The Role of Accounting Information in an Era of Fake News

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Abstract

We investigate the role of accounting information on the incentives to produce financial fake news. We find financial fake news publication trends in line with common media narratives on the expansion of fake news in recent years. In examining fake news publication behavior around earnings announcements, we document a significant increase in fake news around these major accounting information events that peaks directly prior to the announcements. We propose and find evidence consistent with two aspects of accounting disclosures that explain this publication distribution pattern: (1) an attention effect, by which the widespread attention garnered by these highly anticipated disclosures encourage fake news authors to publish more fake news around the event and (2) an information effect, by which the informativeness of such disclosures incentivizes fake news authors to publish prior to the announcement when the accounting information environment is relatively weaker as opposed to directly after the announcement. In further tests investigating the information effect on the broader information environment using other accounting disclosures, we find that fake news authors are less likely to target firms with strong accounting information environments and that publishing in such an environment reduces the market impact of the fake news articles that are published. Overall, we document results consistent with accounting disclosures garnering widespread capital market attention that temporarily fuels increased fake news but also with the informativeness of these accounting disclosures ex ante disincentivizing the relative production of fake news and ex post reducing the market reaction to fake news.

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

– Carvana Co. Prospectus, 5/23/2019

1. Introduction

Fake news—defined as false or misleading information with the intent to deceive—is a significant threat to efficient capital markets. In 2018, "Rota Fortunae" penned a Seeking Alpha article about Farmland Partners, Inc., alleging that "310% of 2017 earnings could be made-up" and that the firm bears "significant risk of insolvency." Despite 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

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[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.

and document interactions between accounting information disclosures and the incentives to publish fake financial news in the capital markets.[2]

We use Seeking Alpha, an independent investor research website, as our setting. Seeking Alpha is conducive to studying financial fake 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; Kogan et al., 2022; Seeking Alpha, 2020). 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 identify 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

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

[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.

classification approach on a sample of known fraudulent Seeking Alpha articles that led to SEC enforcement.[4,5]

We begin by documenting some descriptive statistics of the trends in the content and volume of fake news articles. To analyze the content of fake news, we use Latent Dirichlet Allocation (LDA) to identify the topics covered by the articles. We find significant heterogeneity in the topics spanned by fake articles, such as accounting information and forecasts, specific industry news, legal matters, and macroeconomic conditions. Of particular interest, we find that as many as 86% of fake articles contain content about accounting information. We also note that the percentage of fake articles is amongst the lowest in accounting topics, providing preliminary evidence consistent with potential difficulty in constructing fake news using accounting information. In terms of 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 recent years, documenting 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 across disparate information environments including that of financial news.

To shed light on the potential interactions between accounting information and the publication timing of fake news, we examine the volume of fake news published around earnings announcements as salient accounting information events. To do so, we plot the frequency distribution of fake articles published in the days surrounding earnings announcements. A visual inspection yields that the density of fake articles is significantly higher around the announcement date. Interestingly, the number of fake articles peaks the day prior to the announcement but

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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).

decreases drastically following the announcement, resuming to non-announcement period levels within 2 days. In light of our visual evidence, we propose two aspects of accounting disclosures that may explain the shape of the frequency distribution for fake news publication: an attention effect and an information effect. The former relates to large accounting disclosure events increasing market attention on disclosing firms, while the latter manifests due to the verifiable information that accounting disclosures provide to capital markets. We elaborate on both below.

Accounting information events, such as earnings announcements, management forecasts, and 10-K releases, garner an abnormal spike in attention from the market (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 (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, 2019). To the extent that fake news authors rely on readership for compensation, elevated market attention on the disclosing firm could provide additional incentives to produce fake news if a greater number of readers click into sensationalized fake articles or even change their priors upon reading 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 thus particularly well-suited to counter fake news in the 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 discussion and analyses that preempt or explain changes to business ecosystems (e.g., Ball, Hoberg, and Maksimovic, 2015). To the extent that these disclosures help investors learn the true asset value of the firm, accounting information reduces investor susceptibility to false price signals, disincentivizing the production of fake news.

To investigate whether accounting information influences the strategic publication decisions of fake news authors, we use a bunching identification strategy. Conceptually similar to 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 and a missing mass of avoided outcomes on the other, the anomalous pattern is attributed to the discontinuity in incentives at the threshold. Because prior literature documents significant informativeness linked to earnings announcements (e.g., Beaver, 1968; Atiase and Bamber, 1994), we use these accounting events as a large discontinuous increase in informed investors to study the publication timing preferences of fake news authors in a narrow event window. Overall, we find bunching distributions consistent with both the attention and information effect of accounting disclosures on the incentives to publish fake news: (1) fake news authors generally publish more fake articles near an earnings announcement and (2) they strongly prefer to publish the fake articles prior to the release of accounting information than afterwards.

Finally, we examine the how the broader accounting information environment affects the production and impact of fake news on the market with respect to the information effect, in particular. To complement our bunching findings, we conduct multivariate analysis to investigate whether the general accounting information environment influences the publication of fake news and its subsequent market impact. We choose two proxies for accounting information that are salient to fake news authors: management forecast frequency, a measure for voluntary disclosure, and 10-K readability, a discretionary component of mandatory disclosure.[6]

Within our multivariate analyses, we first 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. We hypothesize and find results consistent with accounting information reducing the production of fake news. A one-standard-deviation increase in management forecast

[6] We acknowledge that we do not study other common measures of accounting information that 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 less likely to affect the publication of fake news articles.

frequency or 10-K readability is associated with an 8-14% decrease in the likelihood that fake news is written. As complementary evidence, we use Poisson pseudo-maximum likelihood estimation to test the effect of accounting information on the number of fake articles written about a firm in a quarter and find qualitatively similar inferences to the logit model. 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.

