The Role of Accounting Information in an Era of Fake News

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Abstract

We document several stylized facts on the role of accounting information in the strategic publication decisions of fake financial news. The amount of fake financial news has increased in recent years, and a significant proportion of fake news pertains to accounting information. With respect to intertemporal publication preferences, fake news authors prefer to (1) publish fake articles near earnings announcements due to the widespread market attention these events garner and (2) avoid publishing fake articles post-announcement when investors are less susceptible to fake news due to the disclosure of accounting information. Lastly, with respect to the accounting information environment in general, fake news authors are less likely to target firms with more robust accounting information and generate lower market reactions when doing so.

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"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."

– Carvana Co. Prospectus, 5/23/2019

1. Introduction

Fake news—defined as false or misleading information with the intent to deceive—is a significant threat to efficient capital markets. 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] Providing broad empirical evidence on the magnitude and speed of investor reaction to fake news, Kogan, Moskowitz, and Neissner (2023) find that market participants cannot distinguish between fake and real news and react equally strongly to both. In response to the risk of fake news, managers are discussing fake news during conference calls (Plymouth Industrial REIT, 2019), disseminating press releases in response to fake news (Regen BioPharma, 2019), and reporting fake news as a material risk in risk factor disclosures (Carvana, 2019). In light of this threat, we document descriptive trends in the content and volume of contemporary fake financial news and examine interactions between accounting information and the incentives to publish fake news in the capital markets.[2]

[1] Farmland Partners later filed a lawsuit against 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 eventually won the case, attesting to the difficulty of recouping the costs from a single fake article even if the firm presses charges.

[2] While accounting information can encompass information produced internally (e.g., voluntary disclosures and mandatory SEC filings) and externally (e.g., analysts, media, etc.), the terms "accounting information" and "accounting disclosures" as used in this paper refer specifically to those created by the firm.

The umbrella of “fake news authors” in financial markets encompasses a disparate, ill-defined group with nebulous motivations. Levying negative consequences, legal or otherwise, on these authors has been difficult due to the relative ease of hiding behind a pseudonym, claiming ignorance without malintent, or seeking some form of free speech protections. Hence, there lacks empirical evidence regarding the primary motivations to publish fake financial news. We conjecture three, as follows. One, some fake news authors are driven to push stock prices in certain directions for monetary profit from short-term positions, much like classic “pump-and-dump” schemes. Two, many modern media platforms compensate their content creators with monetary payment based on views; some writers therefore sensationalize their articles to varying degrees to generate more views (i.e., “clickbait”), akin to a form of modern-day yellow journalism (Mourao and Robertson, 2019). Lastly, some authors write fake news not for monetary compensation but rather for a sense of personal satisfaction in successfully “fooling” market participants (i.e., “internet trolling”).[3] While there are many different motivations, the general objective of fake news authors is to enhance the plausibility of and engagement with fake news.

We begin by providing context on the nature of fake financial news and documenting descriptive evidence on the trends present in the content and volume of fake news articles. We use Seeking Alpha as our setting to collect a large sample of crowdsourced financial news articles from 2005-2018 and classify them as “fake” and “non-fake” following the classification procedure in Kogan et al. (2023). To characterize the content covered by these articles, we use

[3] One recent example is the exploitation of Twitter Blue in November 2022, during which users impersonated prominent companies, such as Lockheed Martin and Eli Lilly, and issued controversial Tweets, plummeting their stock prices by as much as 5%. A relevant news article discussing the event is found here: https://www.wsj.com/articles/whats-real-and-what-isnt-on-twitter-under-elon-musk-it-is-really-unclear-11668184148.

Latent Dirichlet Allocation (LDA), a machine learning algorithm, to identify topics discussed in the article text. We find significant heterogeneity in topical areas, which include accounting information and forecasts, industry-specific news, legal matters, and macroeconomic conditions. Accounting content is particularly pervasive in fake news, spanning over 57% of fake articles.

Next, we examine intertemporal variation in the volume of fake news. A frequency distribution on the annual number of fake articles exhibits a bimodal pattern over our sample period, with one peak occurring around 2007-2009 and a continuous incline from 2014 onwards. Our evidence suggests that the common media narrative on the expansion of fake news is not only a popular phenomenon in the political sphere but also a prominent issue in the financial sector. Motivated by the prevalence of accounting content in financial fake news, we then match articles to the subject firms and plot the frequency distribution of fake articles published in the days relative to one of the most important accounting disclosure events: earnings announcements. A visual inspection suggests that the publication of fake articles is significantly higher in the days adjacent to the announcement. Interestingly, the number of fake articles peaks the day prior to the announcement but declines dramatically following the announcement, resuming non-announcement levels within two days. For comparison, we repeat this procedure for non-fake news and find that non-fake news, in contrast, peaks the day *after* announcement and stays at elevated levels for eight days.

We conjecture that two aspects of major accounting information events help explain the pattern in fake news publication around earnings announcements: an attention effect and an information effect. The former relates to outcomes associated with the widespread market attention that prominent accounting information events garner (e.g., Beaver, 1968). To the extent that fake news authors rely on readership for compensation, highly publicized events raise the probability of generating higher view counts and potentially changing readers' priors or trading behaviors, increasing the incentives to produce fake news. The latter effect manifests in outcomes attributable to the large endowment of accounting information at these events. We argue that accounting information helps investors evaluate and verify the true asset value of the firm (i.e., the valuation role of accounting information), reducing investor susceptibility to false price signals and disincentivizing the production of fake news.

To examine our conjectures of the attention effect and information effect empirically, we use bunching, a methodology that ascribes behavioral distortions to a discontinuous change in incentives, conceptually similar to discontinuities in earnings distributions (e.g., Burgstahler and Dichev, 1997; Kleven, 2016). Using earnings announcements as events that induce sharp increases to market attention and information, we document evidence consistent with both effects: (1) Fake news authors publish more fake articles near earnings announcements when market attention is high, and (2) they strongly prefer publishing fake articles pre-announcement to publishing post-announcement after the release of accounting information. As additional validation, we conduct subsample analyses on cross sections in which we expect the effects to manifest more strongly, such as fake articles published around earnings announcements with high investor attention and fake articles containing content that pertains to accounting information, and continue to find support for our inferences.

We further develop our understanding of the interactions between accounting information and the incentives to publish fake news by examining how the broader accounting information environment affects the publication of fake news and its subsequent market impact using regression analyses. We choose two proxies as measures of the accounting information environment that are likely to be particularly salient to fake news authors: management forecast frequency and 10-K readability.[4] Consistent with prior results that fake news authors strategically avoid publishing after earnings announcements when investors are less susceptible to fake news, we predict that fake news authors are less inclined to write articles about firms with a strong accounting information environment in general. We find that as firms issue more management forecasts or more readable annual reports, there are fewer fake articles written about them. To help mitigate omitted variable concerns, we find that our results are largely unchanged in a battery of robustness tests conducted within subsamples of firms with more similar information environments.

As the last set of empirical tests, we examine interactions between the accounting information environment and the market reaction to fake news. We find that abnormal trading volume and idiosyncratic return volatility attenuates following fake article publications about firms with more management forecasts or more readable annual reports. We offer two interpretations. One is that investors informed by robust accounting information are less susceptible to the misinformation in fake articles, providing justification for the preferences of fake news authors to publish fewer fake articles about firms with relatively stronger accounting information environments. Alternatively, fake news authors, aware of the accounting information disseminated, feel more constrained on what content they deem as plausible to informed investors and limit writing highly fabricated content. Though we offer these two potential interpretations, we leave triangulation to future research.

Our paper makes several contributions to the literature. We provide broad sample evidence on the nuanced interactions between accounting information and incentives to publish

[4] We acknowledge that we do not study other common measures related to the accounting information environment, as they oftentimes 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.

fake news. We first explore descriptive trends in the content and volume of contemporary fake news articles. We then document evidence consistent with incentives to publish fake news increasing with the capital market attention associated with earnings announcements but decreasing with the information released in these disclosures. Lastly, we find that a stronger accounting information environment not only disincentivizes the production of fake news but also mitigates its corresponding market reaction.

Second, we contribute to the limited empirical literature on the effects of public misinformation on the stock market. Historically, broad sample empirical studies of known stock market manipulations, such as “pump-and-dumps”, have been scarce, due to the small number of occurrences enforced by regulators and the difficulty in identifying unenforced market manipulations (e.g., De Franco, Lu, and Vasvari, 2007; Leuz, Meyer, Muhn, Soltes, and Hackethal, 2017; Weiner, Weber, and Hsu, 2017). More recently, researchers have extended this literature by investigating the effects of potentially exploitative behavior on fast-growing investor websites, such as Seeking Alpha (e.g., Hu, 2019; Kogan et al., 2023) and Twitter (e.g., Jia, Shu, and Zhao, 2020), and examining how to address its spread (e.g., Grant, Hodge, and Seto, 2023). We add to this literature by documenting the types of articles written by fake news authors and the influence of accounting information on their incentives to publish. As investor websites without traditional oversight proliferate in the contemporary financial environment, evidence of how accounting information interacts with the fake news disseminated on these websites is especially meaningful.

