The Role of Accounting Information in an Era of Fake News

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

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

December 2022

Abstract

We examine the role of accounting information in the production of fake financial news. To provide context on the nature of contemporary fake financial news, we detail descriptive statistics of trends in the content and volume of fake news articles. Using bunching analyses, we document two observations on the interactions between accounting information and incentives to produce fake news: (1) fake news authors publish more fake articles near earnings announcements due to the widespread market attention these events garner and (2) they strongly prefer to publish fake articles pre-earnings announcement when the accounting information environment is relatively weaker as compared to post-announcement. To complement our bunching results, we use regression analyses to provide evidence consistent with a more robust accounting information environment both disincentivizing the production of fake news and mitigating the market reaction to fake news.

JEL Classification: D82, D83, G14, M41

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

[*] Corresponding author: Betty Liu. Postal address: 1309 E. Tenth Street, Suite 5100, Bloomington, IN 47405.
We thank Robert Holthausen (editor) and an anonymous referee for their insightful suggestions. We are grateful for helpful discussions with Dan Collins, Cristi Gleason, Dennis Hamilton, Christian Hutzler, Paul Hribar, Andrew Imdieke, Tyler Menzer, Ken Merkley, David Volant, Clare Wang, and Sarah Zechman as well as helpful comments from participants at the University of Iowa, the Midwest Accounting Research Conference, and the Cambridge Disinformation Summit. We appreciate Shimon Kogan for providing us with information about the fake news classification methodology as well as Seeking Alpha for their assistance in collecting article data. The authors have no conflicts of interest to disclose.

"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 the company refuting these claims as "false and materially misleading," the article caused investors to sell the firm's stock in a panic, resulting in an approximately 40% drop in share price (Farmland Partners, Inc., 2018).[1] Kogan, Moskowitz, and Neissner (2022) document broad empirical evidence on the magnitude and speed of investor reaction to fake news consistent with this anecdote, finding that market participants react as strongly to fake financial news as real financial news. In response to the risk posed by 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 broadly examine the content and timing of fake financial news and document interactions between accounting information and the incentives to publish fake financial 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.

We use Seeking Alpha, an independent investor research website, as our setting. Seeking Alpha is conducive to studying fake financial news and its interactions with accounting information for several reasons. One, 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., 2022). These factors provide an opportunity for self-interested authors to manipulate market opinions by writing fake news and largely avoid the reputation costs of doing so.[3] Two, 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. Three, 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 fake news. Lastly, Kogan et al. (2022) develop a methodology to identify a large sample of Seeking Alpha articles written with the intent of deceiving readers and validate their classification approach on a sample of known fraudulent Seeking Alpha articles that led to SEC enforcement.[4] We use their approach to identify "fake" and "non-fake" articles. [5]

We begin by documenting descriptive statistics of trends in the content and volume of fake news articles. To analyze the content of fake news, we use Latent Dirichlet Allocation (LDA), a machine learning algorithm, to identify topics covered by the articles. We find

[3] 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.

[4] 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).

[5] See Section 2.3 for details on how we classify articles as "fake" following Kogan et al. (2022).

significant heterogeneity in topics, such as accounting information and forecasts, industry-specific news, legal matters, and macroeconomic conditions. Of particular interest, we find that fifty-seven percent of fake articles contain accounting content. The prevalence of accounting content in fake financial news provides further motivation to investigate the interactions between accounting information and fake news production. In examining publication trends over time, we find that the number of fake articles exhibits a bimodal pattern over our sample period, with peaks occurring around 2007-2009 and 2014 onwards. Hence, we document that the common media narrative on the expansion of fake news is not only a phenomenon in the political sphere but also a pervasive issue in the financial sector.

To shed light on the potential interactions between accounting information and the timing of fake news publication, we examine the volume of fake news produced around earnings announcements, as prior literature documents significant investor interest in these accounting disclosure events (e.g., Beaver, 1968; Atiase and Bamber, 1994). To do so, we plot the frequency distribution of fake articles published in the days surrounding earnings announcements. A visual inspection yields that the publication of fake articles is significantly higher around the announcement date. Interestingly, the number of fake articles peaks the day prior to the announcement but decreases drastically following the announcement, resuming to non-announcement period levels within two days. In contrast, non-fake news peaks the day after announcement and stays at elevated levels for eight days. We propose two aspects of accounting information that help explain the pattern we find in the distribution of fake news publication around earnings announcements: an attention effect and an information effect. The former relates to outcomes associated with large accounting disclosure events attracting widespread market attention, while the latter manifests in outcomes attributed to the verifiability and informativeness associated with accounting disclosures. We elaborate on both below.

Accounting information events, such as earnings announcements, management forecasts, and 10-K releases, garner abnormal market attention (e.g., Beaver, 1968). Highly anticipated disclosures, as in the case of earnings announcements, are oftentimes scheduled months in advance, generating widespread interest both in anticipation of the forthcoming information and after its revelation (e.g., Drake, Roulstone, and Thornock, 2012; Noh, So, and Weber, 2019). Other disclosures, such as 10-Ks and 8-Ks, are released to the public at less predictable times but nevertheless elicit significant market interest when disclosed (e.g., Drake, Johnson, Roulstone, and Thornock, 2020). To the extent that fake news authors rely on readership for compensation, the attention effect speaks to the additional incentives to produce fake news if a greater number of readers click into sensationalized fake articles or even change their priors and trading behaviors upon consuming the fake news.

However, via our proposed information effect, accounting disclosures, in disseminating verifiable financial information about the firm, can also decrease the incentives to produce fake news. 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). By providing a verifiable source of private information about operating profitability, investment opportunities, and, ultimately, fundamental value (i.e., the valuation role of accounting information), accounting information is particularly well-suited to counter fake news in financial markets. For example, as one of the primary forms of voluntary disclosure, management forecasts not only offer private forward-looking information about future earnings (e.g., Hirst, Koonce, and Venkataraman, 2008) but also help investors by clarifying complexities in business transactions or reporting standards (e.g., Guay, Samuels, and Taylor, 2016) as well as signaling the quality of the manager's investment decisions (e.g., Goodman, Neamtiu, Shroff, and White, 2013). These voluntary disclosures are verified *ex post* via subsequent mandatory disclosures, complementing the *ex ante* credibility of the forecasts (i.e., the Confirmation Hypothesis) (e.g., Ball, Jayaraman, and Shivakumar, 2012; Li and Yang, 2016). In addition to their verification role as mandatory disclosures, 10-Ks contain audited financial statements and narrative disclosures that aid investors in understanding the business entity. Specifically, 10-Ks provide disaggregated line items with differential weights in forecasting future profitability (e.g., Fairfield, Sweeney, and Yohn, 1996), segment disclosures detailing profits attributed to major operating or geographical divisions (e.g., Berger and Hann, 2003), as well as management discussions and analyses that preempt or explain changes to business ecosystems (e.g., Ball, Hoberg, and Maksimovic, 2015). To the extent that accounting information helps investors learn the true asset value of the firm, the information effect entails reduced investor susceptibility to false price signals, disincentivizing the production of fake news.

To investigate how the attention and information effect influence strategic publication decisions of fake news authors, we use a bunching identification strategy. Conceptually similar to studies on discontinuities in earnings distributions (e.g., Burgstahler and Dichev, 1997), bunching is an empirical methodology developed in the economics literature to ascribe behavioral distortions to a discontinuous change in incentives at certain thresholds (Kleven, 2016). If the distribution of observed outcomes exhibits a "bunching" of outcomes on the preferred side of the threshold, the anomalous pattern is attributed to a discontinuity in incentives at the threshold. As a continuation from our preliminary timing analysis, our bunching analyses study the publication timing preferences of fake news authors using earnings announcements as a sharp change in how attentive and informed market participants are (e.g., Beaver, 1968). Overall, we find bunching distributions consistent with both the attention and information effect: (1) fake news authors publish more fake articles near an earnings announcement and (2) they strongly prefer to publish fake articles prior to rather than after the release of accounting information. Specifically, we provide evidence for (1) the information effect by documenting divergent publication behavior of fake articles as compared to non-fake articles in the days immediately surrounding earnings announcements, (2) the attention effect by finding that more fake articles are published around earnings announcements with high investor attention than those with low investor attention as proxied by Google search volume, and (3) the validation of these effects by finding evidence of bunching within fake articles discussing accounting topics, the subsample of fake articles which may be more easily disproven using accounting information, and no evidence of bunching within fake articles without accounting content as falsification. Hence, in general, we find evidence consistent with the two effects we propose.

Lastly, to further investigate how other accounting disclosures contribute to the information effect, we examine how the broader accounting information environment affects the publication of fake news and its subsequent market impact using regression analysis. We choose two proxies for accounting information that are particularly salient to fake news authors: management forecast frequency and 10-K readability.[6] To investigate the effect of accounting information on the production of fake news, we use a logit model to test the probability that a fake article is written about the firm and a Poisson model to test the number of fake articles written about a firm in a quarter. We find results consistent with accounting information

[6] 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 prominent to fake news authors and therefore less likely to affect the publication of fake news articles.

decreasing the production of fake news. To help mitigate omitted variable concerns, we find that our results are largely unchanged in additional analyses conducted within subsamples of firms with similar information environments. Next, we examine whether the informativeness of accounting information reduces the market reaction to the fake news that is produced. We find results mostly consistent with accounting information attenuating both abnormal trade volume and idiosyncratic return volatility following fake article publication. Hence, we provide evidence consistent with the information effect in the broader accounting information environment both disincentivizing the production of fake news and mitigating the market reaction to fake news.

Our paper makes several contributions to the literature. First, we provide broad sample descriptive evidence on the nature of fake news as well as evidence on the nuanced interactions between accounting information and fake news production. We document results consistent with accounting information garnering widespread capital market attention that temporarily fuels increased fake news but that the informativeness of these accounting disclosures incentivizes fake news authors to publish at times when the accounting information environment is relatively weaker. Second, we contribute to the limited empirical literature on the effects of public misinformation on the stock market. Historically, 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).[7] More recently, researchers have extended this literature by investigating the effects of potentially exploitative behavior on fast-growing

[7] Pump-and-dumps are market manipulation schemes in which one party takes a position in a stock, disseminates false positive information about that firm to boost its stock price temporarily, and profits by liquidating the position while the stock price is inflated.

investor websites, such as Seeking Alpha (e.g., Hu, 2019; Kogan et al., 2022) and Twitter (e.g., Jia, Shu, and Zhao, 2020). As investor websites are mainstays of the contemporary financial environment, evidence of how accounting information interacts with the fake news disseminated on these websites is especially meaningful, speaking directly to a concern raised by Blankespoor, deHaan, and Marinovic (2020) regarding the lack of traditional oversight on these online platforms and their potential for misinformation. Lastly, we contribute to the broader scientific literature investigating the proliferation 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 countervailing effects of accounting information on the incentives to produce fake news in the financial markets setting but leave evaluations on the generalizability of our results to fake news outside of financial markets to future research.[8]

2. Data, Sample Selection, and Identifying Fake Articles

2.1 Example of 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 that was later prosecuted 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 skyrocketing market share of 30%. The fact

[8] Other than a brief discussion in Section 4, we note that we largely do not speak to the effect of accounting information on total fake news production in equilibrium and leave in-depth investigation to future research.

that the author chose to downplay the validity of the management forecast provides evidence that he is not only aware of these accounting disclosures himself but also aware of investors using management forecasts in judging the veracity of the 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 caused by the fake news surrounding Galena Biopharma by providing internet links to and screen captures of the company's 10-Qs, 10-Ks, and press releases (highlighted throughout the article). The stock price fell by 20% after the publication of this article, partially offsetting the inflated stock price from fake news (SCAC, 2014). In addition to correcting the market, this article demonstrates that the author uses accounting information to verify the news surrounding Galena Biopharma and that he believes he can convince general market participants by referring to the firm's accounting information in his article. These examples provide useful anecdotes into what information a fake article may contain as well as how market participants can counteract the misinformation in fake news using accounting information.