Lastly, we examine whether the informativeness of accounting information alters the market reaction to fake news. We find results mostly consistent with accounting information attenuating both abnormal trade volume and idiosyncratic return volatility following fake article publication. A one-standard-deviation increase in management forecast frequency or 10-K is associated with a 3-6% decrease in abnormal trade volume and a 16-23% decrease in idiosyncratic return volatility to fake news. Hence, we provide evidence consistent with the information effect for other disclosures in the broader accounting information environment in 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 evidence of the unique interactions between accounting information and fake news. We document results consistent with accounting disclosures garnering widespread capital market attention that temporarily fuels increased fake news but also that the informativeness of these accounting disclosures *ex ante* disincentivizes the relative production of fake news and *ex post* reduces the market reaction to fake news. 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 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 how to safeguard the public from its effects. We provide nuanced evidence on two countervailing effects of accounting disclosures on the incentives to produce fake news in financial markets. Specifically, we find that fake news authors (1) publish more fake news around accounting information events due to their publicity but (2) conditional on publishing around these events, prefer to publish prior to the disclosure in relatively weaker accounting information environment than after the disclosure.[8] Further research is needed to evaluate the generalizability of our results to fake news settings outside of financial markets.

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[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.

[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.

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 the firm's 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 that the author chose to downplay the validity of the management forecast provides evidence that he is not only aware of these accounting information 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 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

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[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.

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, 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 articles. 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

[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.

forecasts, industry-specific news, legal matters, macroeconomic conditions, and more. Table 2, Panel A contains the list of identified topics. We compute the probabilities of an article containing each of the 30 topics identified by LDA. It is important to note that one article may 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 with a non-zero probability of 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 number of articles with positive probability of having accounting content, the two topics about accounting information, Topic 5 and Topic 25 (henceforth, "accounting topics") are in the top 3 most popular topics. In untabulated analyses, 32% of articles are assigned 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 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 the subsample of fake articles and that the percentage of "accounting words" used by fake articles is lower. As in Table 2 Panel A, we point to these results as circumstantial evidence that there may exist disincentives to publish fake news about or with accounting information. We also find that fake articles tend to use fewer words per article, higher number of words per sentence. As derived from our LIWC procedure, the average authenticity score for fake articles is significantly lower than that for non-fake articles, while the average clout score, indicating the author's confidence or own perceived social standing, is significantly higher for fake articles. In addition, similar to Kogan et al. (2022), we find that the market reacts to fake articles as strongly or more strongly than non-fake articles, attesting to the way that fake news is deceptively written to impact investor perceptions.

3.2 Timing of Fake News Articles

Next, we examine the publication timing of fake news. As context for aggregate trends in fake news publication during our sample period, we look at the prevalence of fake news publication by looking at the 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 recent years. The peak in recent years aligns with the common media narrative that the amount of fake news has largely 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 across disparate types of information environments including financial news. When we partition the volume of fake articles by whether they contain accounting content, we find the same bimodal distribution. We believe this descriptive evidence may facilitate the creation of testable hypotheses about the determinants of aggregate fake financial news production over time but do not pursue this line of inquiry in our paper.

In the next part of our analysis, we examine the timing of fake news around accounting information releases in particular. To do so, we construct density 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 anticipated events, oftentimes scheduled weeks or months in advance, giving fake news authors advanced notice on when the disclosures will be. This feature allows us to potentially infer authors' preferences by looking at when articles are written relative to earnings announcements. By exploiting the fact that Seeking Alpha authors are freelancers with the discretion on when to publish news articles around earnings announcements, we use these characteristics to examine the incentives behind the publication behavior of fake news authors.

To construct our density 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).[11] 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. *Fake Articles*$_t$ is equal to the number of fake articles published on *Days to EA*$_t$ summed across all earnings announcements.

Figure 2 depicts the resulting density distributions created from *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 around earnings announcements as the increase in fake article publication is much more pronounced prior to earnings announcements than after.

We propose two potentially countervailing aspects of accounting disclosures that may explain the shape of the frequency distribution for fake news publication: an attention effect and an information effect. The former relates to large accounting disclosure events increasing the attention on disclosing firms, while the latter manifests due to the verifiable information that accounting disclosures provide to capital markets. We elaborate on both below.

3.3 Attention and Information Effects

We reference the theoretical literature on strategic communication to motivate our investigation of the effect of accounting disclosures on fake news. Specifically, we refer to the stream of literature on why market participants react to *ex ante* unverifiable information, as is the case with Seeking Alpha articles published under pseudonyms (Dyer and Kim, 2021). Historically, analytical models of strategic communication in financial markets have examined

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

an information sender's reputation as a source of credibility when information is costly to verify (e.g., Benabou and Laroque, 1992; Stocken, 2000; Van Bommel, 2003). However, theories relying on reputation in repeated games to induce credible information sharing cannot rationalize why markets react to *ex ante* unverifiable information (i.e., rumors) from anonymous senders.[12]

Schmidt (2020) proposes a cheap talk model in which *ex ante* unverifiable information from an unknown source can be credible in equilibrium. Rather than relying on reputation as the mechanism to incentivize truthful communication, Schmidt rationalizes market reactions to rumors by allowing investor investment horizons to be occasionally misaligned with the horizon of the investor's private information. For example, an investor has private information about long-term price movements but has a short-term investment horizon. In anticipation, market participants rationalize that, as this investor's investment horizon shortens, his incentive to send truthful information increases in order to accelerate price discovery and maximize the capitalization of his private information into stock price.[13] This truth-telling incentive allows for a credible information sharing equilibrium to develop absent a reputation concern for the information sender.

More importantly, for the context of our paper, Schmidt's model sheds light on how the truth-telling preference of a sender varies with changes to the uninformed and informed market participants. In the model, informed investors disregard false messages and trade according to their own information, while uninformed investors trade based on the sender's signals. An equilibrium results such that a sender's preference for sending untruthful messages varies in two

[12] There is substantial documentation of market reaction to unverified merger or takeover rumors (Greenberg, 2007; Jia, Shu, and Zhao, 2020).

[13] Schmidt extends his original model to a generalized case in which market participants do not need to know the horizon of a specific sender as long as there exists investors with a continuum of investment horizons.

ways of interest. One, it increases as the quantity of uninformed trades increases. Two, it decreases as the proportion of informed investors increases.