Lastly, we contribute to the broader scientific literature investigating the propagation and social impact of fake news. Lazer et al. (2018) note the relative scarcity of research on the effects of fake news and call for interdisciplinary research on the subject. We examine two aspects of accounting information and their impact on the incentives to produce fake news in the financial markets setting but leave evaluations on the generalizability of our results to other sources of information or to fake news outside of 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, as it is conducive to studying fake financial news and its interactions with accounting information for several reasons. Though many authors' identities are hidden under pseudonyms, Seeking Alpha articles are read by 15.2 million visitors every month and elicit sizable market reactions (e.g., Hu, 2019; Seeking Alpha, 2020; Kogan et al., 2023). These factors create a suitable environment for our study by providing opportunities for self-interested authors to manipulate market opinions by writing fake news and largely avoid the reputation costs of doing so.[5] Furthermore, Seeking Alpha's webpage for each public firm allows for easy retrieval of the firm's filings with the Security and Exchange Commission (SEC), earnings call transcripts, and press releases. The saliency and accessibility of accounting information to Seeking Alpha authors and readers facilitates our ability to detect the effect of accounting information on the publication behavior of fake news authors. In addition, Seeking Alpha publishes articles on the universe of firms, affording us a broad cross section of firms to study and increasing the external validity of our paper.

We obtain data from Seeking Alpha for all articles written from 2006 through 2018. We collect the article's text, author, publication date, and the primary stock tickers associated with

[5] Interestingly, Rota Fortunae (from the previously discussed Farmland Partners case) 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 from a different firm, attesting to the difficulty of imposing reputation costs on authors who publish fake Seeking Alpha articles under a pseudonym.

the firms discussed in the article.[6] We eliminate articles without a primary stock ticker and articles written by Seeking Alpha employees. These restrictions eliminate articles on Seeking Alpha news updates and conference call transcripts as well as articles about the economy or other general topics not linked to a specific firm.

We follow the fake news classification method detailed in Kogan et al. (2023) to identify articles as "fake" or "non-fake" using the Linguistic Inquiry Word Count (LIWC2015) model from Pennebaker et al. (2015). This algorithm, built upon linguistic and psychometric research, detects the intent to deceive in written text and calculates an authenticity score using a proprietary formula.[7] Kogan et al. obtain 171 fake articles and 334 non-fake articles written by the same set of Seeking Alpha contributors who were later the subjects of SEC enforcement action.[8] The authors use this cleanly-identified sample to map the LIWC-based authenticity score into the conditional probability of being fake, creating a classification scheme that achieves a type II error (i.e., incorrectly classifying a fake article as non-fake) of less than 10% and a type I error (i.e., incorrectly classifying a non-fake article as fake) of less than 1%. The U.S. Central Intelligence Agency and U.S. Federal Bureau of Investigations use similar linguistic methods to measure the authenticity of written text and speech, providing application-based validity for this methodology.

We use this method from Kogan et al. (2023) to classify articles in our sample as fake and non-fake. To ensure that the linguistic software has sufficient content for classification, we

[6] If an article lists multiple primary stock tickers, the article appears as multiple observations in our sample, with one observation linked to each stock ticker.

[7] The linguistics literature documents that individuals who are being dishonest use less 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).

[8] In 2014 and 2017, the SEC levied enforcement actions against various companies and individuals for fraudulently commissioning authors on Seeking Alpha to write several hundred optimistic, self-promoting articles under the guise of independent analyses (SEC, 2014; 2017).

require articles to have more than 100 words. We then drop articles that are indeterminately classified (i.e., neither fake nor non-fake). In addition, we require non-missing financial data from Compustat, CRSP, and IBES about the firms matched to each article. Our final sample includes 125,475 articles across 37,864 firm-quarters. The proportion of fake articles to the total is 2.5%, quantitatively similar to the 2.8% identified by Kogan et al. Table 1 summarizes our sample selection procedure.

3. Descriptive Evidence on the Content and Timing of Fake News

3.1 Example of Fake News

We begin by offering descriptive evidence on the nature of contemporary fake news. In Appendix B, we provide two example Seeking Alpha articles. The first article, shown in Exhibit A, is a fake Seeking Alpha article later enforced by the SEC for fraud in 2014. In this article, the author provides analyses of Galena Biopharma and its future profitability and share price based on its two major pharmaceutical products, resembling other non-fake articles with fundamental analyses. Interestingly, the author downplays the management forecast of 10-15% long term market share as "conservative" (highlighted under "Best Case"), redirecting instead to a potential future market share that skyrockets to 30%. The fact that the author chose to downplay the validity of the management forecast provides evidence that suggests fake news authors are not only aware of accounting disclosures but also aware that investors use them to judge the veracity of claims in Seeking Alpha articles.

The second article, shown in Exhibit B, is written by a different author disputing the claims made in the first article by referring to the firm's financial statements. Specifically, the author discredits the bullish sentiment on Galena Biopharma by providing references to the company's 10-Qs, 10-Ks, and press releases (highlighted in the exhibit). The stock price fell by 20% after the publication of this article, partially offsetting the inflated price induced by fake news (SCAC, 2014). In addition to correcting the market, this article demonstrates that the author uses accounting information to verify news articles about Galena Biopharma and that he believes he can convince other investors by referring to accounting information. These examples provide useful anecdotes on the content of fake news as well as how market participants perceive fake news through the lens of accounting information.

3.2 Content of Fake News Articles

We next document broad sample descriptive evidence on fake news. We first use Latent Dirichlet Allocation (LDA), a linguistic machine learning algorithm used to identify latent topics in a corpus of text, to characterize the content in our sample of articles (see IA1 and IA2 in the Internet Appendix for implementation details of LDA). We find that articles are written about topics such as accounting information and forecasts, industry-specific news, legal matters, macroeconomic conditions, among others. In addition, one article may span multiple topics (e.g., an article about both accounting forecasts and the pharmaceutical industry). Table 2 Panel A contains the list of our 30 identified topics. For each topic, we tabulate the number of articles containing content for that topic in Column 1 as well as the percentage of articles that are classified as fake within all articles assigned to that topic in Column 2.

We find that a substantial number of Seeking Alpha articles include discussions of accounting content. The two topics specifically about accounting information, Topic 5 and Topic 25 (henceforth, "accounting topics"), are among the top 3 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. We view this evidence as additional support for our choice of setting, as the pervasiveness of accounting content in our broad sample of Seeking Alpha articles increases our power to detect potential interactions between fake news and accounting information. Interestingly, we also note that the percentage of articles classified as fake is among the lowest in accounting topics, potentially suggestive of the difficulty in constructing fake news with or about accounting information. To validate our LDA classification, we compute the percentage of words identified as "accounting words" within each article using the dictionary outlined in Lerman (2020) and tabulate the average percentage for articles under each topic in Column 3. We find that the percentage of "accounting words" are among the highest in accounting topics, providing convergent validity on using LDA to identify articles with accounting content.

In Table 2 Panel B, we provide comparative statistics on the characteristics between fake and non-fake articles. In general, our evidence suggests that fake articles tend to use fewer words per article but more words per sentence. More importantly, we 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, again, providing circumstantial evidence of disincentives to publish fake news with or about accounting information. Nevertheless, a significant portion of fake articles still contain accounting content (57%).

We then investigate the proportion of fake and non-fake articles with positive or negative news. 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%. Interestingly, we find that both the proportions of fake articles classified as positive and as negative are greater than those of non-fake articles across all return thresholds. Our evidence is consistent with the notion that fake news authors may publish exaggerated content in their articles to gain more traction. Lastly, we follow Kogan et al. (2023) in examining the average abnormal volume and idiosyncratic return volatility, as proxies for the magnitude of market reactions to the articles.[9] 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 deceptively written fake news from non-fake news on average.[10]

3.3 Time Trends of Fake News Articles

Next, we provide evidence on aggregate trends in fake news production during our sample period by plotting counts 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 incline from 2014 onwards. Our evidence suggests that the common media narrative on the recent expansion of fake news is not only a popular phenomenon in the political sphere but also a prominent issue in the financial sector as well. When we partition by whether the fake articles contain accounting content, we continue to find the same bimodal distribution. While this descriptive evidence may facilitate future research on the determinants of aggregate fake financial news production over time, we do not pursue this line of inquiry in our paper.

Motivated by our prior finding on the prevalence of accounting content in financial fake news, 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. One, most public firms have earnings announcements, granting us a larger subset of firms than other disclosure events, such as management forecasts. Two, the announcements induce significant

[9] Abnormal volume and idiosyncratic return volatility are defined and examined in detail in Section 5.3.

