentives that change at the threshold of interest. One main benefit of selecting such a counterfactual is that it controls for unobserved factors that influence both distributions, even within the affected region. For our study, we use the publication of non-fake articles as our counterfactual behavior.

To evaluate how well our counterfactual meets the parallel trends assumption, we visually compare the distributions for fake and non-fake articles presented below in Figure IA4. We observe that fake and non-fake articles closely mirror each other outside the earnings announcement window, following the same non-descript oscillating pattern. Furthermore, Figure 3 in the paper, which directly computes the differences between the two distributions, provides additional support that the differences outside the announcement window are very small, especially compared to differences inside the announcement window. We interpret this evidence as validation for using non-fake articles as a reasonable counterfactual for fake articles.

Standard Error Computations

We follow the bootstrap procedure by Chetty et al. (2011) to compute standard errors for statistical inferences in Table 3 of the paper. Specifically, we first create a bootstrap distribution by randomly sampling *Abnormal Mass$_t$* for each of the 90 days with replacement. We then calculate our four variables of interest (i.e., *Pre EA Abnormal Mass, Post EA Abnormal Mass, Total Abnormal Mass,* and *Differential Abnormal Mass*) using the bootstrap distribution. We repeat this procedure 1,000 times and define the standard error using the standard deviation of the estimates from this procedure.

Figure IA4: Parallel Trends
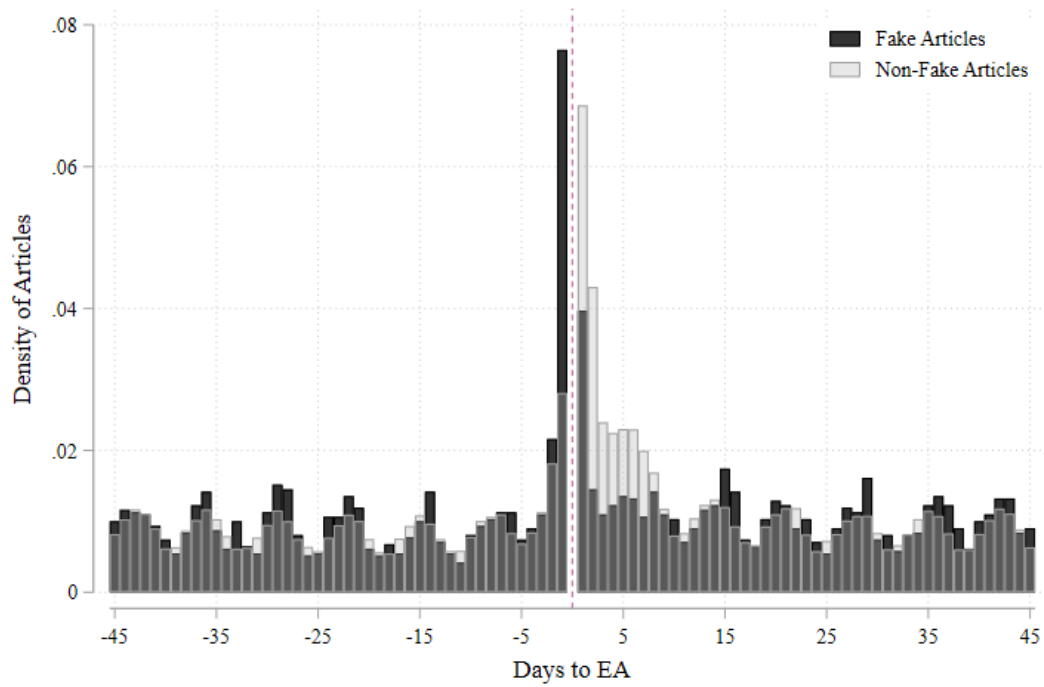
This figure overlays the fake and non-fake article distributions in Figure 2, Panels A and B of the paper after scaling each article type by the total number of articles of that type.

IA5: Sensitivity Analyses
Table IA5: Sensitivity Analyses of The Role of Accounting Information in Disincentivizing Fake News Production

Fake Article as Dependent Variable	Coefficient Estimates for:		
	(1) Management Forecast Frequency	*(2)* 10-K Readability	*(3)* # of Observations
Time Period Subsamples			
Exclude 6 months following 2014 and 2017 scandals	-0.206***	-0.044***	108,414
	(-2.78)	(-5.00)	
Exclude pre-2012	-0.280***	-0.031***	100,656
	(-3.68)	(3.50)	
Alternative Management Forecast Frequency Windows			
180-day Window	-0.254***	-0.041***	124,602
	(-2.62)	(4.33)	
90-day Window	-0.334***	-0.041***	124,602
	(-2.82)	(4.26)	
Other Sensitivity Analyses			
Exclude industry-years with fewer than 50 observations	-0.223***	-0.034***	116,879
	(-3.01)	(-3.66)	