2.2 Data Sources and Sample Selection

To broadly analyze how accounting information may influence the incentives to publish fake news, we collect a large set of crowdsourced investor articles for which we can identity those written with the intent to deceive. We obtain data from Seeking Alpha for all articles written from 2006 through 2018. We gather the article's text, author, publication date, and the primary stock tickers associated with the firms discussed in the article.[9] We eliminate articles

[9] 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.

without a primary stock ticker and articles written by Seeking Alpha employees. These restrictions eliminate news updates and conference call transcripts as well as articles about the economy or other general topics not linked to a specific company. To ensure that the linguistic software used to classify fake news has sufficient content, we require articles to have greater than 100 words. We drop articles that are not classified as fake or non-fake using the methodology discussed in Section 2.3. In addition, we require non-missing financial data from Compustat and CRSP and obtain analyst data from IBES. Our final sample includes 125,475 articles across 37,864 firm-quarters. Table 1 provides details of our sample selection process.

2.3 Identifying Fake News Articles

We follow the fake news classification method detailed in Kogan et al. (2022) 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. The linguistics literature documents that individuals who are being dishonest use less self-reference words, shorter sentences, less insight words, less specific information about time and space, and more discrepancy verbs (Pennebaker, 2011).[10] Kogan et al. (2022) obtain 171 paid-for fake articles and 334 non-fake articles all written by the same set of authors on Seeking Alpha. The authors use this cleanly-identified sample to map the LIWC-based authenticity score into the conditional probability of being fake. The authenticity cutoffs that Kogan et al. (2022) use for classification are conservative in nature, achieving 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,

[10] *Realize*, *understand*, and *think* are examples of insight words. Discrepancy verbs, such as *could*, assert that an event might have occurred but possibly did not.

incorrectly classifying a non-fake article as fake) of less than 1%. The Central Intelligence Agency and Federal Bureau of Investigations use similar linguistic methods to measure the authenticity of written text and speech, providing application-based validity for this methodology. In our sample, the proportion of fake articles to the total number of fake and non-fake articles is 2.5%, quantitatively similar to the 2.8% identified in Kogan et al. (2022).

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

3.1 Content of Fake News Articles

As the first part of our analysis, we use textual analysis to characterize the content of our sample of fake financial news. Specifically, we use Latent Dirichlet Allocation (LDA), a linguistic machine learning method used to identify latent topics in a corpus of text, to analyze all articles in our sample (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. Table 2 Panel A contains the list of identified topics. We compute the percentage of content from each of the 30 topics identified by LDA for each article. One article may thus span multiple topics (e.g., an article about both accounting forecasts and the pharmaceutical industry). For each topic, we tabulate the number of articles in our sample containing content for that topic in Column 1 as well as the percentage of articles classified as fake within the articles assigned to that topic in Column 2.

The results show that a substantial number of Seeking Alpha articles include discussion of accounting content. We find that the two topics 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 have an accounting topic as their most prominent topic. We view this evidence as support for our usage of the broad sample of Seeking Alpha articles, as the pervasiveness of accounting content in our sample of articles increases our power in detecting the potential effects of accounting information on incentives to produce fake news. Interestingly, we also note that the percentage of fake articles is among the lowest in accounting topics, potentially pointing to the difficulty of constructing fake news with or about accounting information. As an additional analysis to help support our usage of LDA, we compute the percentage of words classified as "accounting words" using the dictionary outlined in Lerman (2020) for each topic in Column 3. We find that the percentage of words classified as "accounting words" are among the highest in accounting topics, providing convergent validity in our usage of LDA to identify articles with accounting content.

In Table 2 Panel B, we provide comparative statistics of characteristics between fake and non-fake articles. We find that the percentage of articles with accounting content is lower for fake articles than for non-fake articles. We also find that the percentage of "accounting words" used in fake articles is lower. Again, we point to these results as circumstantial evidence that there may exist disincentives to publish fake news about or with accounting information. Nevertheless, a significant portion of fake articles still contain accounting content (57%), providing further motivation to investigate the role of accounting information in changing incentives for fake news production, given the prevalence of accounting content in fake news articles. In addition, we also find that fake articles tend to use fewer words per article but more words per sentence. Lastly, similar to Kogan et al. (2022), we find that the market reacts to fake articles more strongly than non-fake articles, attesting to the fact that fake news is deceptively written to impact investor perceptions.[11]

3.2 Timing of Fake News Articles

Next, we examine the publication timing of fake news. To provide context for aggregate trends in fake news production during our sample period, we look at the incidence of fake news publication using counts of fake articles summed by calendar year. In Figure 1, we find that the number of fake articles exhibits a bimodal pattern over our sample period, with peaks occurring around 2007-2009 and 2014 onwards. The latter peak aligns with the common media narrative that the amount of fake news has increased in recent years, documenting that the expansion of fake news is not only a phenomenon in the political sphere but also a pervasive issue in the financial sector. When we partition by whether the fake articles contain accounting content, we find the same bimodal distribution. We believe this descriptive evidence may facilitate future research on the determinants of aggregate fake financial news production over time but do not pursue this line of inquiry in our paper.

Next, we examine the timing of fake news around accounting information releases. To do so, we construct frequency distributions of fake article publications around earnings announcements. We use earnings announcements for three primary reasons. One, the majority of public firms announce earnings, allowing us to use a larger subset of firms as compared to other disclosure events, such as management forecasts. Two, the announcements induce significant attention and market reactions, indicating salient information flow into the market (e.g., Beaver, 1968; Atiase and Bamber, 1994; Drake et al., 2012). Three, earnings announcements are highly

[11] 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.

anticipated events, oftentimes scheduled weeks or months in advance, giving fake news authors advanced notice on the date of disclosure. This feature allows us to infer author preferences by looking at when articles are published relative to the day of the earnings announcement. By exploiting the fact that Seeking Alpha authors are freelancers with the discretion on when to publish news articles, we use these aforementioned characteristics to examine the publication incentives of fake news authors.

To construct our frequency distributions, we first match our sample of articles to the earnings announcements of each firm for articles published within 45 days of the announcement date, retaining only matched articles in our bunching sample. We use the number of hours between the time of Seeking Alpha article publication and the earnings announcement to create the *Days to EA* variable. Specifically, we create 90 blocks of 24-hour periods (henceforth, "days") centered on the time of the earnings announcement to the nearest minute. For example, an article published 26 hours prior to an earnings announcement is classified as being two days prior to an earnings announcement (i.e., *Days to EA* = -2).[12] To create distributions of publication behavior for both fake and non-fake articles, we count the number of articles published in event time relative to the earnings announcement date. $\textit{Fake Articles}_t$ is equal to the number of fake articles published on $\textit{Days to EA}_t$ summed across all earnings announcements.

Figure 2 Panel A depicts the resulting frequency distribution created from $\textit{Fake Articles}_t$. For the graphical pattern of fake articles in Panel A, we see a general non-descript oscillation in the days leading up to and following the earnings announcement. There is a marked increase in fake articles directly prior to earnings announcements that falls quickly back to baseline two days after the announcement takes place. Interestingly, the increase in fake articles is not symmetric

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

around earnings announcements, as the peak of the distribution occurs prior to earnings announcements. For comparison, we examine the frequency distribution of non-fake articles in Panel B. We find that, while non-fake articles also increase dramatically around earnings announcements, the peak of the distribution occurs the day after announcement and stays at elevated levels for a prolonged period of eight days.

3.3 Proposing the Attention Effect and Information Effect of Accounting Information

We propose two aspects of accounting information 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. The former relates to outcomes associated with large accounting disclosure events attracting widespread market attention, while the latter manifests in outcomes attributed to the verifiability and informativeness associated with accounting disclosures. We elaborate on the motivation behind these two effects as well as how they interact to form the shape of the frequency distribution of fake news below.

Longstanding theoretical and empirical literatures endorse accounting information as one of the primary mechanisms for informing investors about fundamental value (i.e., the valuation role of accounting information) (e.g., Beyer, Cohen, Lys, and Walther, 2010). Noisy rational expectations models support the usefulness of accounting disclosures in increasing the precision of investor beliefs about future cash flows or earnings by decreasing information asymmetry or investor uncertainty (e.g., Diamond, 1985; Dye, 1985; Verrecchia, 2001). In addition, ample empirical literature documents significant informativeness associated with accounting information events, such as earnings announcements (e.g., Beaver, 1968; Landsman and Maydew, 2002; Collins, Li, and Xie, 2009), 10-K releases (e.g., Stice, 1991; Griffin, 2003; You and Zhang, 2009), and management forecasts (e.g., Jennings, 1987; Yang, 2012; Twedt, 2016).

We conjecture that the informativeness of accounting disclosures limits the ability of fake news authors to write fake articles that are effective in misleading investors. As a result, the information effect decreases incentives to publish fake articles when the accounting information environment is of higher quality immediately after the disclosure of accounting information.

As a consequence of their informativeness, accounting information events, such as earnings announcements, management forecasts, and 10-K releases, garner abnormal market attention (e.g., Beaver, 1968). Certain disclosures, as in the case of earnings announcements, are highly anticipated events scheduled months in advance, eliciting widespread market attention both prior to the forthcoming information and after its revelation (e.g., Drake et al., 2012; Noh et al., 2019). The elevated market attention surrounding these accounting disclosures can increase the views of sensationalized fake articles, increasing their effectiveness in reaching investors and influencing their priors or behavior. Hence, the attention effect of accounting information may increase the incentives to publish fake news articles around accounting disclosures in general.

In conjunction, the attention effect and information effect can interact in producing the frequency distribution of fake articles in Figure 2, Panel A: a sharp increase around earnings announcements due to the attention effect with the peak occurring prior to announcement date, where the accounting information environment is relatively weaker, due to the information effect. In the remainder of our paper, we investigate how the attention and information effects create potentially countervailing incentives in fake news publication behavior.

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 whether accounting information induces behavioral distortions in fake news publication, we formalize our inferences about the attention and information effects of accounting information on the timing of fake news publication using the bunching methodology. In general, bunching is an empirical methodology developed in the economics literature to attribute distortions in behavioral outcomes to a known discontinuous change in incentives at certain thresholds (Kleven, 2016).[13] Intuitively, the existence of certain thresholds with discontinuities in incentives can cause (1) the outcomes in a small window around the threshold to differ in preferences than those outside the window and/or (2) the outcomes on one side of the threshold to dominate those on the other side in preferences. The former induces behavioral distortions in actions or reporting so that the observed outcome is abnormally high or low inside the window as compared to outside the window, while the latter results in observed outcomes on the preferred side of the threshold. In either case, the distribution of outcomes exhibits excess mass (i.e., "bunching") in the region of preferred outcomes.[14] In the context of our study, if accounting information creates distortions in incentives to produce fake news, specifically to publish during periods where its content is most likely to garner the most views or mislead investors, we expect excess mass in the distribution of

[13] 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).