[10] 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 fake articles without accounting content.

attention and market reactions, indicating salient accounting information flow into the market (e.g., Beaver, 1968; Atiase and Bamber, 1994; Drake et al., 2012). Three, earnings announcements are highly anticipated events that are oftentimes scheduled weeks or months in advance, giving fake news authors advanced notice on the date of disclosure. By exploiting the fact that Seeking Alpha authors are freelancers with the discretion on when to publish news articles, we use this feature to infer author preferences by examining when articles are published relative to the day of the earnings announcement.

To study the revealed preferences of fake news authors, we construct frequency distributions of fake article publications around earnings announcements. 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 decimal number of days between the article publication and the earnings announcement 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.[11] We then calculate *Fake Articles*$_t$, the number of fake articles published on *Days to EA* = t summed across all earnings announcements.

Figure 2 Panel A depicts the resulting frequency distribution created from *Fake Articles*$_t$. We see a general non-descript oscillation in the days leading up to and following the earnings announcement. However, there is a marked increase in fake articles directly prior to earnings announcements that reverts quickly to baseline two days after the announcement. Interestingly, the increase is not symmetric around earnings announcements, as the peak of the distribution occurs prior to announcement. For comparison, we also plot the frequency distribution of non-

[11] There are no articles published at the exact same time as an earnings announcement in our data.

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 announcement and stays at elevated levels for a prolonged period of eight days.

3.4 The Attention Effect and Information Effect of Accounting Information

We propose two aspects of accounting information events that help explain the pattern we find 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 as well as how they interact to form the shape of the frequency distribution of fake news, as follows.

Accounting information events, particularly highly anticipated ones as in the case of earnings announcements, elicit widespread market attention both prior to the forthcoming information and after its revelation (e.g., Beaver, 1968; Drake et al., 2012; Noh et al., 2019). Prior literature has documented opportunistic managerial disclosure choices intended to increase the stock price 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 by periods of elevated market attention to publish more fake news; in doing so, they increase the probability of accumulating more views of their sensationalized fake articles and thereby increase the effectiveness in influencing investor priors or behavior. Hence, the attention effect refers to the potential 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 larger proportions of investors are informed (Schmidt, 2020). Longstanding theoretical and empirical literatures 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 fake news authors are disincentivized by large endowments of accounting information to publish fake news. Specifically, to the extent that the accounting information disclosed during earnings announcements helps investors verify the true asset value of the firm, fake news authors are less effective at misleading investors. Thus, the information effect refers to the potential 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 conjecture that the attention effect and information effect jointly produce the frequency distribution of fake articles 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 thereafter. In the remainder of our paper, we conduct empirical tests on how the attention and information effects impact the incentives of fake news authors to write fake news.

4. Bunching Analyses of Fake News Publication Timing Preferences

4.1 Examining the Attention Effect and Information Effect of Accounting Information

To provide empirical evidence on the attention and information effects of accounting information, we formally test for behavioral distortions in fake news publication around earnings announcements using the bunching approach. Bunching estimation is an empirical methodology developed in the economics literature to attribute behavioral distortions around a known threshold to a discontinuous change in incentives (e.g., Kleven, 2016).[12] For intuition on this methodology, we use the setting of Sallee (2011) as an example. The Energy Policy Act of 2005 granted tax credits for consumers who bought hybrid vehicles starting the tax year 2006. The resulting frequency distribution of Toyota Prius purchases across time shows a distinct missing mass in December 2005 and an excess mass (i.e., "bunching") in January 2006. This distribution pattern provides evidence that consumers shifted their hybrid vehicle purchases from December 2005 to January 2006 due to the tax credit (i.e., the discontinuous change in incentives) coming into effect on January 1, 2006 (i.e., the known temporal threshold).[13] In the context of our study, we use earnings announcements as the salient temporal thresholds for which the incentives for fake news authors to publish change. If these accounting information events create distortions in fake news publication behavior in ways 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 is larger than the mass after the announcements.

We use the polynomial bunching approach to empirically test our conjectures about the distribution of fake news publication around earnings announcements shown in Figure 2.[14]

[12] 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).

[13] 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.

[14] Additional details on the specification and implementation of the bunching approach we use are in the internet appendix.

Following prior literature, we first identify the specific window of time suspected to be affected by changes in incentives (i.e., the affected region) using visual inspection.[15] The distribution of fake articles in Figure 2 Panel A suggests that potentially abnormal publication behavior starts two days prior to earnings announcements and lasts until around two days post-announcement. Thus, we set the affected region equal to t-2 to t+2.

We then model counterfactual fake news publication behavior or, in other words, 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, as follows: (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*$_{t+1,t+2}$. (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 by Chetty et al. (2011) to compute standard errors for inferences on 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 in support of 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

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

publication trends outside the window, providing statistical evidence consistent with the attention effect. $\textit{Differential Abnormal Mass}_{t-2,t+2}$ is also positive and significant, indicating that there are significantly more fake articles published directly prior to the earnings announcement than those published directly afterwards and offering prima facie support for the information effect.

To provide more rigorous evidence on the information effect, we use an alternative bunching methodology: 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 using an alternative set of observations as the counterfactual. As previously noted for Figure 2, the distribution of fake articles and that of non-fake articles both exhibit sharp increases around earnings announcements, likely due to the fact that the broad incentives of Seeking Alpha authors to publish are linked to readership (e.g., Seeking Alpha payment per view, internet clout, etc.) (Dyer and Kim, 2021). Hence, using the distribution of non-fake articles to serve as the counterfactual, we implement difference-in-bunching to isolate the information effect of earnings announcements, conditional on changes to publication behavior from heightened market attention.[16]

Prior to comparing the fake and non-fake distributions, we briefly reexamine the non-fake article distribution in Figure 2 Panel B and present corresponding polynomial bunching statistical estimates in Table 3 Row 2. We note that a visual inspection of the distribution of non-fake articles yields different days of elevated publication behavior relative to earnings announcements than that of fake articles; accordingly, we change the affected region to the t-2 to

[16] Discussion and visual evidence on establishing parallel trends are in the internet appendix. We also note that, as an additional safeguard against an inappropriate counterfactual, our standard errors using 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.

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

Difference-in-bunching is conducted similarly to the polynomial bunching approach, with two key differences. 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*. In addition, due to the large difference in the range of fake and non-fake articles, we scale the number of fake articles published on day *t* by the total number of fake articles published on days *t-45* to *t+45* and scale the number of non-fake articles similarly to facilitate a meaningful comparison. Figure 3 plots *Abnormal Mass*$_t$ in 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 announcement and exhibits a missing mass directly afterwards. We interpret this evidence to be 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 is higher than 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 post-announcement, the density of fake articles is 11% lower than that of non-fake articles. In addition, the difference between the two, captured by *Differential Abnormal Mass*$_{t-2,t+8}$, is positive and significant. These results provide statistical support for the visual evidence in Figure 3 that the abnormal density of fake articles bunches prior to earnings announcement and exhibits a missing mass afterwards. 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 afterwards, when market participants are less susceptible to fake news after a large endowment of accounting information.

4.2 Partitioning by Investor Attention

To provide additional supporting evidence on the attention effect around earnings announcements, we compare the distributions of fake articles published around earnings announcements with high and low investor attention, two distributions with known differences in attention-driven incentives. To do so, we partition our sample of fake articles such that the "high attention" subsample comprises articles matched to firms that receive a positive Investor Search Volume Index (ISVI) on the day of the earnings announcement in the prior quarter (Da, Engelberg, and Gao, 2012; deHaan, Lawrence, and Litjens, 2021).[17] To the extent that the attention effect impacts the incentives of fake new authors to publish, we anticipate more fake articles to be published around earnings announcements with high expected investor attention. However, if investor attention does not influence the publication preferences of fake news authors, we should observe minimal differences in distributions between the two subsamples.

[17] We note that, because ISVI is only available from 2010 onwards, analyses using ISVI have a reduced sample of articles.

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. We first note that, within each subsample, we find estimates to be generally consistent with the attention and information effects documented in the overall sample in Row 1. We then compare the two distributions. Visual examination of Figure 4 suggests that there are substantially more fake articles published around earnings announcements with high investor attention than those 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 the low attention subsample during the pre-announcement, post-announcement, and combined announcement windows in Columns 1, 2, and 3, respectively.[18] Hence, our evidence from investor attention subsample analyses are consistent with the attention effect in that fake news authors publish more fake articles for periods of time when they expect greater investor attention.

4.3 Partitioning by Accounting Content

We next address the concern that our results are contaminated by fake articles that do not pertain to any accounting content and thus should not be influenced by accounting information events. As validation, we conduct subsample bunching analyses partitioning by whether the fake articles contain accounting content.[19] The distribution of fake articles with accounting content is graphed in Figure 5 Panel A with numerical estimates from the polynomial bunching approach presented in Table 3 Row 8. Our inferences from this subsample remain the same as those for the

[18] We note that, 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 on drawing inferences based on the estimates of this cell.