Although Schmidt's model is agnostic on how uninformed investors decide to place more trades or how informed investors learn the true asset value of the stock, longstanding theoretical and empirical literatures endorse accounting disclosures as one of the primary mechanisms for informing investors about fundamental value (i.e., the valuation role of accounting information), resulting in their ability to attract abnormal attention from the market. 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 information decreases the effectiveness of fake news, resulting in lower incentives to publish fake articles when the accounting information environment is of higher quality. However, due to their informativeness, many accounting disclosures are highly anticipated events that elicit widespread market attention both in advance of the forthcoming information and after its revelation (e.g., Beaver, 1968; Drake et al., 2012). The elevated market attention surrounding accounting disclosures can increase the views of sensationalized fake articles, increasing their effectiveness in influencing the market and therefore the incentives to publish these articles. Hence, in the remainder of our paper, we investigate how these potentially countervailing forces of accounting disclosures affect the incentives to publish fake news.

4. Distribution Analyses of Fake News Publication Timing Preferences

To provide rigorous empirical evidence on whether accounting disclosures induce potential behavioral distortions associated with fake news publication, we formalize our inferences about the attention and information effects of accounting disclosure on the timing of fake news publication using the bunching methodology and conducting cross-sectional bunching analyses intended to isolate each effect. 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 due to certain thresholds (Kleven, 2016).[14] Intuitively, the existence of certain thresholds with discontinuities in incentives can cause (1) the outcomes on one side of the threshold to dominate those on the other side in preferences and/or (2) the outcomes in a window around the threshold to differ in preferences than those outside the window. The former induces behavioral distortions in actions or reporting so that the observed outcome is on the preferred side of the threshold, while the latter results in abnormally high or low observed outcomes inside the window as compared to outside it. In either case, the density distribution of outcomes exhibits excess mass (i.e., "bunching") in the region of preferred outcomes and a missing mass of avoided outcomes outside this region.[15] In the context of our

[14] 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).

[15] 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.

study, if accounting information creates distortions in incentives to produce fake news, specifically to publish during periods where its content is most likely to mislead investors, we expect excess mass in the density distribution of fake articles (1) in general around earnings announcements from the attention effect and (2) before earnings announcements relative to afterwards 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 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 excluding those local to the threshold causing the theorized behavioral distortions. This approach utilizes the distribution of observed outcomes of interest to estimate the counterfactual for the affected region using theoretically unaffected regions of the distribution. 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.[16] 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. We use both the polynomial and difference-in-bunching methodologies to provide evidence on the incentives on publishing fake news.

[16] 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).

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. Following prior literature, we identify the specific window of the affected region by visually inspecting the distribution of fake articles in Figure 2 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, t+2.[17] We then fit a polynomial function to the distribution of fake news publication 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 news publication and the polynomial estimates of counterfactual fake news publication in the earnings announcement window 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, Friedman, Olsen, and Pistaferri (2011) to compute standard errors for statistical inferences. Specifically, we create a bootstrap distribution by randomly sampling *Abnormal Mass*$_t$ from the observed distribution in Figure 2 Panel A 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.

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

Table 3 presents the numerical density estimates of our polynomial bunching analyses. In Row 1, we present the results from our bunching procedure on the distribution of fake articles from Figure 2. 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 news articles produced within the earnings announcement window than expected based on trends from outside the window, providing evidence that the increased attention around earnings announcements increase fake news production. 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 the earnings announcement than afterwards. 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. Hence, we find that earnings announcements stimulate the production of fake news consistent with the attention effect and that, conditional on increased attention before and after earnings announcements, fake news authors prefer publishing before the release of accounting information, consistent with the information effect of accounting disclosures deterring fake news production.

Next, we use the difference-in-bunching methodology to provide more rigorous evidence on the information effect. We use the distribution of non-fake articles to serve as the counterfactual distribution. We expect that the incentives to publish fake and non-fake articles are similarly affected by the increased market attention around earnings announcements, since on a day-to-day basis, the primary incentive to publish both fake and non-fake articles is compensation linked to readership (e.g., Seeking Alpha payment per view, internet clout, etc.)

(Dyer and Kim, 2021). To the extent that both types of publication are driven by market attention, we are able to examine the information effect of accounting disclosures on the incentives to publish fake news, conditional on heightened market attention.

Prior to comparing the fake and non-fake distributions, we briefly examine 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 Row 2 of Table 3. We note that visual inspection of the distribution of non-fake articles yields different days of elevated publication behavior relative to the earnings announcement. 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 both fake and non-fake articles. Similar to the distribution of fake articles, we find that there is a positive and significant number of abnormal non-fake articles in the pre, post, and overall earnings announcement windows, consistent with increased 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 publication of non-fake articles peaks after earnings announcements, as evidenced by a negative and significant abnormal differential mass in Column 3.

Similar to establishing parallel trends for difference-in-differences analyses, visually examining the trends of the two compared distributions outside the affected window helps evaluate the suitability of the comparison. In Figure 3, we show the overlap (Panel C) and difference (Panel D) in fake and non-fake article distributions. 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 Panel C, we confirm that both fake and non-fake articles closely mirror each other outside the earnings announcement window, following the same non-descript oscillating pattern. Furthermore, the similarity in publications 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 within the earnings announcement window. We interpret this evidence as validation that non-fake articles are a reasonable counterfactual for the publication behavior of fake articles. Hence, we use non-fake article publication as our counterfactual distribution and conduct the bunching statistical procedure as 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*.[18]

Table 3 Row 3 presents the statistical estimates from our difference-in-bunching analysis comparing the 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 is statistically significant as evidenced by the positive and significant estimate for *Differential Abnormal Mass*$_{t-2,t+8.}$ Thus, our bunching analyses suggest that, conditional on writing fake news around earnings announcements, fake news authors prefer to publish fake articles before rather than after earnings announcements when the accounting

[18] 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.

information environment is relatively weaker. 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 in fake news inside the earnings announcement window compared to non-fake news.[19] 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 disclosures decreases the net publication of fake news around earnings announcements in equilibrium or whether the information effect manifests only as a shift in the timing of fake news. We provide more evidence on this question in the following analyses but also believe examining the information effect of accounting disclosures on fake news is a fruitful area for future research.