[14] 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) but is different in certain underlying assumptions. In the context of earnings management, earnings distributions exhibit excess mass just above salient performance thresholds and missing mass just below.

fake articles (1) in general around earnings announcements from the attention effect and (2) before rather than after earnings announcements from the information effect.

We use two variations of the bunching methodology in our analyses: polynomial bunching and difference-in-bunching. Both approaches require the specification of a counterfactual behavior that approximates what would be observed in our behavior of interest absent the change in incentives at the threshold, but the two differ in how the counterfactual is specified. The polynomial approach estimates a counterfactual distribution using a polynomial function fitted to the observed distribution of outcomes but excluding outcomes local to the threshold theorized to cause behavioral distortions. In other words, this approach utilizes the distribution of the observed outcomes of interest to estimate a counterfactual for the outcomes around the threshold by using outcomes away from the threshold. The difference-in-bunching approach follows Sallee (2011) in combining the difference-in-differences and bunching methodology. It uses a second observed distribution as the counterfactual, analogous to the control group in a difference-in-differences research design.[15] Similar to the parallel trends assumption, an assumption in difference-in-bunching is that the behavior of interest and the counterfactual behavior respond similarly to incentives in general, except for incentives that change at the threshold. One main benefit is that directly comparing the observed distribution of interest to another observed distribution designated as the counterfactual controls for unobserved factors that influence both distributions, even if the unobserved influential factors occur within the affected region (i.e., the region with outcomes potentially affected by the threshold). [16] We

[15] Sallee (2011) incorporates a temporal element to bunching to show that consumers accelerated their purchase of the Toyota Prius prior to decreases to hybrid vehicle tax subsidies. Sallee uses a difference-in-bunching approach by utilizing consumer purchases of non-hybrid Toyota sedans as a counterfactual behavior (see Figures 2-7 in his paper).

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

use both the polynomial and difference-in-bunching methodologies to provide evidence on the interactions between accounting information and fake news publication.

We first formalize our inferences about the fake news publication behavior around earnings announcements shown in Figure 2 with statistical analyses using the polynomial bunching approach. We reproduce Figure 2 in Figure 3 Panels A and B. Following prior literature, we identify the specific window of the affected region by visually inspecting the distribution of fake articles in Figure 3 Panel A. Visual inspection indicates that 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. Following Chetty, Friedman, Olsen, and Pistaferri (2011), we then fit a seventh-degree polynomial function to the distribution of fake articles outside of the earnings announcement window to model counterfactual fake news publication behavior both inside and outside the window. We compute *Abnormal Mass*$_t$ as the difference between the observed fake articles and the polynomial estimates of counterfactual 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 statistical inferences. Specifically, we create a bootstrap distribution by randomly sampling *Abnormal Mass*$_t$ from the observed distribution for each of the 90 days of the distribution. We then calculate our four variable estimates using the bootstrap distribution. We repeat this procedure

1,000 times and define the standard error as the standard deviation of the estimates from this procedure.

Table 3 presents the numerical estimates for our bunching analyses. In Row 1, we present the results from our polynomial bunching procedure on the distribution of fake articles from Figure 3 Panel A. We find estimates consistent with our interpretation of the graphical evidence discussed in Section 3.2. Specifically, we find a positive and significant number of abnormal fake articles for the pre-earnings announcement, post-earnings announcement, and total earnings announcement windows. These results indicate that there are more fake articles produced within the earnings announcement window than expected based on trends from outside the window, providing statistical evidence consistent with the attention effect. In addition, we find a positive and significant differential abnormal mass for fake news, offering preliminary support that fake news authors prefer to publish prior to rather than after the earnings announcement. We conjecture that this revealed preference to publish prior to earnings announcements is driven by the fact that the accounting information environment is relatively weaker during this period due to the information effect. Hence, we find empirical estimates that support our previous inferences that earnings announcements temporarily stimulate the production of fake news, consistent with the attention effect, but that, conditional on publishing around earnings announcements, fake news authors prefer to publish prior to the release of accounting information, consistent with the information effect of accounting information.

Next, we use the difference-in-bunching methodology to provide more rigorous evidence on the information effect by choosing the distribution of non-fake articles to serve as the counterfactual distribution. We expect that, on a day-to-day basis, the primary incentive to publish Seeking Alpha articles is compensation linked to readership (e.g., Seeking Alpha payment per view, internet clout, etc.) (Dyer and Kim, 2021). Importantly, this incentive implies that the increased market attention around earnings announcements affects fake and non-fake article publication in similar ways. Hence, using difference-in-bunching allows us to isolate the information effect of accounting information, conditional on changes to publication behavior due to heightened market attention.

Prior to comparing the fake and non-fake distributions, we briefly reexamine and discuss the shape of the non-fake article distribution shown in Figure 3 Panel B with the corresponding polynomial bunching statistical estimates shown in Table 3 Row 2. We note that visual inspection of the distribution of non-fake articles yields different days of elevated publication behavior relative to the earnings announcement than that of fake articles. Thus, we use an affected region of t-2 to t+8 for examining non-fake articles and present results for both the t-2 to t+2 and t-2 to t+8 windows when comparing fake and non-fake articles. We find that, similar to the distribution of fake articles, there is a positive and significant number of abnormal non-fake articles in the pre-earnings announcement, post-earnings announcement, and total earnings announcement windows, consistent with market attention increasing the incentive to publish non-fake articles. However, in contrast to the distribution of fake articles which peaks prior to earnings announcements, the distribution of non-fake articles peaks after earnings announcements, as evidenced by a negative and significant differential abnormal mass in Column 4.

Similar to establishing parallel trends for difference-in-differences analyses, visually examining the trends of the distributions for fake and non-fake articles outside the affected region helps evaluate the suitability of the comparison. Due to the substantial difference in the number of fake and non-fake articles, we scale the number of fake and non-fake articles published each day by the total number of fake and non-fake articles, respectively, over all days to facilitate a meaningful comparison. In Figure 3, we show the overlap (Panel C) and difference (Panel D) in fake and non-fake article density distributions. In Panel C, we observe that fake and non-fake articles closely mirror each other outside the earnings announcement window, following the same non-descript oscillating pattern. Furthermore, this similarity in publication trends between fake and non-fake articles is shown directly in Panel D. Outside the earnings announcement window, differences between the two distributions are very small, particularly in comparison to differences inside the earnings announcement window. We interpret this evidence as validation for using non-fake articles as a reasonable counterfactual for fake articles. Hence, we use the distribution of non-fake articles as our counterfactual distribution and conduct the difference-in-bunching procedure described above, with the exception that *Abnormal Mass*$_t$ is now defined as the difference in publication count between fake and non-fake distributions on day *t*.[17]

Table 3 Row 3 presents the statistical estimates from our difference-in-bunching analysis comparing fake and non-fake distributions for the t-2 to t+8 window. All four estimates are statistically significant at least at the 5% level. The estimates for *Pre EA Abnormal Mass*$_{t-2,t-1}$ and *Post EA Abnormal Mass*$_{t+1,t+8}$ indicate abnormal fake article densities of 5% and -11%, respectively. These results show that, relative to the distribution of non-fake articles, the distribution of fake articles bunch prior to earnings announcement and exhibit a missing mass post-announcement. In addition, the difference in the pre- and post-earnings announcement publication behavior, captured by *Differential Abnormal Mass*$_{t-2,t+8}$, is positive and significant.

[17] 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.

Thus, our difference-in-bunching analyses suggest that, conditional on publishing around earnings announcements, fake news authors prefer to publish fake articles before earnings announcements, when the accounting information environment is relatively weaker, rather than after earnings announcements. Row 4 performs the same analysis but for the shortened t-2 to t+2 window used in Row 1, and we find that our evidence is robust to this alternative specification.

Next, we examine the overall net impact of the information effect of earnings announcements on fake news publication during the announcement window. We find mixed supporting evidence. Our estimate for *Total Abnormal Mass*$_{t-2,t+8}$ indicates that the density of fake articles is 6% lower than the density of non-fake articles during the same time period. These results suggest that there is a relative deficit of fake news inside the earnings announcement window compared to non-fake news.[18] However, using an alternative window of t-2 to t+2 results in *Total Abnormal Mass*$_{t-2,t+2}$ becoming statistically insignificant. Hence, this set of analyses does not offer conclusive evidence on whether the information effect of accounting information, conditional on the increase in fake articles around earnings announcements due to the attention effect, decreases the relative publication of fake news around earnings announcements in equilibrium.

4.2 Partitioning by Investor Attention

We isolate the attention effect of accounting information on fake news by comparing the distributions of fake articles matched to earnings announcements with high investor attention to those with low investor attention. We partition our sample of fake articles into high and low investor attention subsamples based on whether the firm receives a positive Investor Search

[18] In this case, we surmise that, while some fake news authors are able to shift their fake news publication from post-announcement to pre-announcement, others opt to not publish at all, creating short-term slippage in the total amount of fake news.

Volume Index (ISVI) on the day of the earnings announcement (Da, Engelberg, and Gao, 2012; deHaan, Lawrence, and Litjens, 2021).[19] In doing so, we compare two distributions of fake articles with known differences in attention-driven incentives. To the extent that the attention effect impacts the incentives to publish fake news, we expect there to be more fake news published around earnings announcements with high investor attention. However, if the amount of investor attention around earnings announcements does not influence fake article publication preferences, we should observe minimal differences between the fake article distributions around earnings announcements with high and low investor attention.

We first analyze the high and low attention distributions separately using the polynomial bunching approach. The distributions of high and low attention fake articles are shown in Figure 4 Panels A and B, respectively, and the statistical estimates are shown in Table 3 Rows 5 and 6, respectively. Within both subsamples, the sign and statistical significance of the estimates are similar to the overall sample of fake articles in Row 1. Furthermore, there is evidence of bunching within each subsample as indicated by visual inspection that the peak of both distributions occurs prior to earnings announcements and by the positive and significant estimates in Column 4. Hence, within each subsample, we continue to find distributions consistent with our prior findings on the attention and information effects.

Table 3 Row 7 presents statistical estimates comparing high and low investor attention distributions using difference-in-bunching. Consistent with the attention effect incentivizing fake news publication, the high attention subsample has significantly more fake articles published during the pre-earnings announcement, post-earnings announcement, and total earnings announcement windows (Columns 1-3). Interestingly, while there is evidence of bunching

[19] We note that ISVI is only available from 2010 onwards. Hence, analyses conducted using ISVI uses a reduced sample of articles.

consistent with the information effect within each subsample separately, there is no evidence of a *difference* in the magnitude of bunching across the two subsamples (Column 4). We cautiously interpret the lack of a difference in bunching between the distributions with high and low investor attention as evidence that the attention effect and information effect are distinct constructs when using Google search volume as the proxy for investor attention.

4.3 Partitioning by Accounting Content

To validate the attention effect and information effect of accounting information on fake news publication, we conduct the same set of bunching analyses as the previous subsection but partitioning by whether the fake articles contain accounting content.[20] 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 for both the graphical and statistical evidence remain the same as those for the full sample. Of note, within the subsample of articles without accounting content (Figure 5 Panel B; Table 3 Row 9), there is no meaningful publication pattern with regards to earnings announcements. As expected, when comparing these two distributions with starkly different patterns using the difference-in-bunching approach, we find evidence of greater bunching in the subsample of fake articles containing accounting content (Figure 5 Panels C and D; Table 3 Row 10).

