Financial analysis on social media and disclosure processing costs: Evidence from Seeking Alpha

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Abstract:

Less-informed investors face greater costs of processing earnings news into actionable information. Our findings suggest financial analysis on social media reduces less-informed investors' disclosure processing costs. Specifically, we document an attenuated spike in earnings announcement information asymmetry for quarters containing more financial analysis on social media in the weeks prior to the EA. Cross-sectional evidence suggests this finding is stronger when coverage from traditional intermediaries is lower, for financial analyses written by more credible authors, and for financial analyses that is more likely relevant to evaluating the EA. Further evidence suggests retail trades, but not institutional trades, at EAs are significantly more profitable in quarters with greater financial analysis on social media, consistent with financial analysis on social media benefitting traders who are otherwise less-informed. Overall, our evidence suggests that financial analysis on social media plays an important role in aiding less-informed investors by helping them better process EA news.

Key Words: Social Media, Information Asymmetry, Earnings Announcements

JEL Classifications: G14, M41

I. INTRODUCTION

Social media is playing an increasingly important role in capital markets. Existing research documents many capital markets benefits of social media, including providing information that predicts future performance (Chen et al. 2014), disseminating earnings information (Blankespoor et al. 2014), and increasing stock price sensitivity to earnings information (Curtis et al. 2016). However, existing work says little about whether the benefits of social media extend equally to all investors. Because investors vary in their ability to process firm disclosures (Blankespoor et al. 2020; Kim and Verrecchia 1994), we posit that they also differ in how they benefit from information on social media. In this paper, we examine whether financial analysis on social media helps prepare otherwise less-informed investors (investors with less private information and fewer resources) to better understand and process earnings disclosures.[1]

Understanding how financial analysis on social media affects less-informed investors' ability to process earnings disclosures is important for at least three reasons. First, differences in investors' ability to process earnings news increases information asymmetry among investors at earnings announcements (EAs), which exacerbates trading costs. Our estimates suggest that trading costs at EAs constitute nearly 11 percent of total quarterly trading costs. Second, regulators are concerned with trading disadvantages faced by less-informed investors. For example, former SEC chair Mary Jo White notes that less-informed, retail investors "must be a constant focus of the SEC—if we fail to serve and safeguard the retail investor, we have not fulfilled our mission." Third, although existing literature documents capital markets benefits associated with social

[1] Consistent with Blankespoor (2020), we use the term "processing" to refer to how investors convert the information in a disclosure into actionable information.

media, there is still concern that some investors rely too heavily on misleading information in social media. For example, Clarke et al. (2021) highlight the prevalence of fake news spread via social media, and evidence in Jia et al. (2020) suggests less-informed, retail investors are most susceptible to inaccurate rumors spread on social media. Regulators have also expressed concern about investors relying on opinions posted on social media (SEC 2015; FINRA 2017).

To examine whether financial analysis on social media helps prepare less-informed investors to better process earnings disclosures, we require empirical proxies for both (1) financial analysis on social media, and (2) differences in investor groups' EA processing abilities. To measure financial analysis on social media, we count the number of long-form, firm-specific articles containing analyses written by users on Seeking Alpha (SA) that are posted in the weeks prior to an earnings announcement. We use SA for three reasons. First, SA is the most widely used social media platform focused on investing, boasting a following of more than 20 million monthly users (Seeking Alpha 2019). This large user base allows the "wisdom of the crowds" to be distilled into high quality analysis (Chen et al. 2014). Second, SA content is low cost, frequently published, and widely accessible, making it more likely that less-informed investors can and will access it in preparation for earnings disclosures. Third, it is likely SA provides information that is incremental to existing information sources. Specifically, SA articles contain original analyses and opinions from SA authors. Articles discuss key indicators and industry-specific factors relevant to upcoming earnings news, providing readers with a detailed analysis of current performance and clarifying expectations about metrics that could help less-informed investors interpret upcoming EAs.

We use changes in bid-ask spreads around EAs to measure differences between less- and more-informed investors' EA processing abilities because differences in EA processing abilities exacerbate information asymmetry, and bid-ask spreads are a widely accepted measure of information asymmetry (Blankespoor et al. 2020). As noted by Kim and Verrecchia (1994; p. 41), earnings announcements "provide information that allows certain traders to make judgements about a firm's performance that are superior to the judgements of others." These superior disclosure processing abilities result in increased information asymmetry between less- and more-informed investors at EAs (Kim and Verrecchia 1994; Lee et al. 1993; Blankespoor et al. 2020).