In the following two subsections, we conduct additional bunching analyses that compare distributions of articles partitioning by how the attention effect or information effect impact them. Specifically, we examine distributions of (1) fake articles around earnings announcements with relatively higher and lower market attention and (2) fake articles containing accounting and

[19] We have two conjectures for these results. One, 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. Two, the spike in information search and acquisition around earnings announcements increases the proportion of informed investors, disincentivizing fake news authors from writing during the announcement window in general (e.g., Drake, Roulstone, and Thornock, 2012).

no accounting content. These analyses yield additional insights about the attention effect and information effect of accounting information on fake news publication behavior.

4.1 Partitioning by Market Attention

We further explore the attention effect of accounting disclosures on fake news by comparing the distributions of fake articles with high earnings announcement attention to those with low earnings announcement attention. We proxy for high and low attention by partitioning the sample of fake articles by median Investor Google Search Index (ISVI) on earnings announcement day (Da, Engelberg, and Gao, 2012; deHaan, Lawrence, and Litjens, 2021). In doing so, we compare two distributions of fake articles with known differences in attention-driven incentives. To the extent that the attention effect of accounting disclosures impacts the incentives to publish fake news, we expect there to be more fake news published around earnings announcements with high attention. However, if the amount of attention around earnings announcements does not influence fake article publication preferences, we should observe minimal differences between the fake article distributions about earnings announcements with high and low market attention.

We first analyze and discuss 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 Panel A and Panel 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 that there is an abnormal number of fake articles in the pre, post, and overall earnings announcement windows as shown in Columns 1-3. Furthermore, there is evidence of bunching within each subsample as indicated by the high amount of fake news prior to earnings announcements relative to afterwards as shown in

Column 4. These bunching results are consistent with our prior findings that, conditional on publishing fake news during periods of heightened attention, fake news authors choose to publish articles prior to earnings announcements relative to afterwards.

Table 3 Row 7 presents the statistical estimates from our difference-in-bunching analysis comparing the high and low earnings announcement attention distributions. Consistent with attention impacting the publication of fake news, the high attention subsample has significantly more fake articles published during the pre, post, and overall earnings announcement windows (Columns 1-3). Interestingly, while there was evidence of bunching within each subsample separately, there is no evidence of a *difference* in the amount of bunching across the two subsamples (Column 4). We interpret the lack of a difference in the amount of bunching across the distributions of high and low attention earnings announcements as evidence that the information and attention effects are distinct, at least when using Google search volume as the proxy for attention.

4.2 Partitioning by Accounting Content

To further validate the information effect of accounting disclosures on fake news publication, we conduct the same set of bunching analyses as in the previous two subsections but partition our sample of fake articles by whether they contain accounting content.[20] For the subsample of articles with accounting content, the distribution of fake articles is graphed in Figure 4 Panel A with numerical estimates from the polynomial bunching approach presented in Table 3 Row 8. Our inferences from both the graphical and statistical evidence remain the same as the full sample. In addition, within the subsample of articles without accounting content (Figure 4 Panel B and Table 3 Row 9), there is no meaningful publication pattern nor

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

discontinuity around earnings announcements, providing falsification evidence against correlated omitted variables expected to influence the publication of fake non-accounting articles. We find similar inferences from these subsample analyses when we directly compare the two distributions using the difference-in-bunching approach (Figure 4 Panels C and D; Table 3 Row 10).

These analyses provide validation that our results are driven by articles for which accounting information is particularly relevant. Finding our hypothesized pattern in the expected subsample (i.e., articles with accounting content) and not in the subsample where we do not expect a pattern (i.e., articles without accounting content) bolsters our inferences on the information effect of accounting disclosures 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 providing evidence consistent with both the attention and information effects of accounting disclosures on fake news production. Specifically, we find that fake news authors publish a higher amount of fake news on the days surrounding earnings announcements with relatively more fake articles published pre-earnings announcement than post earnings announcement on these days. These findings are consistent with fake news authors publishing more fake news when there is heightened attention surrounding an accounting disclosure but also 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 market attention than those with lower market attention. We also find that the bunching behavior we attribute to the information effect manifests in a restricted subsample of articles containing accounting content but not within the subsample of articles without accounting content, providing not only reassurance on the information effect of accounting disclosures appearing in the expected subsample but also that the behavioral patterns we document are not artifacts of the publication of fake articles without accounting content.

5. Regression Analyses and Results

In this section, we broadly explore the information effect by examining whether fake news authors are less likely to target firms with more robust accounting information environments in general. Specifically, we examine two common measures of accounting information derived from other accounting disclosures: (1) management forecast frequency and (2) 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, Cohen, Lys, and Walther, 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 the provision of management forecasts informs investors, including their assistance in projecting bottom line 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 in 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 Deterring Fake News Production

5.2.1 Accounting Information and the Probability of Fake News

We examine the role of accounting information in deterring the production of fake news by estimating the conditional probability that an article is fake. In accordance with our first hypothesis, 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 versus non-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 influence 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 deterring 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 deterrence to fake news publication over our accounting information variables. Both *Analyst Coverage* and *Institutional Ownership* are insignificant or inconsistently significant.

[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.

Media Coverage is positive and significant with an economic magnitude of 13%, comparable to our effect estimates for our accounting information variables of 8-14%. This result indicates that more media articles in the press are associated with a higher probability that a fake article is published. We conjecture that the positive coefficient is potentially caused by attention effects in that fake news authors want to write about firms with increased investor attention to maximize readership and influence of their fake articles. 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 not try to hypothesize why these opposing signs occur and leave the investigation of the link between performance and fake news publication 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 fake article sample discusses content for which accounting information can deter, (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 Row 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 non-accounting articles. 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 attention from fake news authors. 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 driven 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 them in Rows 4 and 5 of Table 6. We continue to find statistically significant results in both partitions for both accounting information variables, alleviating 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 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, reducing the likelihood of an unobserved variable driving our results.