The results of these analyses are useful for two reasons. One, because we conjecture that fake articles referencing accounting-related content are more easily disproven by accounting information, we expect to find the bunching pattern in our main sample to manifest in this subsample of articles. Our results are consistent with this intuition. Two, we do not find any form of bunching present in the subsample of fake articles with no accounting content, providing a

[20] We use the same LDA methodology described in Section 3.1.

form of falsification evidence that our bunching results are not driven by correlated omitted variables that influence the publication of fake non-accounting articles. Hence, finding our hypothesized bunching pattern in the subsample that we expect a pattern to manifest (i.e., articles with accounting content) and not in the subsample that we do not expect a pattern (i.e., articles with no accounting content) bolsters our inferences for both the attention effect and information effect of accounting information by showing that the bunching behavior is driven by articles for which accounting information is particularly relevant.

Overall, our bunching analyses document several stylized facts that we interpret as evidence consistent with both the attention effect and information effect of accounting information 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-earnings announcement than post-earnings announcement. These findings are consistent with fake news authors publishing more fake articles when there is heightened investor attention but strategically avoiding 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 also validate that the bunching behavior manifests in a restricted subsample of articles containing accounting content but not within a subsample of articles without accounting content as falsification. This pair of results 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 with no accounting content.

5. Regression Analyses and Results

In this section, we explore the information effect in a broader context by examining (1) whether fake news authors are less likely to target firms with more robust accounting information environments in general and (2) whether targeted firms with more robust accounting information experience less market impact from fake news. We use two proxies for accounting information derived from other accounting disclosures that we believe 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 important 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 future earnings as well as other key line items from the income statement (Lansford, Lev, and Tucker, 2007), explaining complex financial statements (Guay et al., 2016), and signaling the manager's corporate investment efficiency (Goodman et al., 2014). To the extent that management forecasts provide detailed forward-looking information about anticipated earnings, sales projections, and potential growth, fake articles that portray exaggerated future firm conditions 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 salient 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). According to the disclosure processing cost framework presented in Blankespoor et al. (2020), 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. In support of this framework, empirical evidence finds that more readable disclosures increase trading on information (Bloomfield, 2002; Miller, 2010) as well as individual investors' understanding of financial disclosures (Lawrence, 2013). In the context of our paper, 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, fake news that inaccurately portray details about firm operations is less persuasive. 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

5.2.1 Accounting Information and the Probability of Fake News

We examine the role of accounting information in disincentivizing the production of fake news by estimating the conditional probability that an article is fake. In accordance with our proposed information effect, 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 firm's operating environment. Appendix A contains definitions for variables used in our analyses. Accounting characteristics are measured as of the fiscal quarter end in which the earnings announcement for the quarter occurs on or before the article publication date. We also include industry and year fixed effects, unless noted otherwise, 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. We note that all dependent variables are tabulated at their corresponding observation level in regressions and that all independent variables are tabulated at the article level.

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. We discuss economic magnitudes relative to the unconditional probability that an article is fake. In Column 1, we examine whether the number of management forecasts affects the likelihood of a fake article. 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 examines how the readability of the 10-K affects the likelihood of a fake article. The negative and significant coefficient for *10-K Readability* 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, we are reassured that our main independent variables capture distinct measures of accounting information and offer convergent validity for our inferences on the role of accounting information in disincentivizing fake news.[21]

We briefly note the effects of our control variables on the publication of fake articles. We find that variables capturing firm monitors or information intermediaries largely do not offer incremental effects on fake news publication over our accounting information variables. Both *Analyst Coverage* and *Institutional Ownership* are insignificant or inconsistently significant. *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 indicates that more media articles in the press are associated with a higher probability that a fake article is published, potentially due to the increased attention surrounding these firms. We also note that poor past performance (i.e., *Adj. ROA* and $Returns_{m-12,m-1}$) increases the likelihood of a fake article publication but poor short-term news (i.e. $Returns_{t-10,t-1}$) decreases the likelihood. We do

[21] Our results in Column 3 are robust to using either a 180-day or 90-day window for measuring management forecast frequency as well as dropping industry-years with less than 50 observations. See IA3 in the Internet Appendix for tabulated results. Further, see IA4 in the Internet Appendix for a visual analysis of Equation (1) using binned scatterplots.

not attempt to hypothesize why these opposing signs occur and leave the investigation of the link between past performance and fake news production to future research.

One concern with our interpretation of the results in Table 5 is that we primarily rely on cross sectional variation to identify the association between accounting information and the production of fake news, resulting in potential omitted variable bias. 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 particularly effective in addressing, (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 more similar general information environments. These tests limit the variation of both observed and unobserved variables, providing 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 fake non-accounting articles that cannot be influenced by accounting information. Rows 1 and 2 of Table 6 present our main specification partitioning by whether the article contains accounting content. We tabulate the results of running our main test using only articles that contain accounting content in Row 1. Both accounting information coefficients remain statistically significant in the expected direction. As a complement, Row 2 displays the results of using articles without accounting content. 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 that do not contain accounting content. This pair of analyses provides solace that our results are driven by articles for which accounting information is particularly relevant.

Next, we address the concern that firm performance determines both accounting disclosure policy and fake news production. Prior literature documents the relation between bad performance and decreased voluntary disclosure or 10-K readability (e.g., Li, 2008; Chen, Matsumoto, and Rajgopal, 2011). To the extent that fake news authors are drawn towards writing about firms with worse performance, our results may be affected by this omitted variable. In addition to using return on assets, short-run past returns, and long-run past returns as controls, we perform our main test partitioning by the sign of the earnings surprise of the last earnings announcement and tabulate the results in Table 6 Rows 3 and 4. We continue to find statistically significant results in each partition for both accounting information variables, 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 rather than accounting information in particular. In other words, firms with systematically better general information environments may provide more management forecasts or more readable 10-Ks than firms that do not, creating uncertainty about whether we can attribute our inferences specifically to accounting information. To alleviate this concern, we run our main test within subsamples of firms likely to have similar general information environments, limiting the amount of unobserved variation that exists in our models. We use management forecasts, analyst coverage, institutional ownership, and size as our partitioning variables, 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 Rows 5-12 of

Table 6 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. In summary, our series of additional tests yield largely robust results in support of our main inferences.

Overall, our results in this section are consistent with the information effect of accounting information disincentivizing the production of fake financial news. The estimated effect sizes are economically meaningful and reasonable, with both measures of accounting information incremental to each other. Further, the results continue to be largely significant and in the expected direction in a series of additional tests.

5.2.2 Accounting Information and the Quantity of Fake News

To provide additional evidence on the role of accounting information in disincentivizing the production of fake news, we examine an alternative dependent variable *# of Fake Articles,* the count of the number of fake Seeking Alpha articles published in a firm-quarter. Since *# of Fake Articles* only takes nonnegative integer values, we use Poisson pseudo-maximum likelihood estimation at the firm-quarter level to analyze how accounting information affects the amount of fake news published about a firm within a quarter:[22]

$$\textit{\# of Fake Articles}_i = \beta_1 \textit{ Accounting Information}_i + \sum \beta \textit{ Controls}_i + \sum \textit{Fixed Effects} + \varepsilon. \qquad (2)$$

We modify our independent variables to adjust for the change from estimating Equation (1) on an article level to estimating Equation (2) on a firm-quarter level. *Management Forecast*

[22] We use Poisson pseudo-maximum likelihood estimation as it offers consistent estimators for over-dispersed (i.e., the variance is greater than the mean), highly skewed data distributions (e.g., Gourieroux, Monfort, and Trognon, 1984; Santos Silva and Tenreyro, 2011).

Frequency, *10-K Readability*, and our control variables are now measured as of the first article of the quarter. We continue to use the same control variables and fixed effects as described in Section 5.2.1 with the addition of *Seeking Alpha Articles*, the number of Seeking Alpha articles written about the firm in the quarter.

Table 7 presents the results from estimating Equation (2) using Poisson pseudo-maximum likelihood estimation. Consistent with our results in Tables 5 and 6, we find negative and significant coefficients for *Management Forecast Frequency* and *10-K Readability*. The coefficient estimates in Columns 1 and 2 continue to be economically meaningful. A one-standard-deviation increase in the number of management forecasts reduces the amount of fake news by 8%. A one-standard-deviation increase in *10-K Readability* is associated with 18% fewer fake articles. In Column 3, both coefficient estimates remain significant and in the expected direction when estimated in the same regression. Overall, we continue to find evidence in Table 7 consistent with the information effect of accounting information disincentivizing the production of fake news.

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

Next, we examine the effect of accounting information on the market reaction to fake news. In accordance with the information effect, we expect that accounting information decreases the ability of fake news to influence investor judgments, resulting in a lower market reaction to these fake articles. We estimate the following model using ordinary least squares (i.e., OLS) regression at the article level:

$$\begin{aligned} \textit{Market Reaction}_{t,t+2} = \beta_1\, \textit{Accounting Information}_i + \sum \beta\, \textit{Controls}_i \\ + \sum \textit{Fixed Effects} + \varepsilon. \end{aligned} \tag{3}$$

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 between 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. We measure a firm's abnormal return as the daily return minus the return on a 5x5x5 size-, B/M-, and momentum-matched portfolio (Daniel, Grinblatt, Titman, and Wermers, 1997). We avoid using a signed measure of price reaction because assigning an expected direction of price movement to Seeking Alpha articles is challenging and noisy (Kogan et al., 2022). We use both trade- and price-based reaction variables to obtain a more holistic view on the market reaction to fake news and to address 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).

We control for market reactions to other events in two ways. First, 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.[23] Second, we include single-day measurements of our two market reaction variables for the three trading days before article publication to control for other unobserved events that cause market reactions. We continue to use the control variables and fixed effects described in Section 5.2.1.

[23] Due to the importance and informativeness of these events, market reactions measured during this window are likely to be overwhelmingly in response to the event and not the Seeking Alpha article.

Table 8 presents the results examining whether accounting information affects the market reaction to fake news. Panel A estimates Equation (3) with *Abnormal Volume* as the dependent variable. In Column 1, we examine the association between *Management Forecast Frequency* and *Abnormal Volume* and find a negative but statistically insignificant coefficient. In Column 2, we examine whether a more readable 10-K results in a lower market reaction to fake news. The negative and significant coefficient estimate for *10-K Readability* implies that a one-standard-deviation increase in *10-K Readability* is associated with a 6% decrease in *Abnormal Volume*. Column 3 estimates Equation (3) including both accounting information variables and yields similar inferences, except that *Management Forecast Frequency* is now statistically significant at the 10% level.

Table 8 Panel B reports the results from estimating Equation (3) using *Idiosyncratic Return Volatility* as the dependent variable. We find that a one-standard-deviation increase in the number of management forecasts is associated with a 16% decrease in return volatility in Column 1. In Column 2, we find that a one-standard-deviation increase in *10-K Readability* is associated with a 23% lower *Idiosyncratic Return Volatility*. Our inferences from Column 3 that includes both accounting information variables are consistent with those from Columns 1 and 2. Overall, we find evidence in support of accounting information attenuating the market reaction to fake news.