This table reports sensitivity analyses of our primary specification (Col. 3 in Table 5, Panel A of the paper) examining the role of accounting information in disincentivizing fake news. The dependent variable is *Fake Article*. The first set of subsample tests examine the robustness of our results to the exclusion of articles potentially affected by scandals at Seeking Alpha in 2014 and 2017 involving the SEC crackdown fraudulent articles and to the exclusion of articles in the early years of Seeking Alpha when the platform was less popular. The second set of subsample tests examine alternative specifications for management forecast frequency windows. The last subsample test examines whether our results are sensitive to the exclusion of industry-years with fewer than 50 observations. The coefficients for the accounting information variables are reported in columns 1 and 2 as indicated for each sensitivity analysis. All analyses include the control variables and fixed effects specified in Table 5, Panel A Column 3, but we do not report the coefficients for brevity. See Appendix A in the paper for variable definitions. The table reports marginal effect estimates from a logit regression and (in parentheses) *z*-statistics based on robust standard errors clustered by firm. Marginal effect estimates are calculated at the means of the regressors and multiplied by 100 so that they can be interpreted directly as percentage changes. Observations for which the fixed effects perfectly predict *Fake Article* are dropped from the estimation sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

IA6: Binned Scatterplots of The Role of Accounting Information in Disincentivizing Fake News Production

Panel A: Management Forecast Frequency (Count)

Panel B: 10-K Readability
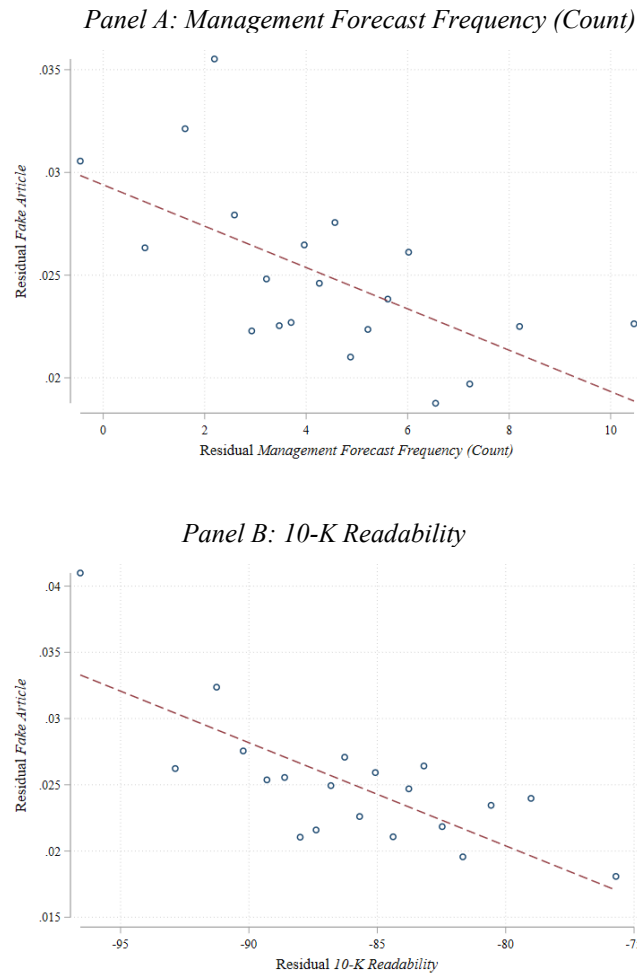
This figure plots the conditional probability of a fake news article versus our three measures of accounting information. Panel A is a binned scatterplot of the probability of a fake article (i.e., *Fake Article*) versus the number of management forecasts in the past year (i.e., *Management Forecast Frequency (Count)*). Panel B is a binned scatterplot of *Fake Article* versus the Bog Index from Bonsall et al. (2017) multiplied by -1 (i.e., *10-K Readability*). To construct these binned scatterplots, we first residualize both *Fake Article* and the respective accounting information variables (collectively referred to as *Accounting Information*) with respect to the control variables described in Table 4 as well as industry (two-digit SIC) and year fixed effects using partitioned regressions following the Frisch-Waugh-Lovell theorem. We then rank and divide the observations into 20 equal-size groups (ventiles) based on residual *Accounting Information* and plot the means of residual *Fake Article* within each bin against the mean value of residual *Accounting Information* within each bin. Finally, we add back the unconditional mean of *Fake Article* and *Accounting Information* in the estimation sample to facilitate interpretation of the scale. We use the binscatter Stata program for this procedure (Stepner, 2014). The dashed line shows the best linear fit estimated on the underlying sample of articles using an OLS regression. All three slope estimates are significantly different than zero at conventional significance levels (i.e., p-value < .05).