Overall, our results in this section are consistent with the information effect of accounting information in disincentivizing the production of financial fake 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 deterring 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]

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

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 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 deterring the production of fake news.

[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).

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. To test our hypothesis, we estimate the following model using OLS at the article level:

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

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 of the market reaction to fake news as well as 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 both prior to and after these events 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.

Table 8 presents the results for our second hypothesis 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* to the publication of fake news. Column 3 estimates Equation (3) including both accounting information variables and yields similar inferences.

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 following a fake news article 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

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[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.

from Columns 1 and 2. Overall, we find evidence in support of accounting information attenuating the market reaction to fake news.

6. Conclusion

Our paper documents several stylized facts about the role of accounting information in an era of fake news using a sample of Seeking Alpha articles. We begin by documenting some descriptive statistics of the trends in the content and volume of fake news articles. Of particular interest, we find that as many as 86% of fake articles contain content about accounting information. We also note that the percentage of fake articles is amongst the lowest in accounting topics, providing preliminary evidence consistent with potential difficulty in constructing fake news using accounting information. Looking at fake news publication around earnings announcements, we show 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 2 days.

We propose two aspects of accounting disclosures that may explain the shape of the frequency distribution for fake news publication: an attention effect and an information effect. The former relates to large accounting disclosure events increasing market attention on disclosing firms, while the latter manifests due to the verifiable information that accounting disclosures provide to capital markets. In bunching analyses, we find distributions consistent with both the attention and information effect of accounting disclosures on the incentives to publish fake news: (1) fake news authors generally publish more fake articles near an earnings announcement and (2) they strongly prefer to publish the fake articles prior to the release of accounting information than afterwards.

Lastly, using multivariate analyses, we investigate the effect of accounting information on the production of and the market reaction to fake news. We choose two proxies for accounting information that are salient to fake news authors: management forecast frequency, a measure for voluntary disclosure, and 10-K readability, a discretionary component of mandatory disclosure. Our results are consistent with accounting information reducing the production of fake news. Additionally, we find results mostly consistent with accounting information attenuating both abnormal trade volume and idiosyncratic return volatility following fake article publication.

Overall, our results are consistent with accounting disclosures garnering widespread capital market attention that temporarily fuels increased fake news but also that the informativeness of these accounting disclosures *ex ante* disincentivizes the relative production of fake news and *ex post* reduces 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

Galena Biopharma: Best And Worst Case Scenario

Aug 14 2013, 04:09 | about: GALE

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

Seeking Alpha α
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Matt Gravitt
Long/short equity, value, special situations, momentum
Profile | Send Message | + Follow (125)

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.

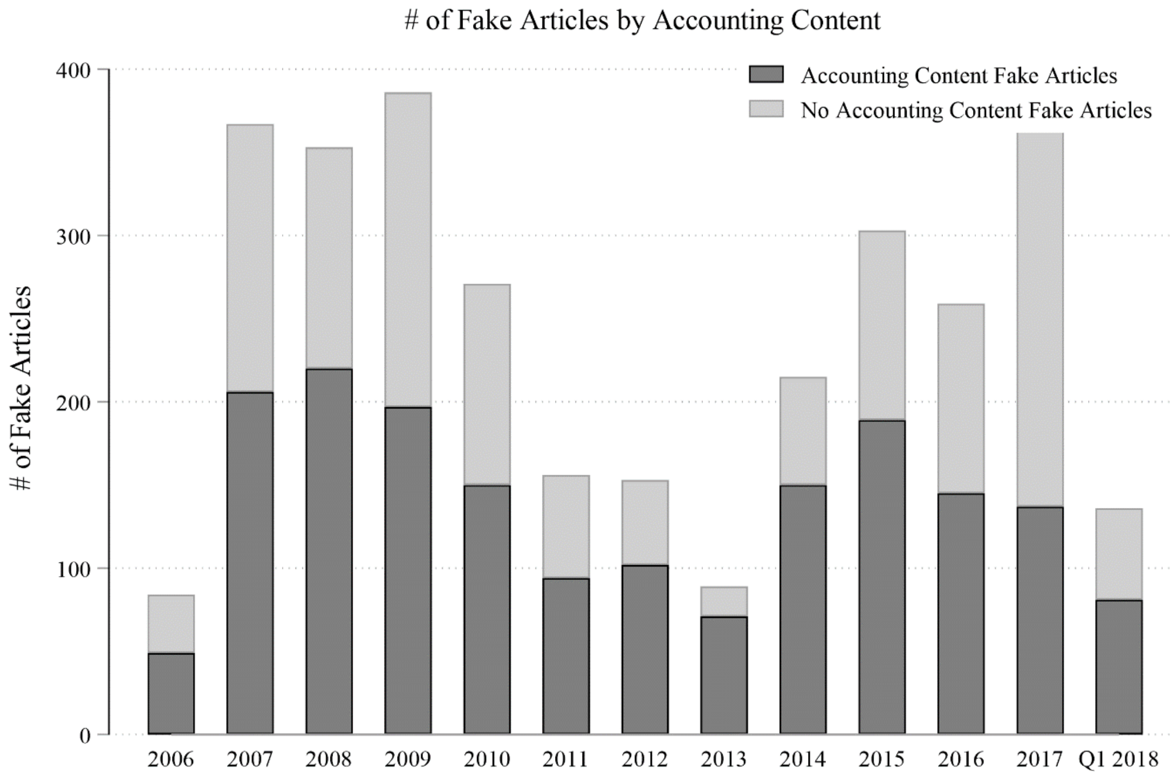
Transaction Date	Name	Position	Type	Shares	Range	Market Value	Total Holdings
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	250,000	$0.72 - $1.18	180.0K	255,000
01/22/2014	KRIEGSMAN, STEVEN A.	Director	Sell	250,000	$6.13	1.5M	5,000
01/17/2014	KRIEGSMAN, STEVEN A.	Director	Option Execute	200,000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