6. Conclusion

We examine the content and timing of fake financial news and document interactions between accounting information and the incentives to publish fake financial news in the capital markets. We begin by detailing descriptive statistics of trends in the content and volume of fake news articles. Using Latent Dirichlet Allocation to identify topics covered by the articles, we find significant heterogeneity in topics, such as accounting information and forecasts, industry-specific news, legal matters, and macroeconomic conditions. Of particular interest, we find that a significant portion of fake articles contain accounting content. In examining publication trends over time, we find that the number of fake articles exhibits a bimodal pattern over our sample period, with peaks occurring around 2007-2009 and 2014 onwards. Hence, we document that the common media narrative on the expansion of fake news is not only a phenomenon in the political sphere but also a pervasive issue in the financial sector.

Using bunching analyses, we document several stylized facts that we interpret as evidence consistent with both the attention effect and information effect of accounting information 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-earnings announcement than post-earnings announcement. These findings are consistent with fake news authors publishing more fake articles when there is heightened investor attention but strategically avoiding 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 also validate that the bunching behavior manifests in a restricted subsample of articles containing accounting content but not within a subsample of articles without accounting content as falsification. This pair of results 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 with no accounting content.

Lastly, to further investigate how other accounting disclosures contribute to the information effect, we examine how the broader accounting information environment affects the publication of fake news and its subsequent market impact using regression analysis. We find results consistent with accounting information decreasing the production of fake news. In addition, we find that accounting information attenuates the market reaction to the fake news that is produced. Hence, we document evidence consistent with the information effect in the broader accounting information environment both disincentivizing the production of fake news and mitigating the market reaction to fake news.

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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. (2022). Source: Seeking Alpha
# of Fake Articles$_q$	The number of fake articles written about a firm in the quarter. 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

Brian Nichols

3 on Quick Picks & Lists

Articles (441)
Instablog (4)
StockTalks (113)
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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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Matt Gravitt
Long/short equity, value, special situations, momentum
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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.

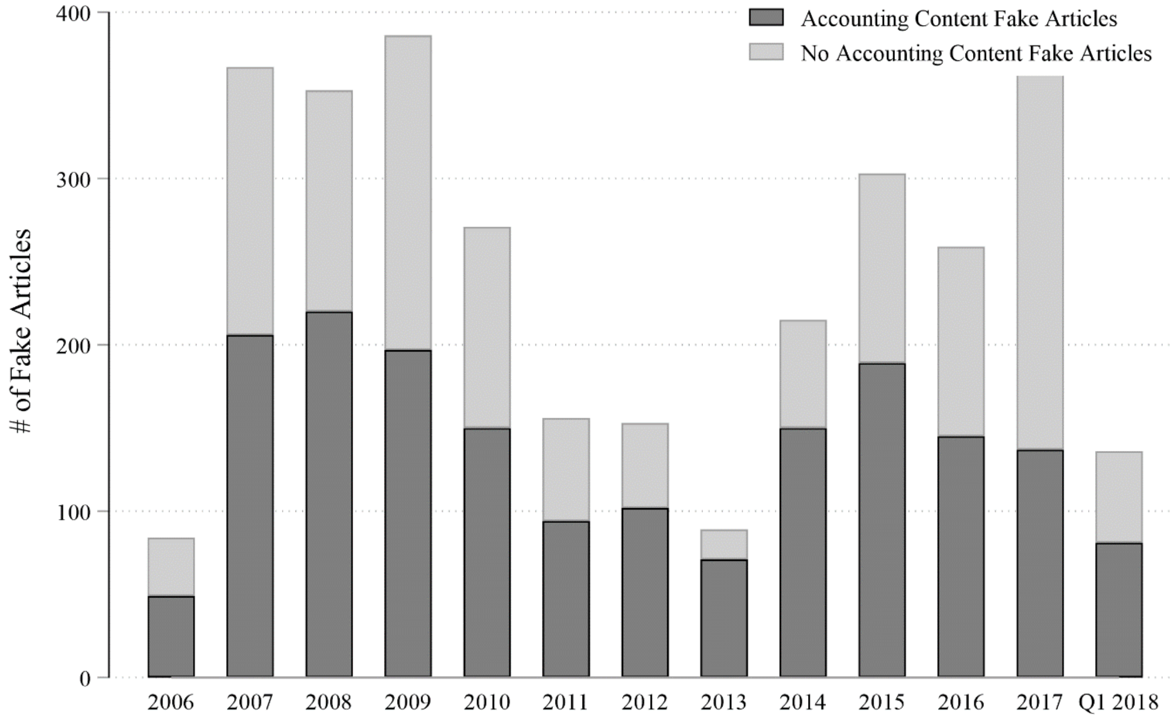
Transaction Date	Name	Position	Type	Shares	Range	Market Value	Total Holdings
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	250,000	$0.72 - $1.18	180.0K	255,000
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Sell	250,000	$6.13	1.5M	5,000
01/17/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	200,000	$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.

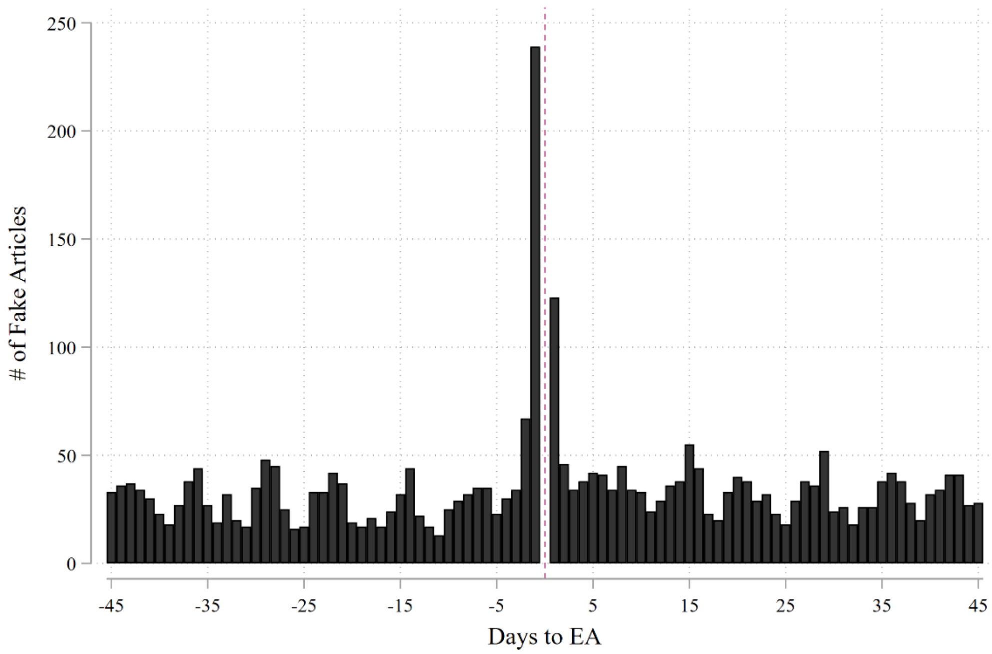
Figure 1: Fake News Production Over Time for Articles With and Without Accounting Content



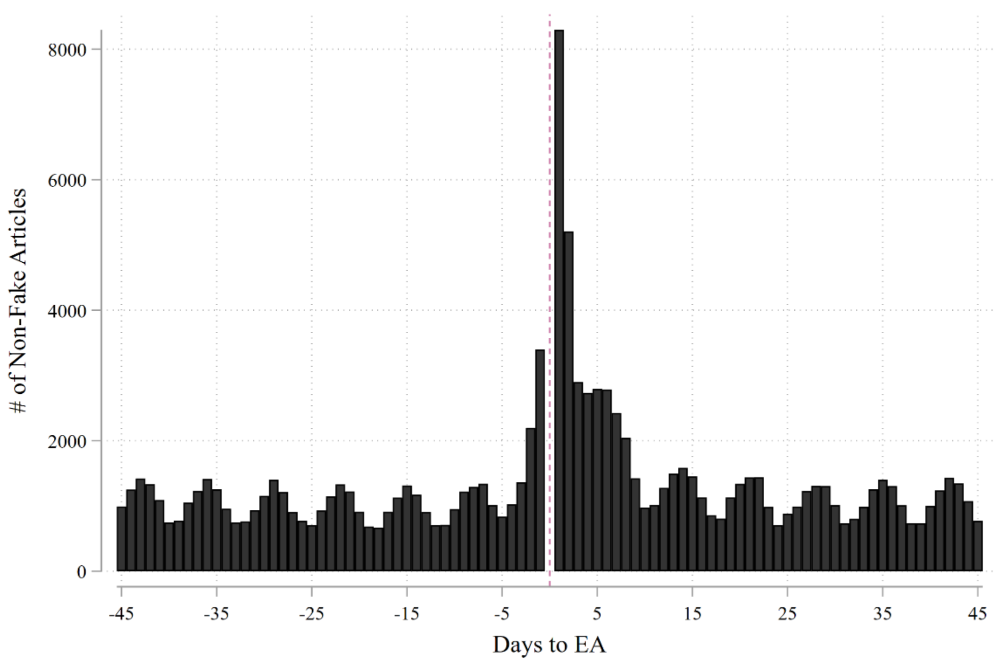
This figure presents the number of fake articles published on Seeking Alpha for each year during our sample. Within the total number of fake articles published each year, the figure also shows the number of fake articles containing accounting content. Note that our sample only includes the first three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



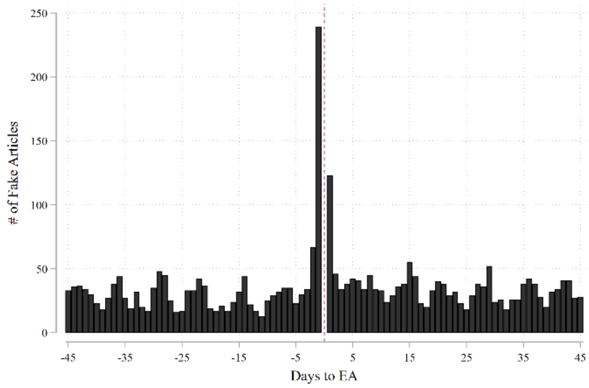
Panel B: Distribution of Non-Fake Articles Around Earnings Announcements



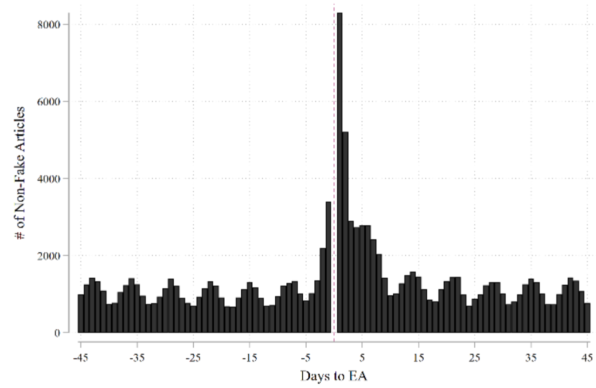
This figure presents graphical evidence on the publication timing of fake and non-fake articles relative to earnings announcements. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles.