[19] We use the same LDA methodology described in Section 3.2 for classifying whether the fake article contains accounting content.

full sample. The distribution of fake articles with no accounting content is depicted in Figure 5 Panel B with corresponding polynomial bunching estimates in Table 3 Row 9. We note the striking difference in the distributions of these two subsamples. Specifically, while the familiar bunching pattern is present for the distribution of fake accounting articles, there is no meaningful publication pattern for fake non-accounting articles with regards to earnings announcements. We tabulate the difference in these two distributions for completeness in Table 3 Row 10.

The results of these analyses are useful for two reasons. One, finding that the distributional pattern of the main sample manifests in the subsample of fake accounting articles is consistent with the intuition underlying the attention and information effects. Specifically, fake news authors publish more fake articles with accounting content around earnings announcements potentially to take advantage of the demand for accounting information, but they publish relatively fewer accounting-related fake articles post-announcement, as such articles are more easily disproven after verifiable accounting information is released. Two, as there are no distributional patterns using the subsample of fake articles without accounting content, we provide a form of falsification evidence that our results are not driven by correlated omitted variables that influence the motivations to publish fake articles pertaining to both accounting and non-accounting content. Hence, we demonstrate that the results in the main sample are primarily driven by fake articles for which accounting information is particularly relevant.

Overall, we document evidence from our bunching analyses consistent with both the attention effect and information effect 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 pre-announcement than post-announcement. These findings are consistent with fake news authors strategically choosing to publish more fake articles when there is heightened investor attention but to avoid publishing in relatively more robust accounting information environments. In addition, consistent with the attention effect, we show there are more fake articles published around earnings announcements with higher investor attention than those with lower investor attention. We provide validation for our main results by demonstrating that the bunching behavior manifests in a restricted subsample of articles containing accounting content but not within a subsample of articles without accounting content. This pair of findings provides reassurance not only that our proposed effects manifest in the subsample of articles for which accounting information is particularly relevant but also that the behavioral patterns we document are not artifacts of fake articles without accounting content.

5. Regression Analyses and Results

To further develop our understanding of the interactions between accounting information and the incentives to publish fake news, we explore the incentives to publish fake news in the context of the broader accounting information environment by examining (1) the likelihood of fake news authors targeting firms with more robust accounting information environments and (2) the market impact of fake news targeted towards firms with more robust accounting information. We use two proxies for accounting information derived from accounting disclosures we perceive to be particularly salient to fake news authors: management forecast frequency and 10-K readability.

5.1 *Measures of Accounting Information*

5.1.1 *Management Forecast Frequency*

Management forecasts serve as prominent voluntary disclosures that reduce information asymmetry in the market (e.g., Verrecchia, 2001; Healy and Palepu, 2001; Beyer et al., 2010). Beyer et al. (2010) show that management forecasts provide 55% of the firm's accounting-based information in explaining stock returns. In addition, prior literature documents many specific avenues in which management forecasts inform investors, including projecting key line items in financial statements (Lansford, Lev, and Tucker, 2007), clarifying complexities in business transactions (Guay et al., 2016), and reducing uncertainty in the business environment (Billings, Jennings, and Lev, 2015). To the extent that management forecasts provide detailed forward-looking information about anticipated earnings, sales projections, and potential growth, fake news authors may be less inclined to target these firms for which misleading portrayals of future prospects are less likely 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 of the Seeking Alpha article publication date.

5.1.2 *10-K Readability*

Our second proxy, the linguistic readability of the firm's 10-K, captures a prominent element of mandatory accounting information quality. Though the 10-K contains mandatory disclosures crafted to follow standards set forth by the Financial Accounting Statement Board and vetted by legal and audit teams, there is nevertheless considerable variation in the writing style and length of 10-Ks (e.g., Li, 2008; Bonsall, Leone, Miller, and Rennekamp, 2017). The lower information acquisition and integration costs associated with clearer textual disclosures allow investors to incorporate more information from the disclosure into their valuation and investment decisions (e.g., Blankespoor, deHaan, and Marinovic, 2020). If investors can more easily glean narrative information from the firm's annual reports about its operating environment, such as product line synergies, peer competition, and risk factors, we conjecture that fake news authors are less likely to target firms for which investors are more likely to refute misinformation about firm operations. We measure *10-K Readability* as the Bog Index from Bonsall et al. (2017) multiplied by -1 for ease of interpretation.

5.2 *The Role of Accounting Information in Disincentivizing Fake News Production*

We examine the role of accounting information in the strategic publication decisions of fake news authors by estimating the conditional probability that an article about a firm is fake. We expect an increase in *Management Forecast Frequency* or *10-K Readability* to decrease the probability that a fake article is written. To analyze the determinants of fake articles, we estimate the following model at the article level:

$$Pr(Fake\ Article_j) = \beta_1\ Accounting\ Information_i + \sum \beta\ Controls_i + \sum Fixed\ Effects + \varepsilon. \quad (1)$$

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 regression 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 variables used in our analyses. 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 provides the results of estimating Equation (1) using a logit regression model. We present coefficients as marginal effect estimates multiplied by 100 to interpret them as percentage changes 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* prior to the article publication date reduces the probability that an article is fake by 8%. Column 2 presents 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 of our variables of interest has an incremental effect on the production of fake news. The coefficient estimates on both accounting information variables remain significant in the expected directions without notable decreases in magnitude. Thus, our evidence suggests that the main independent variables capture distinct measures of accounting information and offers convergent validity for the result that fake news authors are less likely to target firms with a relatively more robust accounting information system.[20]

We briefly note the coefficient estimates on a few control variables. Both *Analyst Coverage* and *Institutional Ownership* are largely insignificant. This evidence suggests that fake news authors do not incrementally consider professional information intermediaries or firm

[20] Our results in Column 3 are robust to a number of sensitivity analyses, which are tabulated in IA4-IA6 of the internet appendix. Specifically, our results are robust to using Poisson pseudo-maximum likelihood estimation at the firm-quarter level (IA 4), using either a 180-day or 90-day window for measuring management forecast frequency (IA5), and dropping industry-years with less than 50 observations (IA5). Additionally, see IA6 in the Internet Appendix for a visual analysis of Equation (1) using ordinary least squares estimation and binned scatterplots.

monitors 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 our accounting information variables of 8-10%. This result is consistent with the attention effect in that more media attention is associated with a higher probability that a fake article is published.

One concern with our results in Table 5 is the potential omitted variable bias due to relying primarily on cross sectional variation in these tests. We address this concern with a series of additional tests, as follows: (1) partitioning our sample by whether the article contains accounting content to provide validation that our results are driven by fake articles for which accounting information is pertinent, (2) partitioning our sample by the sign of the earnings surprise of the last earnings announcement to account for firm performance as a confound, and (3) performing a host of additional subsample analyses within firms with similar general information environments. These tests limit the variation of both observed and unobserved variables to provide robustness for our inferences.

Table 6 presents the results of these additional tests using the same specification as Table 5 Column 3, unless noted otherwise. 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 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 expected to influence the publication of fake articles in general that may not pertain to accounting information. This pair of analyses provides solace 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 publication behavior of fake news authors. 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.

Lastly, we 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 have systematically 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 documents these characteristics as particularly 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 articles that are ultimately published. In accordance with the information effect, we expect investors to react less to fake articles about firms with a strong accounting information environment due to two primary mechanisms. One, investors may use accounting information to cast doubt on or outright disprove misinformation, resulting in decreased investor reaction to the fake news. Two, in anticipation of this possibility, fake news authors may feel limited in the content they can publish to still elicit a market response and therefore temper their use of greatly embellished or unsubstantiated claims that may have otherwise garnered higher market reactions. To test our prediction, we estimate the following model using ordinary least squares regression at the article level:

$$\begin{aligned} \textit{Market Reaction}_{t,t+2} = \beta_1 \textit{ Accounting Information}_i + \textstyle\sum \beta \textit{ Controls}_i \\ + \textstyle\sum \textit{Fixed Effects} + \varepsilon. \end{aligned} \tag{2}$$

Our dependent variable *Market Reaction* is one of two variables used to measure the market response to fake Seeking Alpha articles: *Abnormal Volume,* a measure based on trading activity, and *Idiosyncratic Return Volatility,* a measure based on price movement. *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 scaled by the average trading volume in the 20 and 140 trading days prior. *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-, B/M-, and momentum-matched portfolio (Daniel, Grinblatt, Titman, and Wermers, 1997). We use both trade- and price-based reaction variables to present a more holistic view of the market reaction to fake news and to mitigate concerns that excess trading can occur without impacting prices (e.g., Fama, 1970) or that substantial price movement can occur without any trade (e.g., Milgrom and Stokey, 1982).