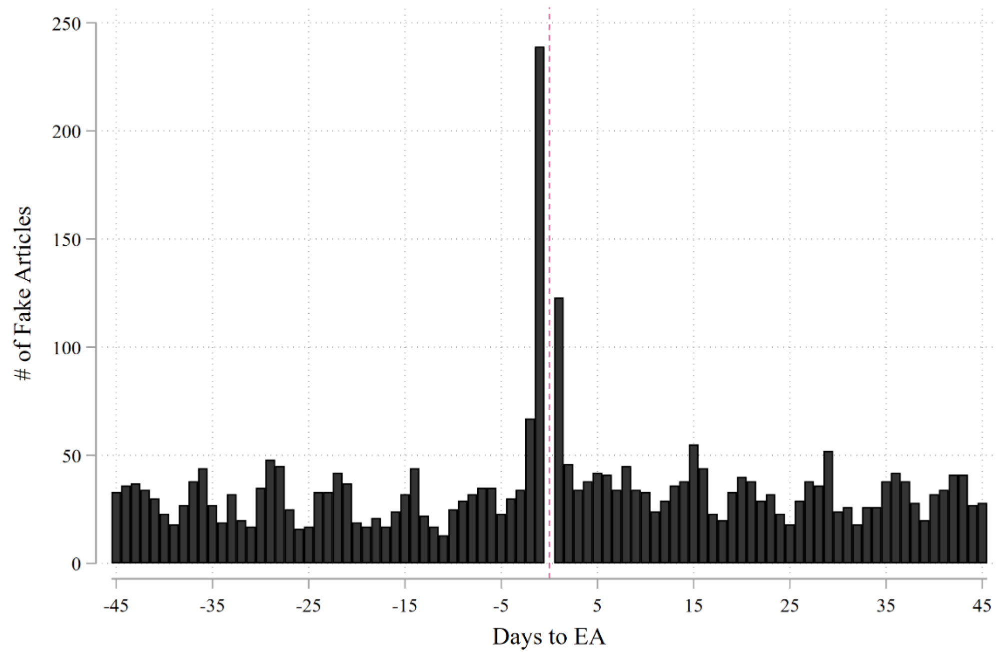
Figure 1: Fake News Production Over Time for Articles with and without Accounting Content



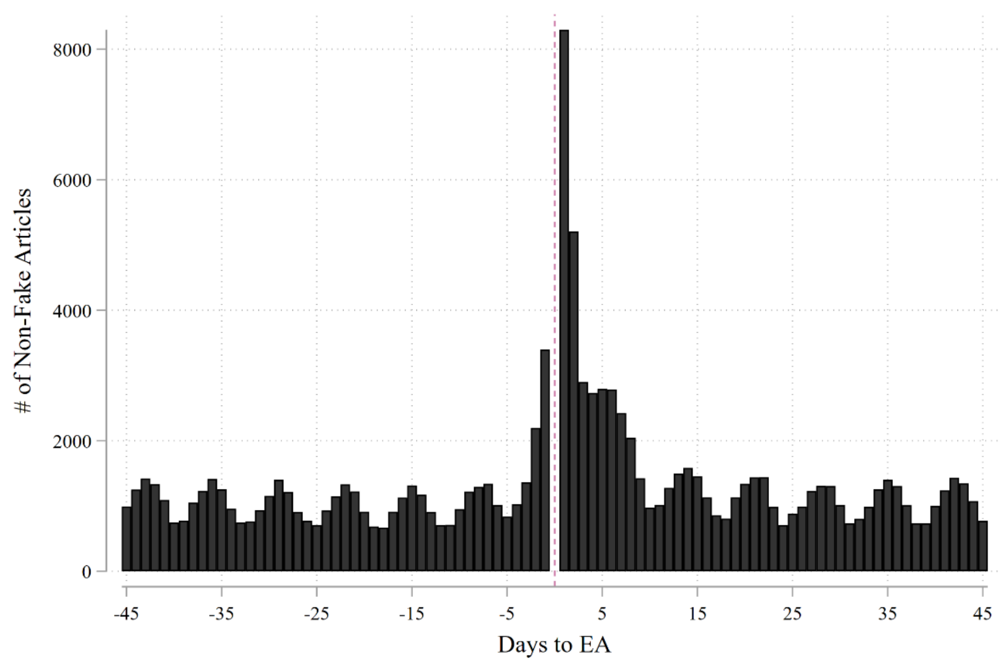
This figure presents the number of fake articles published on Seeking Alpha for each year during our sample. Within the total number of fake articles published each year, the figure also shows the number of fake articles containing accounting content. Note that our sample only includes the first three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

Figure 2: Distribution of Fake Seeking Alpha Articles Around Earnings Announcements

Panel A: Distribution of Fake Articles Around Earnings Announcements



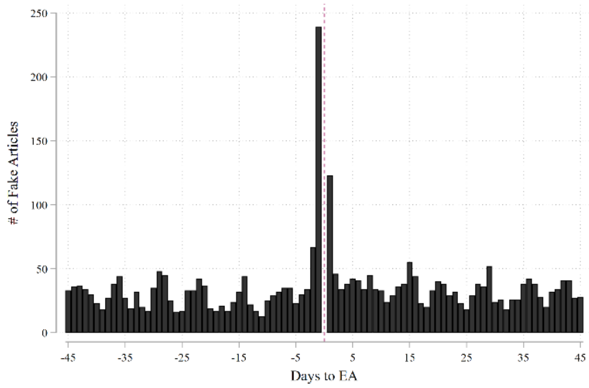
Panel B: Distribution of Non-Fake Articles Around Earnings Announcements



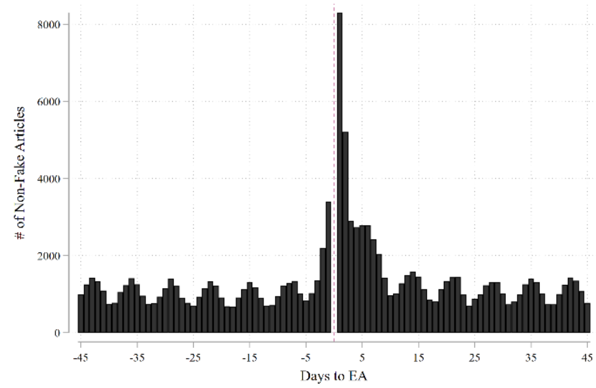
This figure presents graphical evidence on the publication timing of fake and non-fake articles relative to earnings announcements. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles.