Figure 3: Bunching Analyses of Fake and Non-Fake Articles Around Earnings Announcements

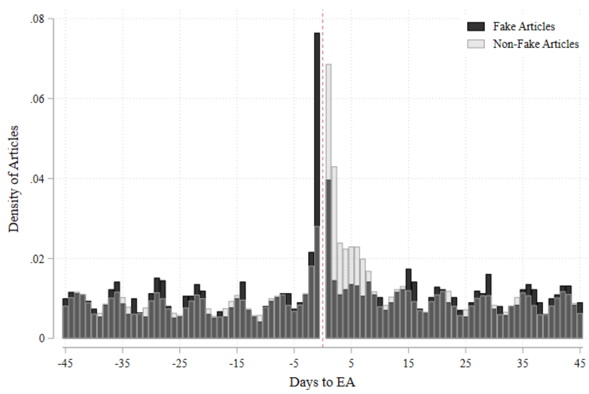
Panel A: Fake Articles



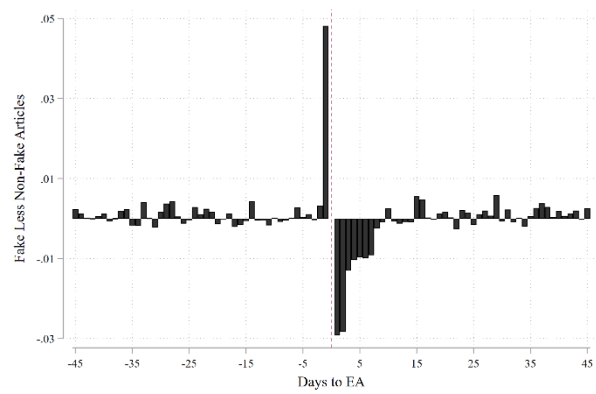
Panel B: Non-Fake Articles



Panel C: Fake and Non-Fake Articles



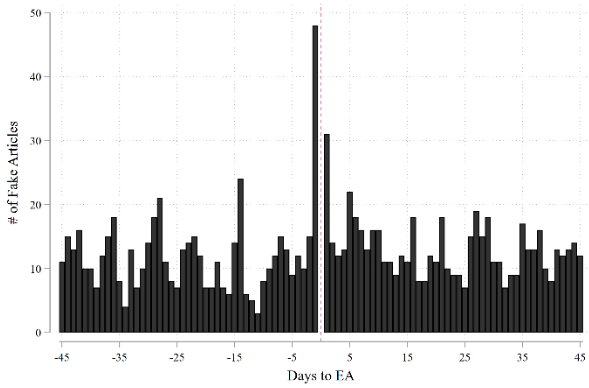
Panel D: Differences Between Fake and Non-Fake Articles



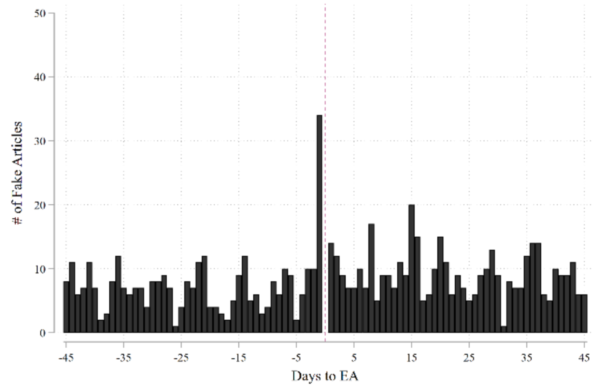
This figure presents graphical evidence from bunching analyses using the full sample of fake and non-fake articles. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles. Panel C overlays the fake and non-fake article distributions after scaling each article type by the total number of articles of that type. Panel D plots the differences between the fake and non-fake article distributions shown in Panel C.

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

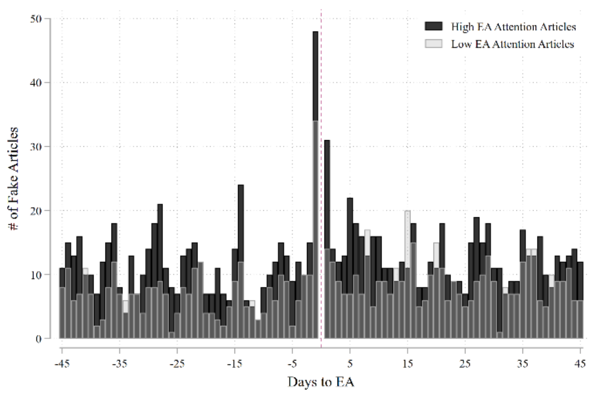
Panel A: High EA Attention Fake Articles



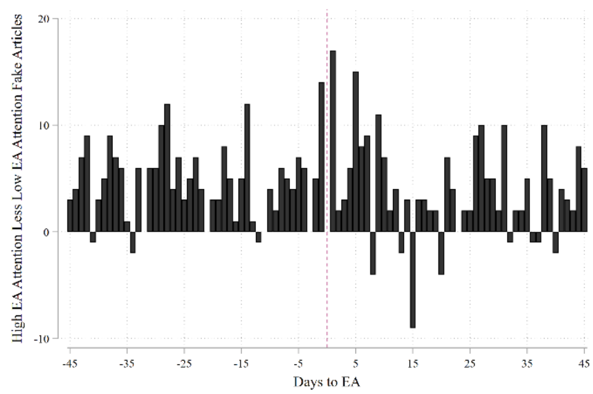
Panel B: Low EA Attention Fake Articles



Panel C: High and Low EA Attention Fake Articles



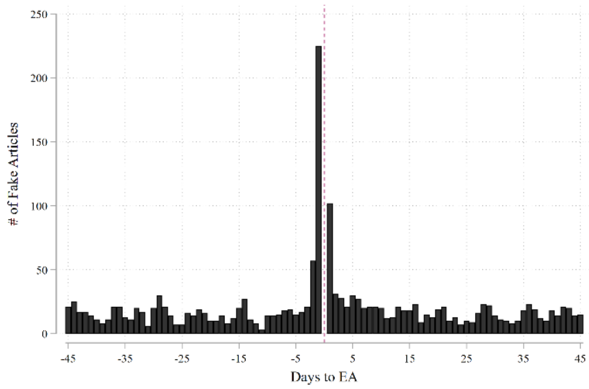
Panel D: Differences Between High and Low EA Attention Fake Articles



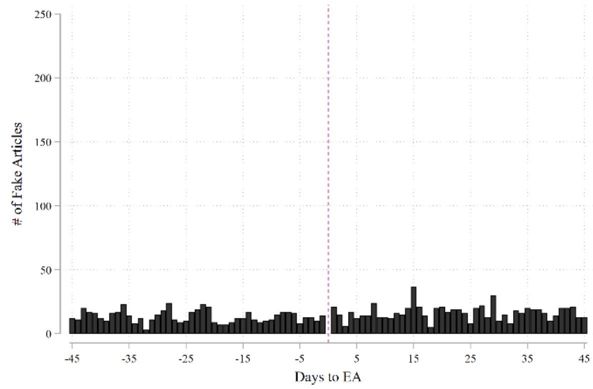
This figure presents graphical evidence from bunching analyses using the sample of fake articles partitioned by earnings announcement attention. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day for high attention earnings announcements, while Panel B does the same for low attention earnings announcements. Panel C overlays the fake article distributions for each earnings announcement attention subsample. Panel D plots the differences between the fake article distributions shown in Panel C.

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

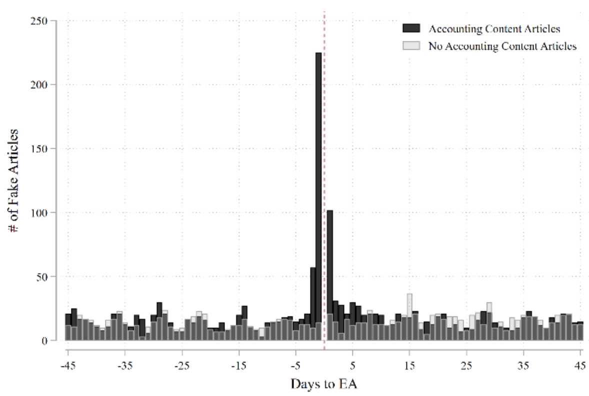
Panel A: Accounting Content Fake Articles



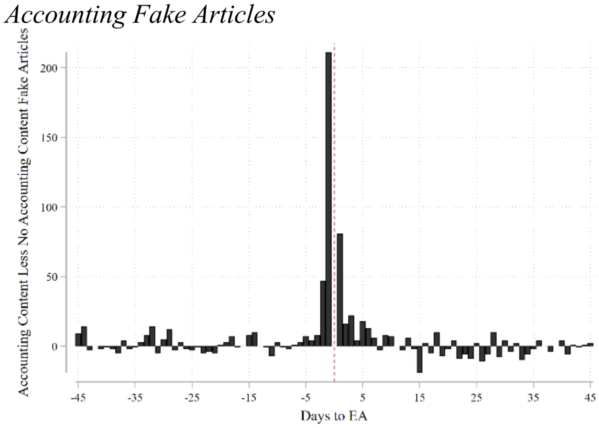
Panel B: No Accounting Content Fake Articles



Panel C: Accounting and No Accounting Content Fake Articles



Panel D: Differences Between Accounting and No Accounting Fake Articles



This figure presents graphical evidence from bunching analyses using the sample of fake articles partitioned by whether the article contains accounting content. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day for articles containing accounting content, while Panel B does the same for articles that do not contain accounting content. Panel C overlays the fake article distributions for each accounting content subsample. Panel D plots the differences between the fake article distributions shown in Panel C.

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. The starting point for our sample is a file, provided by Seeking Alpha, of 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. We have 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. (2020), 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
Accounting Information			
% Articles with Accounting Content	57.1	88.1	-31.0***
% Accounting Words	2.2	3.1	-0.9***
Other Article Characteristics			
Word Count	458.6	620.5	-161.8***
Words Per Sentence	28.4	26.8	1.5***
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 the 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. *% Articles with Accounting Content* is the percentage of articles that contain accounting content. *Word Count* and *Words Per Sentence* are defined as named. 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	242***	101***	343***	141***
	(7.19)	(3.11)	(7.08)	(3.14)
(2) # Non-Fake Articles(t-2,t+8)	3,246***	19,182***	22,428***	-15,937***
	(2.25)	(6.91)	(7.16)	(-5.10)
(3) Fake - Non-Fake(t-2,t+8)	0.051***	-0.112***	-0.061***	0.164***
	(5.04)	(-5.38)	(-2.65)	(6.95)
(4) Fake - Non-Fake(t-2,t+2)	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	39***	19***	58***	19*
	(4.98)	(2.54)	(5.16)	(1.82)
(6) # Fake Articles – Low EA Attention	28***	9*	37***	20***
	(4.99)	(1.55)	(4.43)	(2.53)
(7) # Fake Articles – High vs Low EA Attention	19***	19***	38***	0
	(3.13)	(3.16)	(4.50)	(0.00)
Accounting vs No Accounting Content:				
(8) # Fake Articles – Accounting Content	244***	93***	337***	152***
	(7.65)	(3.03)	(7.41)	(3.53)
(9) # Fake Articles –No Accounting Content	-3	8	5	-11
	(-0.36)	(1.06)	(0.48)	(-1.03)
(10) # Fake Articles – Accounting vs No Accounting Content	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. 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					
# of Fake Articles$_q$	37,864	0.088	0.328	0	0	0	0	2
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, # of Fake Articles, 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*. Dependent variables are tabulated at the same level as the analysis in which they appear. Independent variables are tabulated at the article level. The definitions for all these variables can be 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. (2020). Our primary independent variables of interest are: (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. See Appendix A for details 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. We include industry (two-digit SIC) and year fixed effects in the regressions as indicated 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