In addition, we exclude articles from these analyses if they are published within two days of an earnings announcement, management forecast, 10-K, 10-Q, or 8-K 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 article publication 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, and we find that both coefficient estimates remain significant in the expected direction 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. For 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 that includes both accounting information variables are consistent with those from Columns 1 and 2. Hence, we provide evidence supporting the inference that the market reaction to fake news attenuates when the targeted firm has a strong accounting information environment.

6. Conclusion

We document general characteristics of fake financial news and examine how accounting information interacts with the incentives to publish fake financial news in the capital markets. We first detail descriptive statistics on the types of content in fake news articles. Using Latent Dirichlet Allocation to identify topics in the articles, we find significant heterogeneity in topical areas. Interestingly, accounting content is prominent in fake news, spanning over 57% of fake articles. We then examine the volume of fake news articles over time. We find that the publication trend of fake articles exhibits a bimodal pattern over the last two decades, with one peak occurring around 2007-2009 and a continuous incline from 2014 onwards.

Motivated by the prevalence of accounting content in financial fake news, we investigate the publication of fake articles relative to one of the most important accounting disclosure events: earnings announcements. Using bunching analyses, we document evidence consistent with the following stylized facts: (1) Fake news authors strategically publish more fake articles near earnings announcements to take advantage of elevated market attention, and (2) they strongly prefer publishing fake articles pre-announcement to publishing post-announcement when the disclosure of accounting information decreases investor susceptibility to false price signals. Additional subsample analyses on cross sections in which we expect the effects to manifest more strongly, such as fake articles published around earnings announcements with high investor attention and fake articles containing content that pertains to accounting information, support our inferences.

To further develop our understanding of the interactions between accounting information and the incentives to publish fake news, we use regression analyses to examine how the broader accounting information environment affects the publication of fake news and its subsequent market impact. We find that as firms improve their accounting information environment by issuing more management forecasts or more readable annual reports, there is less fake news written about them. In addition, we find a lower market reaction to fake news targeting firms with more robust accounting information environments. Hence, in these analyses, we document evidence that a more robust accounting information environment both disincentivizes the production of fake news and mitigates its subsequent market impact.

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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
Abnormal Volume$_{t,t+2}$	The sum of the scaled trading volume on the day of publication and the following two trading days. Scaled trading volume is defined as trading volume scaled by the average trading volume between 20 and 140 trading days prior. Source: CRSP
Idiosyncratic Return Volatility$_{t,t+2}$ (%)	The sum of the squared abnormal returns on the day of publication and the following two trading days multiplied by 100. Abnormal return is defined as a firm's daily return minus the daily return on a 5x5x5 size-, B/M-, 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) 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 $t = 0$.

Appendix B
Exhibit A: Fake News Article on Galena Biopharma

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Galena Biopharma: Best And Worst Case Scenario

Aug 14 2013, 04:09 | about: GALE BOOKMARK / READ LATER

CONTRIBUTOR


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3 on Quick Picks & Lists

Articles (441)
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Disclosure: I am long GALE. **(More...)**

Last Thursday, Needham & Company initiated coverage on shares of **Galena Biopharma** (GALE) with a "Buy" rating and a $3.50 price target. According to streetinsider.com, Galena has "Buy" or "Outperform" ratings by all of the analysts who cover the stock. Yet, certain bloggers and retail investors have been quite cynical about the company's future. Thus, let's look at both the best and worst case scenario with Galena Biopharma to determine if the risk is worth the reward.

Abstral: Now Available

Abstral is a rapidly-dissolving sublingual tablet for the management of breakthrough pain. The drug is a best-in-class fentanyl product, with plasma concentrations of fentanyl seen within 10 min. This rapid absorption is what separates Abstral from other breakthrough pain and fentanyl drugs and is why many believe it will be a successful product.

According to Galena's recent quarterly report, Abstral is now available at nationwide pharmacies. Galena will now market the drug, and hopes to create a profit by next year.

Best Case

In Europe, Abstral produced sales of $54 million in 2012. In Q4 2012, Abstral sales grew 42% year-over-year, thus showing that it could be a success in the U.S.

In the U.S., the market for fentanyl products is $400 million annually, and Galena believes that it can control 10%-15% of the market within five years. This means that Abstral could generate annual sales of $60 million.

If Abstral is viewed as reliable and efficient, it is highly likely that Abstral could command an even larger share of the fentanyl market, or expand the market in size. At first glance, it appears as though Galena is being conservative with their guidance, as Abstral continues to grow and maintains a 30% market share in Europe.

If Galena can control a 30% market share in the U.S., sales could rise to $120 million. If we use a four times sales ratio then we arrive at a market capitalization of $480 million, or $5.75, and that's only accounting for Abstral.

Worst Case

The worst case is that Abstral is a dud and never reaches $60 million in sales. Currently, Galena is trading with a market cap of $150 million. On March 18, when Galena announced the acquisition of Abstral, it traded with a market cap of $166 million.

Due to Galena being cheaper today than it was in March, we can conclude that none of Galena's valuation is tied to Abstral's success or failure. This means that any upside will be viewed as a bonus, also suggesting that a failed Abstral campaign should not alter the stock.

NeuVax: Blockbuster Potential

NeuVax is a Phase 3 vaccine that is being tested to prevent breast cancer recurrence in the 50%-75% of patients who are not eligible for Herceptin. The vaccine targets those who have low to intermediate levels of HER2, while Herceptin targets those who have high levels of HER2.

In a Phase 2, 187 patient study, NeuVax reduced the risk of recurrence by 78% in patients who were node-positive. Compared to the control arm of the study, only 5.6% of patients recurred after 60 months compared to 25.9% of those who were not vaccinated with NeuVax. In the company's ongoing Phase 3 study, the company hopes to prove that NeuVax can keep patients from redeveloping the disease.

Best Case

As of now, we have no way of knowing how much revenue NeuVax can produce if proven successful in its Phase 3 study. NeuVax is being tested alone, with Herceptin, and as a booster. If all three studies are successful, then we know that NeuVax will be a blockbuster product.

In comparison, Herceptin generates $7 billion annually by targeting just one-fourth to one-third of breast cancer patients. If NeuVax is successful, it will target at least one-half of patients. Hence, it is not unreasonable to estimate $2 billion in peak sales, which is most likely conservative.

At $2 billion in sales, adding a four times sales multiple, Galena could be worth $8 billion long-term. After approval, and awaiting an FDA decision, if Galena trades at 0.5 times peak sales then it would support a $1 billion valuation. In other words, Galena has upside of 700% short-term, and over 5,000% long-term if NeuVax is proven successful.

Worst Case

If NeuVax fails, then Galena would fall sharply. Right now, all of the stock's valuation is tied into the potential of NeuVax, not quite accounting for any success or lack thereof in marketing Abstral.

If unsuccessful, a 50% loss should be expected, or a market cap of $75 million. The unknown piece of the puzzle will be sales of Abstral. If Abstral is successful and generates sales between $60 and $120 million, then Galena's market capitalization will likely carry a 100% to 300% increase from its current price.

This means that if Abstral is successful, Galena should trade higher as data progresses. Then, if NeuVax fails, Abstral's success should still carry a stock price that is greater than its current price.

Overall Outlook

In bringing this discussion back down to earth, let's pretend that you invest $7,500 in Galena, or purchased 4,000 shares. Below I have included a table to show how each of the discussed scenarios could play out in stock performance.

Situation	Stock Price	Return (rounded)
Abstral fails + NeuVax fails	$0.90 or less.	($3,600)
Abstral $60m + NeuVax fails	$2.88	$11,500
Abstral $120m + NeuVax fails	$5.75	$43,000
Abstral $60m + NeuVax @ 0.5x peak sales	$15	$60,000
Abstral $60m +NeuVax @ 4x peak sales	$100	$400,000

As charted, there aren't too many scenarios where an investment returns a loss, which may be the driving force behind positive sentiment from analysts. Granted, this is speculative and theoretical in using standard price times sales ratios, but given each situation it's reasonable that the noted stock price should follow.

Like I explained, the wild card is Abstral. We don't know how it will perform. But NeuVax looks to be a very compelling product, that when used on the appropriate patient population, produced significant results. After assessing the company, including its risk and reward, it is difficult to determine why some could be overly bearish, as the downside is extraordinarily minimal. The decision of whether to invest is then determined on your own assessment of risk: Is the risk worth the reward

Exhibit B: Article Disputing Bullish Sentiment on Galena Biopharma
We reproduce only the most relevant sections of this article for brevity. Full article is found here: https://web.archive.org/web/20140301202559/https://seekingalpha.com/article/1984371-galena-biopharma-numerous-red-flags-suggest-a-significant-overvaluation

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Galena Biopharma: Numerous Red Flags Suggest A Significant Overvaluation

TOP IDEA Jan. 31, 2014 10:15 AM ET | About: GALE
Disclosure: I am short GALE. **(More...)**

Disclosure

I am short Galena Biopharma (GALE) in via the purchase of put options at varying expiration dates/strike prices.