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

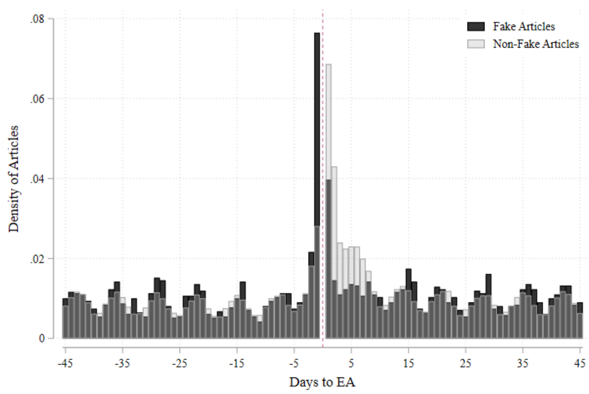
Panel A: Fake Articles



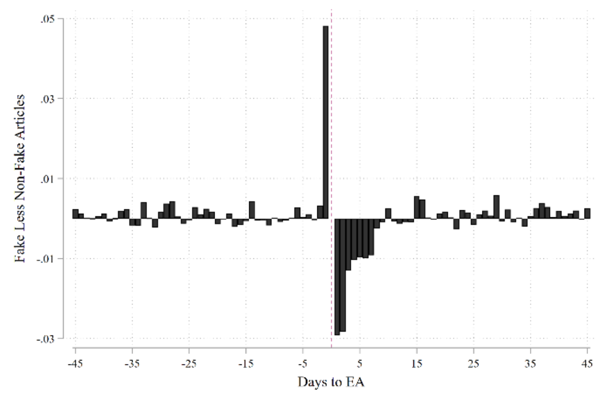
Panel B: Non-Fake Articles



Panel C: Fake and Non-Fake Articles



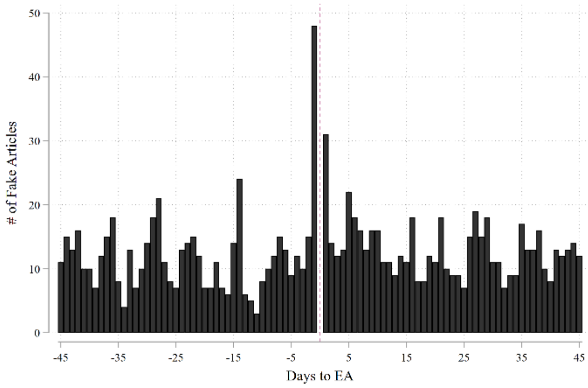
Panel D: Differences Between Fake and Non-Fake Articles



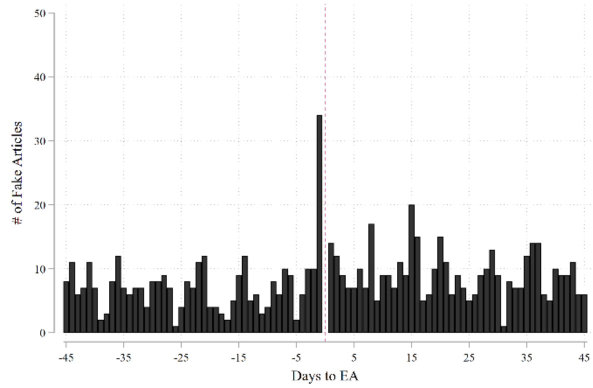
This figure presents graphical evidence from bunching analyses using the full sample of fake and non-fake articles. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day, while Panel B does the same for non-fake articles. Panel C overlays the fake 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: Distribution Analyses of Fake Articles Around High and Low Attention Earnings Announcements

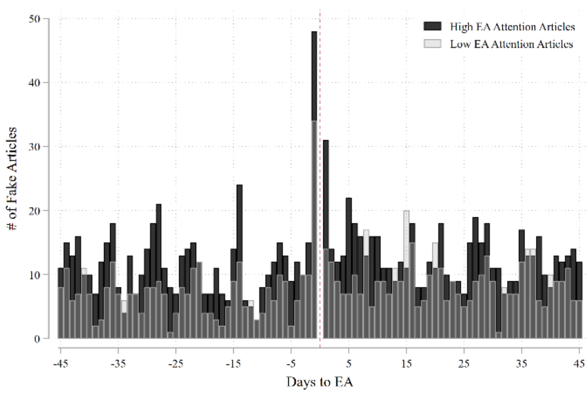
Panel A: High EA Attention Fake Articles



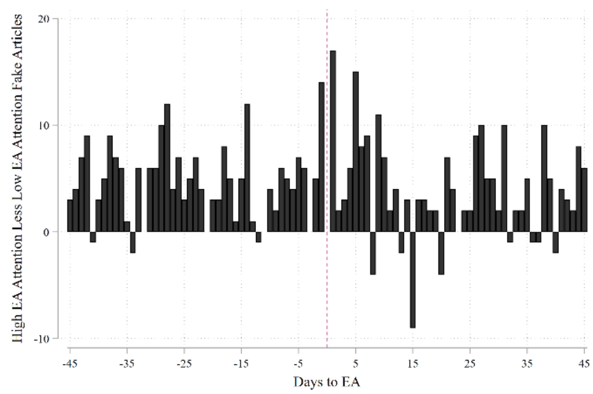
Panel B: Low EA Attention Fake Articles



Panel C: High and Low EA Attention Fake Articles



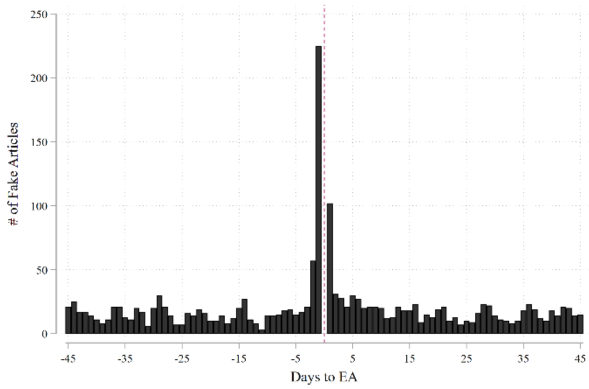
Panel D: Differences Between High and Low EA Attention Fake Articles