Fake Article as Dependent Variable	Coefficient Estimates for: *(1)* *Management Forecast Frequency*	*(2)* *10-K Readability*	*(3)* *# 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 corresponding to the specification presented in Table 5 Column 3. The coefficients for the accounting information variables are reported in columns 1-3 as indicated for 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. See Appendix A for other variable definitions. The table reports marginal effect estimates from a logit regression and (in parentheses) *z*-statistics based on robust standard errors clustered by firm. Marginal effect estimates are calculated at the means of the regressors and multiplied by 100 so that they can be interpreted directly as percentage changes. Observations for which the fixed effects perfectly predict *Fake Article* are dropped from the estimation sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

Table 7: The Impact of Accounting Information on the Production of Fake News

# of Fake Articles as Dependent Variable	*(1)*	*(2)*	*(3)*
Accounting Information Variables:			
Management Forecast Frequency	-0.111***		-0.109**
	(-2.60)		(-2.85)
10-K Readability		-0.026***	-0.026***
		(-6.05)	(-5.84)
Control Variables:			
Adj. ROA	-2.043***	-1.725***	-1.522***
	(-4.52)	(-3.83)	(-3.45)
Analyst Coverage	0.033	-0.013	0.022
	(0.63)	(-0.23)	(0.44)
Business Segments	0.014	0.001	0.006
	(0.74)	(0.09)	(0.34)
Institutional Ownership	-0.132	-0.214**	-0.180*
	(-1.21)	(-2.02)	(-1.68)
M/B	-0.001	-0.000	-0.000
	(-0.21)	(-0.02)	(-0.11)
Media Coverage	0.124***	0.118***	0.117***
	(3.63)	(3.50)	(3.47)
$Returns_{m-12,m-1}$	-0.141***	-0.136***	-0.143***
	(-2.94)	(-2.91)	(-3.01)
$Returns_{t-10,t-1}$	0.129	0.151	0.140
	(0.69)	(0.82)	(0.76)
Size	0.101***	0.099***	0.102***
	(3.88)	(3.74)	(3.95)
Additional Variables:			
Seeking Alpha Articles	0.044***	0.046***	0.045***
	(25.36)	(26.97)	(25.42)
Industry & Year Fixed Effects	Included	Included	Included
Economic Magnitude (%)	-8.9	-18.5	-
Pseudo R^2	0.207	0.209	0.209
N	37,690	37,690	37,690
Estimation Method	Poisson	Poisson	Poisson

(Continued)

Table 7 (Continued)

The table reports analyses on the effect of accounting information on the quantity of fake news. The observations in this analysis are aggregated to the firm-quarter level. The dependent variable is *# of Fake Articles*, which is a count of fake articles written about the firm in a quarter. In this analysis, *Management Forecast Frequency*, *10-K Readability*, and the control variables are measured as of the first article of the quarter. In addition to the control variables used in Table 5 Column 3, we also include *Seeking Alpha Articles,* which is the number of Seeking Alpha articles written about the firm in a quarter. See Appendix A for other variable definitions. The table reports Poisson pseudo-maximum likelihood regression coefficient estimates and (in parentheses) z-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 exponentiating the reported Poisson regression coefficient multiplied by the standard deviation of the *Accounting Information* variable (untabulated), and then subtracting off one.

Table 8: 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	-0.126		-0.122*
	(-1.60)		(-1.70)
10-K Readability		-0.026**	-0.026**
		(-2.53)	(-2.55)
Control Variables:			
Adj. ROA	-1.672	-1.466	-1.278
	(-1.58)	(-1.37)	(-1.21)
Analyst Coverage	-0.281**	-0.311**	-0.274**
	(-2.02)	(-2.20)	(-1.97)
Business Segments	-0.009	-0.029	-0.024
	(-0.31)	(-0.93)	(-0.76)
Institutional Ownership	0.496	0.326	0.386
	(1.26)	(0.86)	(1.01)
M/B	0.002	0.002	0.002
	(0.57)	(0.58)	(0.50)
Media Coverage	-0.086	-0.078	-0.081
	(-1.12)	(-1.02)	(-1.06)
Returns$_{m-12,m-1}$	-0.245**	-0.256**	-0.268**
	(-2.00)	(-2.09)	(-2.18)
Returns$_{t-10,t-1}$	0.067	0.017	0.030
	(0.08)	(0.02)	(0.04)
Size	0.101*	0.104*	0.101*
	(1.80)	(1.84)	(1.80)
Lagged Abnormal Volume Variables	Included	Included	Included
Industry & Year Fixed Effects	Included	Included	Included
Economic Magnitude (%)	-3.2	-6.2	-
Adjusted R^2	0.504	0.506	0.506
N	1,371	1,371	1,371
Estimation Method	OLS	OLS	OLS

(Continued)

Table 8: 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	-0.040*		-0.039*
	(-1.79)		(-1.88)
10-K Readability		-0.006***	-0.006***
		(-2.60)	(-2.68)
Control Variables:			
Adj. ROA	-0.929***	-0.901***	-0.841**
	(-2.74)	(-2.64)	(-2.50)
Analyst Coverage	-0.025	-0.036	-0.024
	(-0.57)	(-0.81)	(-0.53)
Business Segments	0.006	0.001	0.002
	(0.71)	(0.10)	(0.29)
Institutional Ownership	0.029	-0.015	0.003
	(0.33)	(-0.17)	(0.03)
M/B	-0.001	-0.001	-0.001
	(-1.18)	(-1.13)	(-1.21)
Media Coverage	0.035	0.038*	0.037*
	(1.58)	(1.73)	(1.70)
Returns$_{m-12,m-1}$	-0.014	-0.016	-0.020
	(-0.39)	(-0.43)	(-0.53)
Returns$_{t-10,t-1}$	-0.250	-0.261	-0.256
	(-1.18)	(-1.24)	(-1.22)
Size	-0.029*	-0.028*	-0.029*
	(-1.75)	(-1.71)	(-1.78)
Lagged Idiosyncratic Return Volatility Variables	Included	Included	Included
Industry & Year Fixed Effects	Included	Included	Included
Economic Magnitude (%)	-16.5	-23.0	-
Adjusted R^2	0.246	0.248	0.250
N	1,370	1,370	1,370
Estimation Method	OLS	OLS	OLS

(Continued)

Table 8 (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. 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. See Appendix A for other variable definitions. 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 (untabulated) and then scaled by the mean of the dependent variable.

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

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

IA1. Latent Dirichlet Allocation (LDA) implementation details

IA2. LDA Top 10 most prominent words per topic

IA3. Sensitivity analyses

IA4. Binned Scatterplots of Accounting Information Environment Variables on Fake News Publication

IA1: Latent Dirichlet Allocation (LDA) Implementation Details

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

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

Preliminary Cleaning

We first separate each document into a list of words. We stem each word into its root form (e.g., "education" becomes "educat") and discard any common stop words (e.g., "the", "about", etc.), words fewer than 3 letters, as well as numbers and symbols. These lists of words are combined into a dictionary of words with an accompanying count of how many documents each word appears in. We filter out extremely common and uncommon words by discarding any words that appear in fewer than 15 documents and in more than 50% of the documents. From these words, we identify the 100,000 most frequently used words and keep only these words in each document's word list for analysis.

Estimating the Number of Topics Present

LDA requires researcher input on how many topics to identify in a corpus. We want to avoid running LDA for too low or too high a topic number, as the resulting model may not appropriately assign words into semantically coherent topics. As a first step, we generate LDA models for a wide range of potential topic numbers from 10 topics up to 100 topics in multiples of 10 (e.g., 10, 20, 30, etc.). To determine the model with the appropriate number of topics, we use the *C_v* coherence score to evaluate the coherence of the salient words within the topics generated by each of the models (Roder, Both, and Hinneburg, 2015; Syed and Spruit, 2017). A high coherence score implies that the salient words in determining a topic produce well-defined topics across documents and guards against selecting models that produce topics that are mere statistical artifacts. We compute the coherence score for each of our models. In Figure IA1, we plot the coherence scores and find that the coherence score peaks at around 30 topics. Thus, we keep the model utilizing 30 topics as input for our LDA analysis.

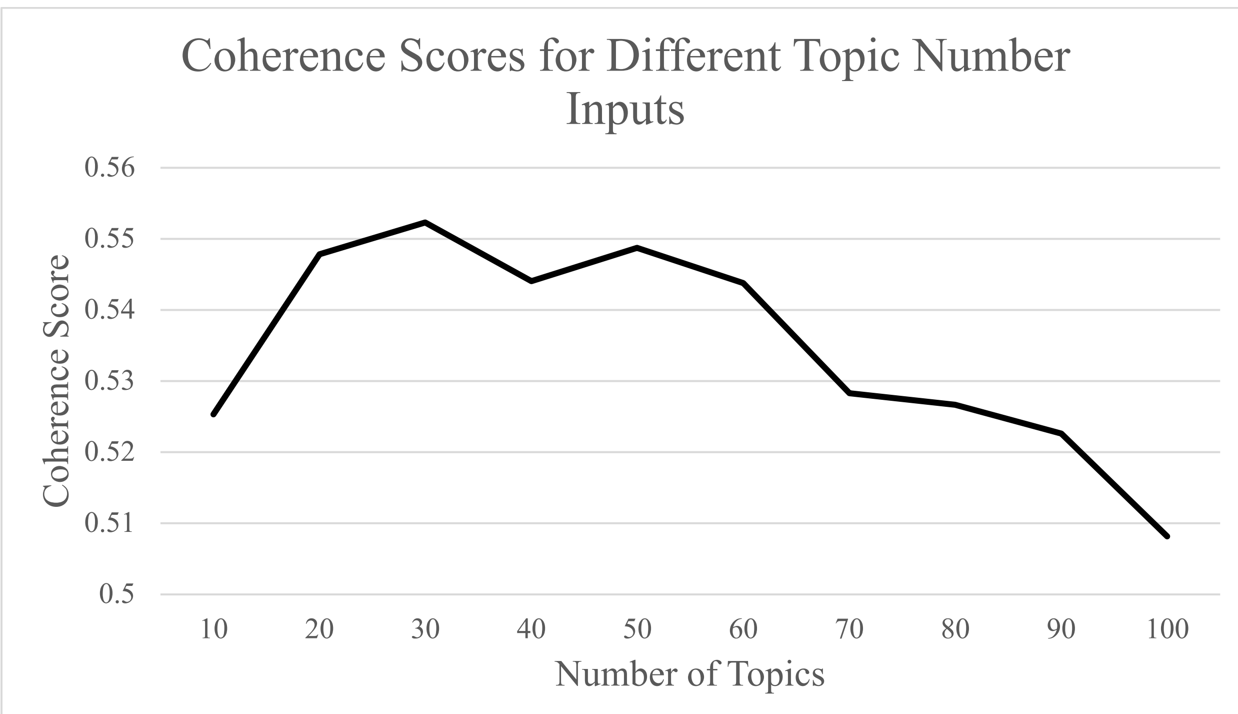
Identifying Representative Topics

While LDA can detect which words belong in latent topics, it is up to the researchers to assign a label or theme to the group of words that comprise a detected topic. Hence, using the LDA model with 30 identified topics, we want to assign each topic a relevant title. To do so, we obtain the top 10 words predictive of a particular topic. Both authors independently went through each set of words and assigned overarching themes to each of the set of the words, compared the potential topic names together, and selected the most suitable topic name for each set of words. We include the sets of words and the topics identified for each of the 30 topics in IA2.