Summary

> *"There is no training - classroom or otherwise - that can prepare for trading the last third of a move, whether it's the end of a bull market or the end of a bear market. There's typically no logic to it; irrationality reigns supreme..."* - Paul Tudor Jones

While pondering of a way to sum up Galena Biopharma (GALE), I remembered that quote from Paul Tudor Jones and realized how applicable it is to GALE. The ~200% rise GALE has seen over the past two months is nothing short of incredible. After trading range bound for over three months, shares of GALE saw a massive break-out in mid-November and momentum traders who got in on the move during the early stages were handsomely rewarded with triple digit returns by early January.

Now that the parabolic move has finally exhausted itself and momentum traders (along with company insiders) are exited out of their long positions, reality and logic can set in.

On the surface one *might* think that Galena is a good speculative biotech stock with a nice risk/reward profile. However, the purpose of this article is to shed some light on the numerous risks the GALE poses and present the case for why the risk/reward profile favors the short side.

Before we start moving on to the more interesting topics, there are a couple of key points that should be taken away here:

- Interim results the NueVax phase II trial data were presented in 2006 by Dr. George Peoples. (That is an important name to remember as well)
- It took 4 years of the market essentially writing off NeuVax as a legitimate therapy before they found a willing buyer.
- The combination of a spin-off, mergers, and name changes make it extremely difficult to track down accurate data/SEC filings.

Galena Lacks Vital Exclusivity Rights to NeuVax

Even PRESENT Phase III trial does prove to meet its agreed endpoint, and the FDA does not require an additional Phase III study (which is possible based on GALE's assessment of the situation stated in their latest 10K), Neuvax faces some difficult challenges as it relates to intellectual property.

Galena's Pipeline and "Partnerships" add very little value

The Press Releases concerning partnerships have been misleading.

In December 2012, GALE announced "signature of commercialization partnership with Teva in Israel". (Link to PR Here)

However, GALE's sec filings provide some clarity into the specifics of the "partnership" with Teva. *"Effective December 3, 2012, we entered into a license and supply agreement with ABIC Marketing Limited."*

This press release raises a red flag for a couple of reasons:

1. While the full financials terms haven't been disclosed, it appears GALE did not receive any upfront payment in the deal. It seems GALE will be entitled to royalties based on future sales of Neuvax in Israel. My question is, if Neuvax was the potential blockbuster drug like GALE management claims, then why would they agree to a deal with such miniscule financial benefit?
2. The timing of the press release, coupled with the terminology and verbiage used seems to be misguided.

Abstral

In fact, Galena warns about the potential for Generic competition in their 10Q filed in August 2013:

> ***"We may not be able to obtain and enforce patent rights or other intellectual property rights that cover Abstral and that are of sufficient breadth to prevent third parties from competing against us.***
>
> *Our success with respect to Abstral will depend in part on our ability to obtain and maintain patent protection in the United States, to preserve our trade secrets, and to prevent third parties from infringing upon our proprietary rights. Fentanyl, the sole active pharmaceutical ingredient, or "API," in Abstral, has been approved for many years and therefore our ability to obtain any patent protection is limited. Composition of matter*

> *patents are a particularly effective form of intellectual property protection for pharmaceutical products, as they apply without regard to any method of use. However, we will not be able to obtain composition of matter patents or methods of use patents that cover the APIs in Abstral. As a result, competitors who obtain the requisite regulatory approval can offer products with the same active ingredients as Abstral so long as the competitors do not infringe any formulation patents that we may have or may obtain or license, if any"*

It is also concerning that GALE limited their contractually obligated marketing responsibilities to a two-year span. Logic would dictate that if a company expected a drug to succeed and achieve growth in sales, they would have no problem committing to marketing it throughout its lifespan.

GALE states the following in their latest 10Q:

> *"Under our agreement with Orexo, we assumed responsibility for the U.S. commercialization of Abstral and for all regulatory and reporting matters in the U.S.* ***We also agreed to establish and maintain through 2015 a specified minimum commercial field force to market, sell and distribute Abstral and to use commercially reasonable efforts to reach the specified sales milestones.*** *Orexo is entitled to reacquire the U.S. rights to Abstral from us for no consideration if we breach our obligations to establish and maintain the requisite sales force throughout the marketing period."*

Paying Companies for Stock Promotion and Significant Insider Selling are Major Red Flags

Stock Promotion

When I first started investing in/trading biotech stocks, I was fortunate enough to have several trading mentors impart valuable insight and words of wisdom that has helped contribute to my success. These "words of wisdom" included a warning about stocks that are constantly "pumped" over the internet.

As outlined in a March 2012 article by SeekingAlpha contributor Michael Morhamus, GALE's moves higher can be partially attributed to heavy promotion of the stock via the internet. After reading the article, I thought it brought up some interesting points and additional research into the matter was warranted. Needless to say, I came across some noteworthy pieces of information as it relates to Galena's stock being "promoted" via various outlets.

However, further investigation revealed that Galena was paying for these promotions. This, for me, is definitely a red flag.

According to a disclaimer found on the tip.us website, MissionIR received compensation from "GALE for 240 days of advertising, branding, marketing, investor relations and social media services provided by MissionIR and affiliate DreamTeamGroup Business Brands."

This potentially explains a part of the massive increase in the company's SG&A Expenses (obviously a large part of the increase was due to the Abstral launch).

Selling, General and Administrative Expense

Selling, general and administrative expense includes compensation-related costs for our employees dedicated to sales and marketing, general and administrative activities, legal fees, audit and tax fees, consultants and professional services, and general corporate expenses. Selling, general and administrative expense for the three and nine month periods ended September 30, 2013 and 2012 , was as follows (dollars in thousands):

	Three Months Ended September 30,			Nine Months Ended September 30,		
	2013	2012	% Change	2013	2012	% Change
Selling, general and administrative expense	$ 4,129	$ 1,359	204%	$ 8,369	$ 5,068	65%

Selling, general and administrative expense increased $2.8 million for the three months ended September 30, 2013 , compared with the three months ended September 30, 2012 . The increase was primarily due to a $2.7 million increase in personnel related costs, associated with the establishment of our Abstral commercial force and marketing team, and professional and outside services, and a $0.2 million increase in non-cash employee stock based compensation expense.

Selling, general and administrative expense increased $3.3 million for the nine months ended September 30, 2013 , compared with the nine months ended September 30, 2012 . The increase was primarily due to a $3.3 million increase related to personnel related costs, associated with the establishment of our Abstral commercial force and marketing team, and professional and outside services, and a $ 0.4 million increase in non-cash employee stock based compensation expense, which was partially offset by a decrease of $ 0.4 million in non-cash non-employee stock based compensation expense.

Insider Selling

As shown in the illustration below, there has been significant insider selling in GALE since the beginning of 2014. The insider-selling activity was also called out in a recent article by SeekingAlpha contributor Markus Aarnio.

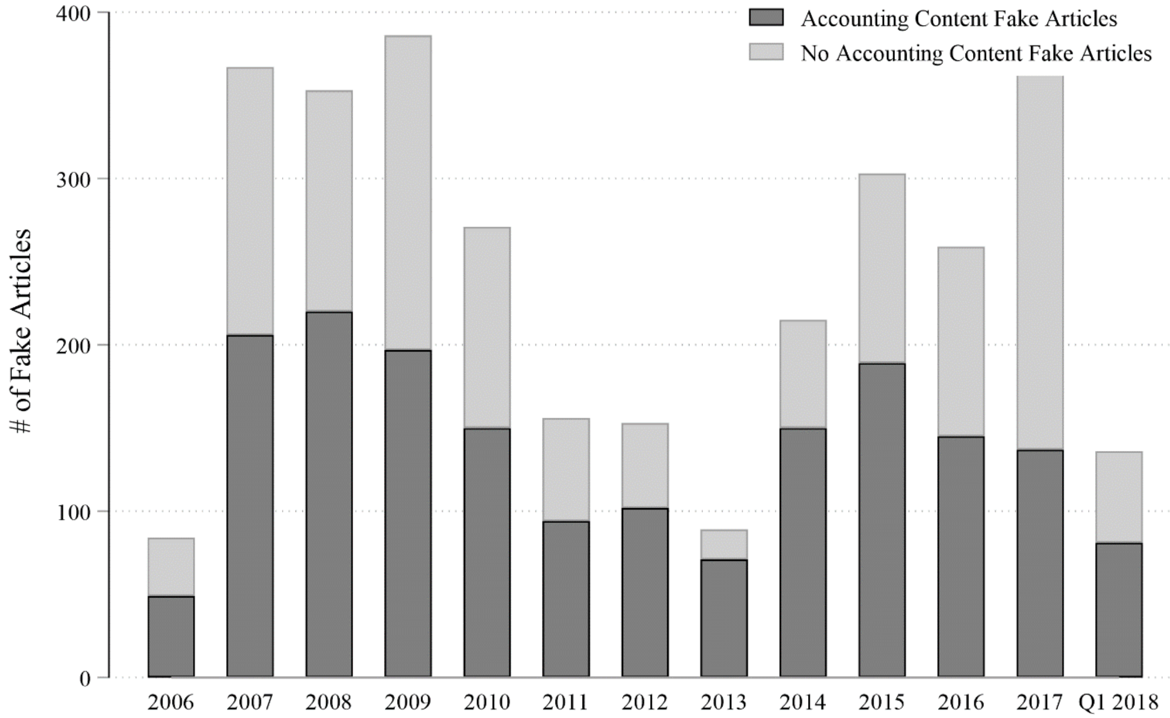
Transaction Date	Name	Position	Type	Shares	Range	Market Value	Total Holdings
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	250,000	$0.72 - $1.18	180.0K	255,000
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Sell	250,000	$6.13	1.5M	5,000
01/17/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	200,000	$0.85	170.0K	205,000
01/17/2014	KRIEGSMAN, STEVEN A.	Director	Sell	200,000	$7.00	1.4M	5,000
01/17/2014	HILLSBERG, SANFORD	Director	Sell	200,000	$6.93	1.4M	110,447
01/17/2014	NISI, RUDOLPH	Director	Sell	200,000	$6.90	1.4M	3,500
01/15/2014	NISI, RUDOLPH	Director	Option Execute	200,000	$0.85 - $1.18	170.0K	203,500
01/14/2014	HILLSBERG, SANFORD	Director	Disposition (Non Open Market)	24,426	$6.96	170.0K	310,447
01/14/2014	HILLSBERG, SANFORD	Director	Option Execute	200,000	$0.85	170.0K	334,873