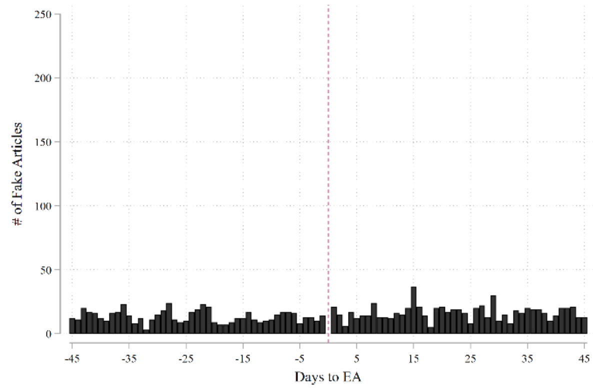
This figure presents graphical evidence from bunching analyses using the sample of fake articles partitioned by earnings announcement attention. Panel A plots the number of fake articles published on each day relative to a firm's earnings announcement day for high attention earnings announcements, while 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: Distribution Analyses of Accounting and No Accounting Content Fake Articles Around Earnings Announcements

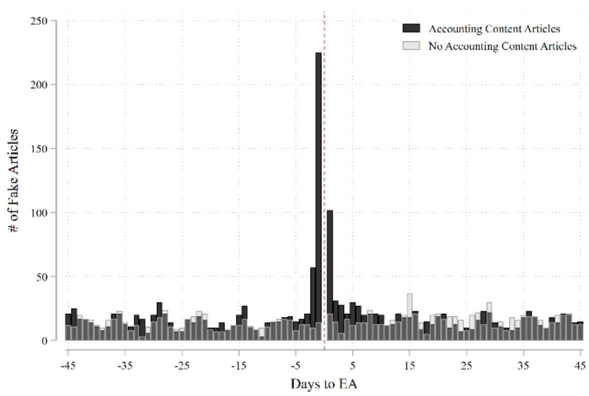
Panel A: Accounting Content Fake Articles



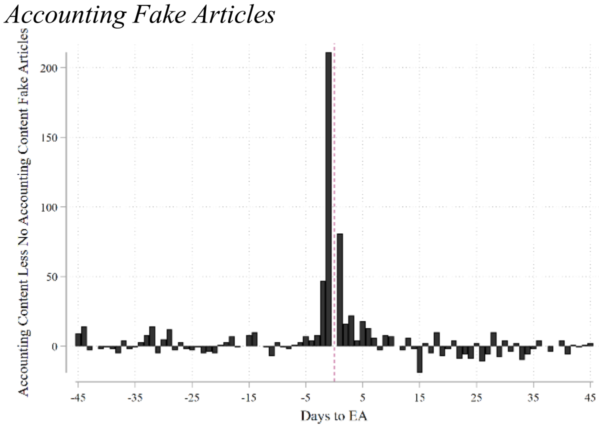
Panel B: No Accounting Content Fake Articles



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. (2022), excluding 2,789 and 86,205 articles, respectively. The Bog Index from Bonsal et al. (2017) is available for 10-Ks filed on or prior to March 31st, 2018, and requiring this variable eliminates 4,440 articles. Requiring the control variables used in our primary analyses eliminates an additional 2,194 articles. Our final sample comprises of 125,475 articles and 37,864 firm-quarters. The exact number of observations in regression analyses will differ slightly because we drop observations for which the fixed effects perfectly predict the dependent variables from estimation samples as needed across different models.

Table 2: Characteristics of Seeking Alpha Articles

Panel A: Determining Content of Articles Using Latent Dirichlet Allocation Textual Analysis

		(1)	(2)	(3)
Topic #	*Topic Label*	*# of Articles with Pr(Topic) > 0*	*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***
Authenticity	5.8	50.1	-44.3***
Clout	61.4	52.0	9.4***
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 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 with Pr(Topic) > 0 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. ***, **, 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 $EA_{t-2,t-1}$	*(2)* Post $EA_{t+1,t+2}$	*(3)* Full $EA_{t-2,t+2}$	*(4)* Pre EA less Post EA
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+2)	0.052***	-0.057***	-0.006	0.109***
	(5.04)	(-5.88)	(-0.43)	(7.67)
(4) Fake - Non-Fake(t-2,t+8)	0.052***	-0.112***	-0.060***	0.164***
	(5.07)	(-5.36)	(-2.61)	(6.95)
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)	(1.66)	(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 Non-Accounting Content:				
(8) # Fake Articles – Accounting Content	244***	93***	337***	152***
	(7.65)	(3.03)	(7.41)	(3.53)
(9) # Fake Articles –Non-Accounting Content	-3	8	5	-11
	(-0.36)	(1.06)	(0.48)	(-1.03)
(10) # Fake Articles – Accounting vs Non-Accounting	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 Fake News Deterrence Role of Accounting Information

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

(Continued)

Table 5 (Continued)

This table reports analyses on the effect of accounting information on the probability of fake news. The dependent variable is *Fake Article*, which is an indicator variable equal to one when the article is classified as fake and equal to zero for non-fake articles using the methodology in Kogan et al. (2022). Our primary independent variables of interest are: (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 Fake News Deterrence Role of Accounting Information

	Coefficient Estimates for:		
	(1)	*(2)*	*(3)*
Fake Article as Dependent Variable	*Management Forecast Frequency*	*10-K Readability*	*# of Observations*
Article Content			
(1) Accounting	-0.161***	-0.033***	108,614
	(-2.79)	(-4.94)	
(2) Non-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 Fake News Deterrence Role of Accounting Information

# 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.