Assigning Topics to Articles

We categorize each article into a specific topic to facilitate descriptive statistics. For each article, the LDA algorithm will generate a list of probabilities of that article containing content in each of the topics. We assign each article to the topic with the highest probability for our descriptive statistics in Table 2. In addition, we compute two numbers for each topic: (1) the number of Seeking Alpha articles that is assigned to that topic and (2) the percentage of fake articles out of the articles classified as that topic.

Figure IA1: Coherence Scores for LDA Implementation



IA2: LDA Top 10 Most Prominent Words Per Topic

Topic 1
Fiscal Policy

polici	1.33%
economi	1.30%
econom	1.19%
trump	1.01%
govern	0.98%
inflat	0.89%
debt	0.73%
money	0.72%
financi	0.66%
central	0.63%

Topic 2
Green Technology

electr	2.32%
vehicl	2.11%
power	2.02%
industri	1.79%
model	1.58%
energi	1.56%
cost	1.56%
solar	1.45%
manufactur	1.44%
car	1.30%

Topic 3
Energy

product	3.46%
energi	2.32%
natur	1.53%
barrel	1.26%
crude	1.14%
produc	1.14%
million	0.94%
drill	0.85%
demand	0.80%
suppli	0.77%

Topic 4
Passive Management

fund	3.60%
index	3.10%
sector	2.63%
return	2.03%
perform	1.87%
portfolio	1.60%
volatil	1.37%
etf	1.24%
hold	1.21%
analyst	1.19%

Topic 5
Accounting

cash	2.97%
valu	2.25%
flow	2.02%
valuat	1.72%
earn	1.56%
debt	1.50%
margin	1.45%
oper	1.40%
ratio	1.18%
capit	1.08%

Topic 6
Retail Industry

sale	3.62%
store	3.27%
brand	2.26%
retail	2.19%
food	1.31%
product	1.27%
consum	1.10%
custom	0.76%
ford	0.71%
busi	0.70%

Topic 7
Streaming Services

subscrib	5.16%
netflix	5.01%
content	3.57%
stream	2.84%
gilead	2.72%
servic	2.14%
subscript	1.76%
nflx	1.58%
gild	1.42%
warner	1.37%

Topic 8
Real Estate

reit	5.43%
properti	3.10%
real	2.57%
estat	2.42%
home	2.16%
hous	1.68%
leas	1.62%
mortgag	1.40%
trust	1.03%
rent	0.97%

Topic 9
Macroeconomy

declin	1.48%
percent	1.46%
data	1.30%
rise	1.28%
rate	1.18%
remain	1.13%
econom	1.11%
report	1.06%
demand	1.00%
economi	0.97%

Topic 10	
Entertainment Industry	
game	2.40%
disney	2.10%
hotel	1.40%
sport	1.13%
movi	1.07%
entertain	1.03%
travel	0.94%
revenu	0.92%
million	0.84%
film	0.82%

Topic 11	
Graphical Evidence	
week	3.85%
chart	2.09%
level	1.59%
short	1.46%
averag	1.29%
click	1.21%
enlarg	1.11%
move	1.00%
indic	0.98%
higher	0.91%

Topic 12	
Precious Metals	
gold	12.46%
silver	3.15%
metal	2.94%
mine	2.65%
miner	1.91%
product	1.77%
copper	1.54%
project	1.47%
ounc	1.45%
resourc	1.19%

Topic 13	
Mobile Device Technology	
mobil	3.30%
game	2.23%
micron	1.50%
verizon	1.35%
qualcomm	1.21%
wireless	1.17%
network	1.06%
semiconductor	1.04%
tencent	1.02%
billion	0.91%

Topic 14	
Unclassified / General	
go	2.01%
think	2.00%
good	1.18%
thing	1.02%
sell	0.97%
right	0.90%
want	0.86%
know	0.85%
say	0.83%
point	0.73%

Topic 15	
Healthcare	
product	2.30%
boe	2.26%
healthcar	2.24%
sale	1.97%
health	1.90%
medic	1.83%
drug	1.54%
care	1.37%
order	1.29%
airbus	1.21%

Topic 16	
Risk Modeling	
risk	1.28%
articl	0.76%
valu	0.71%
differ	0.71%
model	0.67%
return	0.59%
strategi	0.58%
chang	0.56%
import	0.53%
futur	0.52%

Topic 17	
General Business	
busi	2.42%
servic	2.08%
revenu	1.80%
custom	1.72%
product	1.71%
technolog	1.70%
provid	1.03%
manag	1.02%
industri	1.00%
data	0.97%

Topic 18	
Legal	
report	1.58%
say	1.27%
legal	0.89%
regul	0.85%
claim	0.81%
state	0.79%
street	0.73%
court	0.71%
case	0.71%
issu	0.67%

Topic 19

Portfolio Management

fund	4.79%
manag	3.70%
portfolio	3.18%
asset	2.47%
hedg	1.67%
capit	1.67%
hold	1.65%
valu	1.56%
stake	1.34%
berkshir	1.33%

Topic 20

Dividend Investing

dividend	14.46%
yield	4.94%
incom	3.01%
portfolio	1.97%
payout	1.45%
ratio	1.24%
return	1.19%
distribut	1.18%
pay	1.18%
annual	1.16%

Topic 21

Bonds

bond	4.49%
yield	4.29%
rat	4.26%
rate	3.38%
risk	2.24%
treasuri	1.72%
fund	1.45%
inflat	1.37%
rise	1.27%
asset	1.23%

Topic 22

Capital Raises

million	3.08%
cash	1.26%
deal	1.12%
sharehold	1.06%
manag	1.00%
offer	0.94%
capit	0.93%
sell	0.85%
debt	0.84%
valu	0.83%

Topic 23

Social Media

googl	3.33%
user	2.57%
facebook	2.40%
advertis	1.63%
platform	1.34%
media	1.34%
revenu	1.34%
video	1.01%
content	0.93%
social	0.91%

Topic 24

Technology Industry

appl	9.39%
intel	3.20%
iphon	2.34%
aapl	2.19%
nvidia	1.87%
product	1.61%
devic	1.28%
sale	1.17%
cola	1.01%
chip	0.98%

Topic 25

Accounting Forecasts

quarter	7.39%
million	5.12%
revenu	4.99%
earn	3.99%
billion	2.93%
report	2.37%
sale	1.99%
result	1.94%
estim	1.68%
guidanc	1.38%

Topic 26

Global Markets

china	5.67%
global	2.53%
countri	2.39%
chines	2.16%
world	1.73%
currenc	1.70%
emerg	1.32%
dollar	0.98%
export	0.97%
foreign	0.96%

Topic 27

Pharmaceutical Industry

patient	2.26%
drug	1.77%
trial	1.73%
phase	1.52%
approv	1.32%
studi	1.27%
treatment	1.18%
data	1.05%
develop	0.99%
clinic	0.97%

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

IA3: Sensitivity Analyses

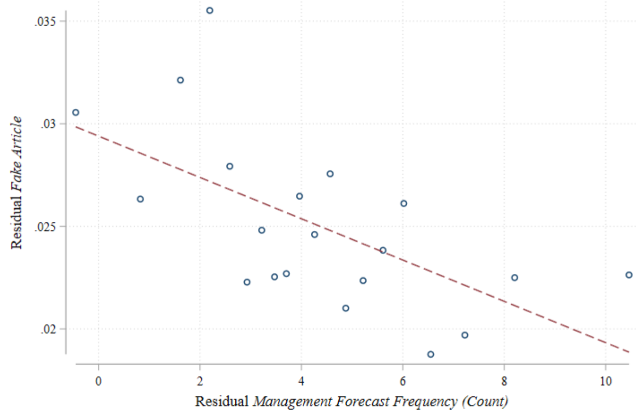
Table IA3: Sensitivity Analyses of Accounting Information Environment Variables on Fake News Publication

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

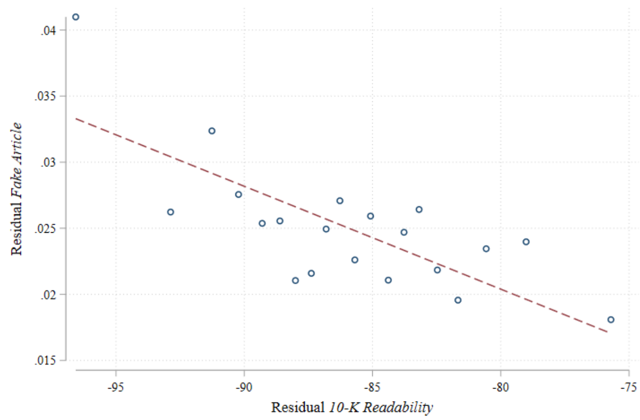
This table reports sensitivity analyses of our primary specification (Col. 4 in Table 4) examining the role of accounting information in deterring fake news. The dependent variable is *Fake Article*. The coefficients for the accounting information variables are reported in columns 1-2 as indicated for each sensitivity analysis. All analyses include the control variables and fixed effects specified in Table 4 Column 3, but we do not report the coefficients for brevity. See Appendix A for variable definitions. The table reports marginal effect estimates from a logit regression and (in parentheses) *z*-statistics based on robust standard errors clustered by firm. Marginal effect estimates are calculated at the means of the regressors and multiplied by 100 so that they can be interpreted directly as percentage changes. Observations for which the fixed effects perfectly predict *Fake Article* are dropped from the estimation sample. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% p-levels (two-tailed), respectively.

IA4: Binned Scatterplots of Accounting Information Environment Variables on Fake News Publication

Panel A: Management Forecast Frequency (Count)



Panel B: 10-K Readability



This figure plots the conditional probability of a fake news article versus our three measures of accounting information. Panel A is a binned scatterplot of the probability of a fake article (i.e., *Fake Article*) versus the number of management forecasts in the past year (i.e., *Management Forecast Frequency (Count)*). Panel B is a binned scatterplot of *Fake Article* versus the Bog Index from Bonsall et al. (2017) multiplied by -1 (i.e., *10-K Readability*). To construct these binned scatterplots, we first residualize both *Fake Article* and the respective accounting information variables (collectively referred to as *Accounting Information*) with respect to the control variables described in Table 3 as well as industry (two-digit SIC) and year fixed effects using partitioned regressions following the Frisch-Waugh-Lovell theorem. We then rank and divide the observations into 20 equal-size groups (ventiles) based on residual *Accounting Information* and plot the means of residual *Fake Article* within each bin against the mean value of residual *Accounting Information* within each bin. Finally, we add back the unconditional mean of *Fake Article* and *Accounting Information* in the estimation sample to facilitate interpretation of the scale. We use the binscatter Stata program for this procedure (Stepner, 2014). The dashed line shows the best linear fit estimated on the underlying sample of articles using an OLS regression. All three slope estimates are significantly different than zero at conventional significance levels (i.e., p-value < .05).