So if members of Senior Management (including the CEO) are liquidating significant portions of their holdings at current levels, what does that suggest about their views of future prices?

Per the latest 10Q, GALE has approximately 35M in shares reserved for future issuance. And if history is any indication of future actions, I am a strong believer that those warrants and options will be exercised well before they expire. Additionally, the large number of warrants add another negative dimension due to the potential for an increase in short interest. It is common to see an increase in selling pressure on stocks with a large number of warrants, let me explain. Once the stock price reaches a level that satisfies a warrant holder's expectations and desired return, they will short/sell the stock at those levels and essentially lock in a fixed return while using the warrants as a cover.

In the long term, GALE's stock price will be determined by most of the underlying factors I discuss in this article. And for reasons that I discuss in this article, I remain quite bearish in the long term.

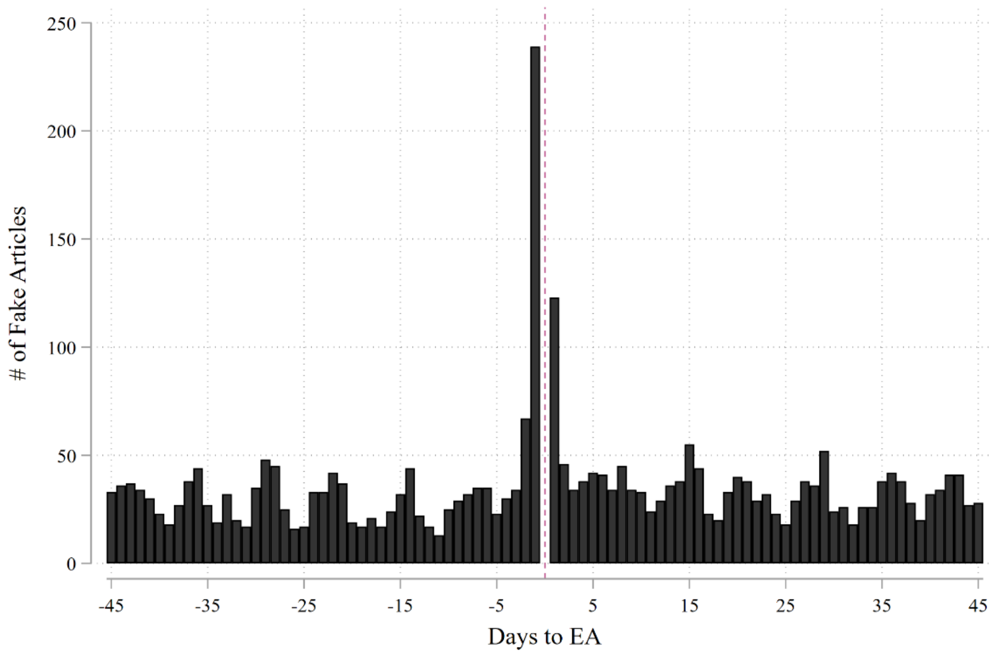
Figure 1: Fake News Production Over Time for Articles With and Without Accounting Content



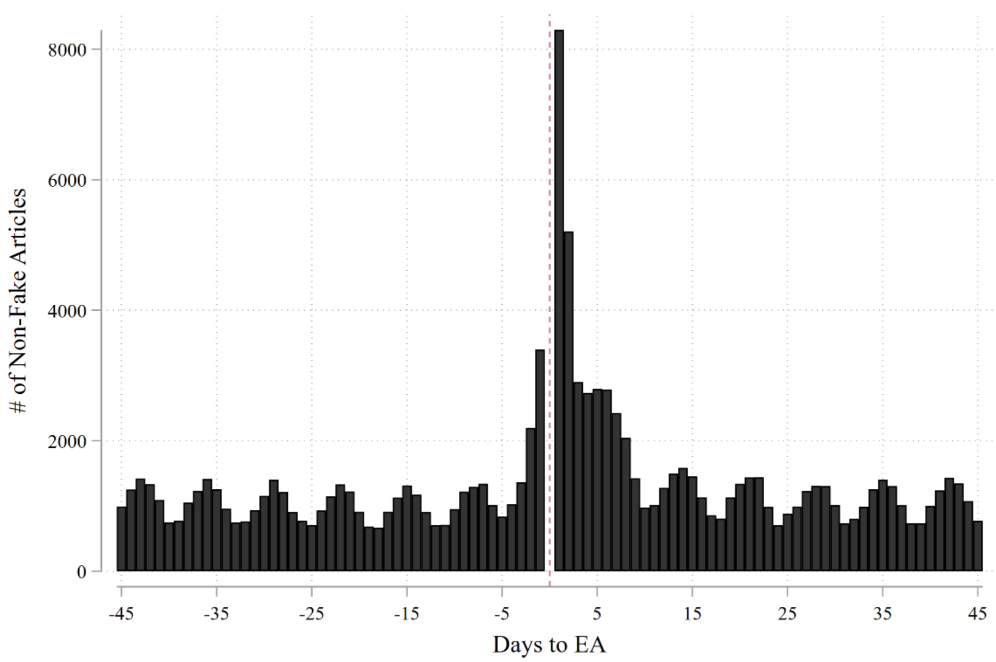
This figure presents the number of fake articles published on Seeking Alpha for each year during our sample. Within the total number of fake articles published each year, the figure also shows the number of fake articles containing accounting content. Note that our sample only includes the first three months of 2018.

Figure 2: Distributions of Fake and Non-Fake Seeking Alpha Articles Around Earnings Announcements

Panel A: Distribution of Fake Articles Around Earnings Announcements

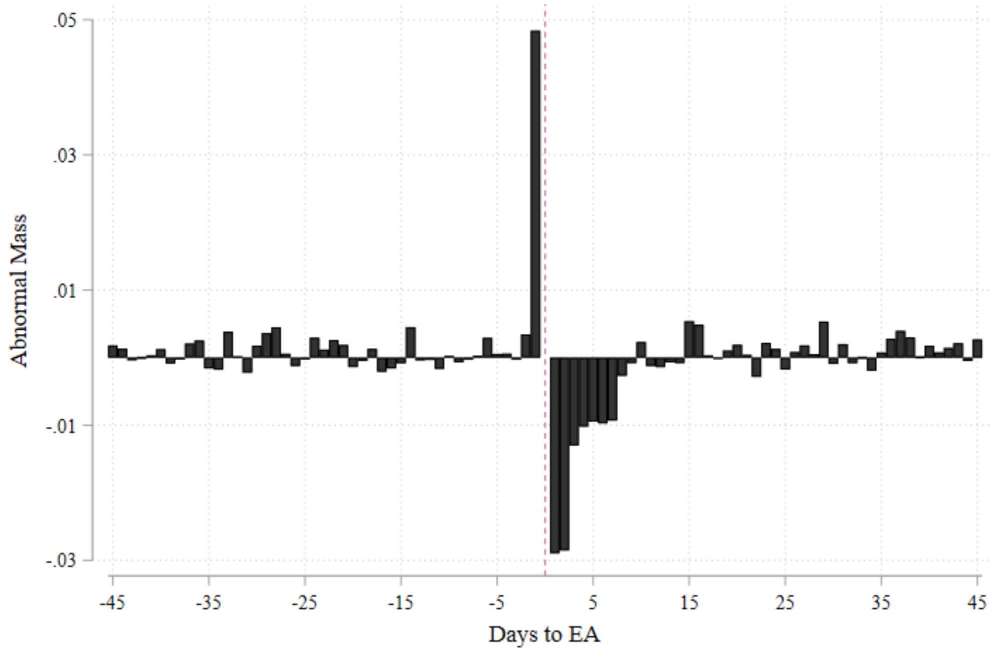


Panel B: Distribution of Non-Fake Articles Around Earnings Announcements



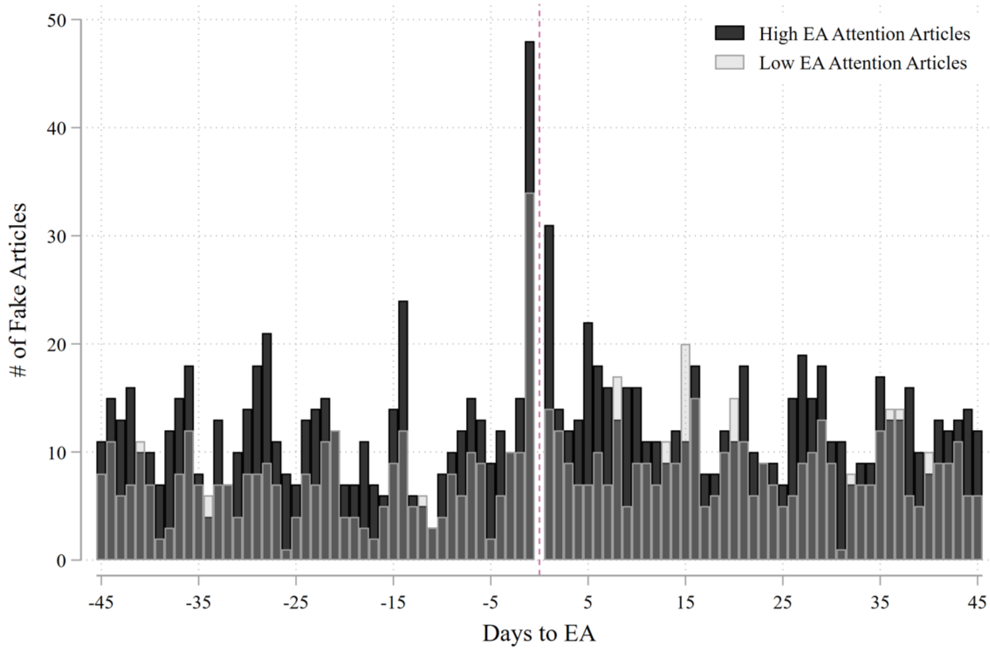
This figure presents graphical evidence on the publication timing of fake and non-fake articles relative to earnings announcements. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles.

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 announcement. In these analyses, *Abnormal Mass* is specified as the difference between fake and non-fake article distributions.

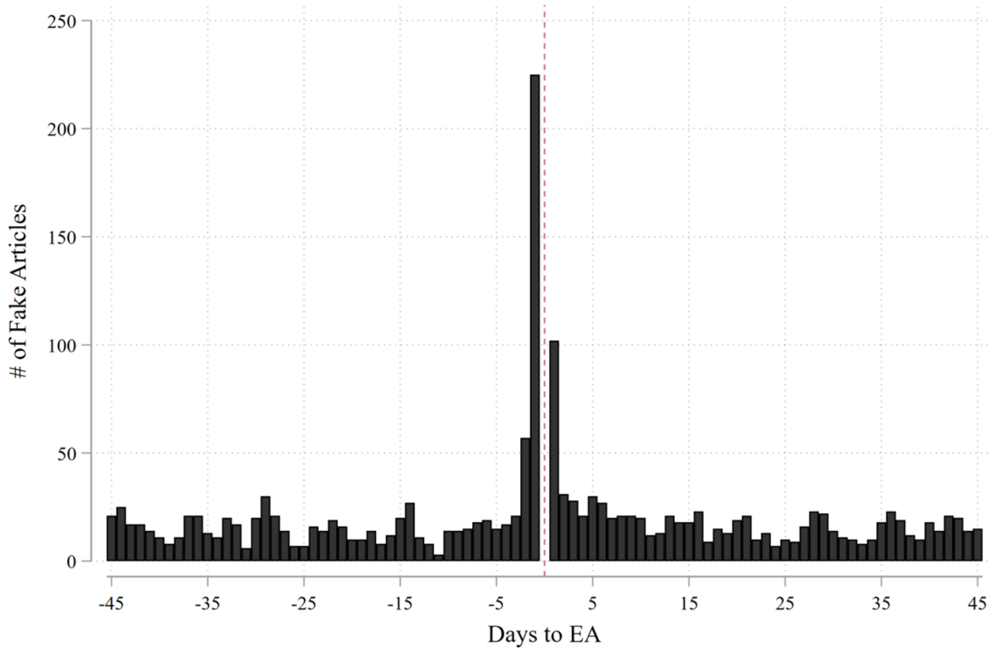
Figure 4: Distributions of Fake Articles Around High and Low Attention Earnings Announcements



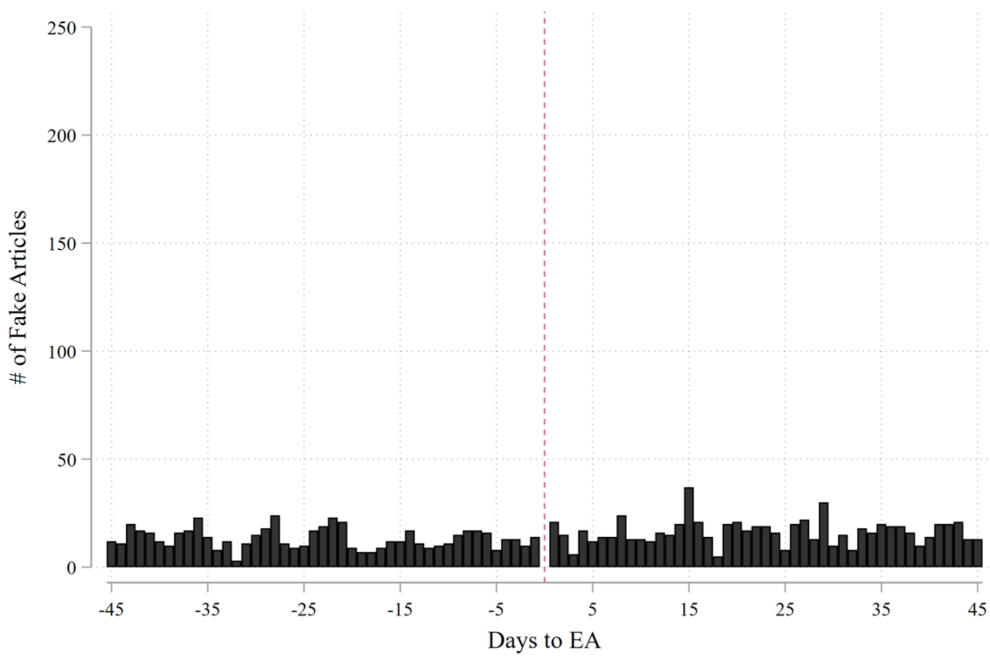
This figure presents a graphical depiction of the main result from the analyses in Table 3 Row 7 by plotting the fake article distributions for high and low attention earnings announcements.

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	(4,440)	
Exclude: Missing firm-level controls	(2,194)	
Article 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. (2022), 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: Determining 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 ≥ 0.5%)	40.6	38.5	2.1**
% Negative Articles (Return ≤ -0.5%)	38.0	35.9	2.1**
% Positive Articles (Return ≥ 1%)	31.3	28.3	3.0***
% Negative Articles (Return ≤ -1%)	30.0	26.4	3.6***
% Positive Articles (Return ≥ 2%)	18.8	15.4	3.4***
% Negative Articles (Return ≤ -2%)	19.1	15.0	4.1***
Market Impact			
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*. ***, **, 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					
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, 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

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 (Continued)

This table reports analyses on the effect of accounting information on the probability of fake news. 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. (2022). 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) multiplied by -1. 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 *Fake Article* 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 Dependent Variable	*Management Forecast Frequency*	*10-K Readability*	*# of 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 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 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 Impact of Accounting Information on 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 Impact of Accounting Information on 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)

The 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. Articles published within two days of an earnings announcement, management forecast, 10-K, 10-Q, or 8-K are excluded from the analysis because we cannot attribute the market reaction to the Seeking Alpha article itself. Similarly, we 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 the scaled volume on the day of publication and the following two trading days. Scaled volume is defined as volume scaled by the average volume between 20 and 140 trading days prior. The dependent variable in Panel B is *Idiosyncratic Return Volatility*, which is the sum of the squared abnormal returns on the day of publication and the following two trading days. Abnormal return is defined as a firm's daily return minus the daily return on a 5x5x5 size-, B/M-, 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.