Consistent with prior research, we observe a significant spike in bid-ask spreads on the day of and day following the EA, indicating an increase in information asymmetry immediately following the EA (Lee et al. 1993; Amiram et al. 2016). Our primary finding is that financial analysis on social media attenuates the spike in EA information asymmetry. Specifically, we observe a significantly smaller spike in spreads at EAs for quarters containing more SA articles about the firm published in the weeks prior to the EA. This finding is robust to including a variety of controls for dissemination of earnings news (e.g., number of Dow Jones articles and SA news flashes) and for professional analyst outputs (e.g., number of analyst forecasts prior to the EA). Our estimates suggest economically meaningful effects. In firm-quarters with the most SA articles, the spike in bid-ask spreads is 28 to 44 percent smaller than in those with the fewest SA articles. This result suggests that financial analysis on social media in the weeks before an EA provide analyses that helps less-informed investors process earnings disclosures.

While we control for other sources of information in our primary analyses, we acknowledge that we cannot fully rule out the possibility that SA articles, to some degree, reflect or disseminate the content from other news sources (e.g., the business press, professional analyst reports, Twitter, etc.). To further address the concern that SA articles simply reflect information from other sources, we exploit plausibly exogenous reductions in SA coverage. We identify SA authors who write about multiple firms in our sample but then abruptly stop contributing to SA, making it unlikely that events pertaining to any one firm drove the decision to stop contributing to SA. Using both an event study and a difference-in-differences design, we find that EA information asymmetry is significantly higher in the two quarters following the loss of SA author coverage, particularly for firms with relatively limited levels of SA coverage before the loss. This analysis supports the idea that it is SA coverage leading up to the EA that reduces less-informed investors' earnings disclosure processing costs.

In our next analysis, we address the extent to which SA authors benefit from information from other intermediaries (i.e., the business press and professional analysts) when developing their own article content. On one hand, it is possible that SA authors read and rely on the information in business press articles and analyst reports that they use when developing their own SA article content. If this is the case, then SA articles will help less-informed investors more in the presence of greater coverage by other intermediaries because SA authors have more other information and resources available to them when developing their SA content. On the other hand, if SA articles serve to fill information gaps, then SA articles will help less-informed investors' more when coverage by other intermediaries is lower. We find that when a firm receives below median coverage from both other intermediaries, SA articles are more effective at attenuating the spike in information asymmetry at EAs. These results are more consistent with SA coverage being especially important when information gaps exist, and less consistent with SA articles being useful primarily because SA authors benefit from information in the press and analyst reports.[2]

We next perform cross-sectional tests based on SA article and author characteristics to shed light on the characteristics of SA that make the platform more useful for processing earnings news.

[2] In addition, we consider the timing of intermediary publications during the quarter. We find that SA articles and business press articles come out relatively consistently during the quarter, while analyst reports are disproportionately released immediately after the EA. This suggests that relative to analyst reports, SA articles (and business press articles) may be more equipped to prepare investors to process upcoming earnings news. See Section IV for details.

First, we find that the attenuation of EA spikes in information asymmetry is concentrated in SA articles written by more credible authors (as measured by number of articles written, number of followers, and tenure on SA). Second, we find that SA articles written closer to the EA have a greater impact on reducing EA information asymmetry, consistent with these articles being most relevant to the upcoming EA. Third, our evidence suggests SA articles focusing on accounting performance and industry topics are associated with the largest attenuation of EA spikes in information asymmetry.[3] This set of results provides insight into the characteristics of SA content that makes it particularly useful to less-informed investors in processing earnings disclosures.

Our evidence from analyses of spreads is consistent with SA helping to reduce the information disadvantage that less-informed investors face at EAs. However, bid-ask spreads do not identify which investors are less- versus more-informed. In our final analysis, we identify trades by retail investors and, separately, by institutional investors to provide evidence about which traders benefit from SA coverage. Research supports that institutional traders obtain information advantages that are likely difficult for retail traders to obtain (e.g., Ben-Rephael et al. 2017; Ben-Rephael et al. 2022; Blankespoor et al. 2018; Henry and Koski 2017; Puckett and Yan 2011). We use the Boehmer et al. (2021) method to identify trades likely initiated by retail traders and data from Abel Noser to identify trades initiated by institutions. We examine how SA coverage during the quarter relates to the profitability of trades at the EA made by retail traders and by institutions. Our evidence suggests higher retail trading profitability at EAs when there is greater Seeking Alpha coverage in the weeks prior to the EA. For institutional trades, our estimates suggest their trades are unconditionally profitable, but their profitability does not vary with SA coverage. These results are consistent with SA content benefiting less-informed investors and support SA's claim

[3] We categorize articles into Industry (20%), Stock performance (55%), Accounting performance (21%), and Other (4%) using k-means clustering, an unsupervised machine learning algorithm. See our Online Appendix for details.

that financial analysis on the platform is beneficial to otherwise informationally disadvantaged investors.

While we interpret our evidence as consistent with SA providing information to less informed investors that aids in processing earnings news, we recognize that, despite our best efforts, some time-varying omitted factor could explain both variation in SA coverage and spikes in information asymmetry. Consequently, we cannot definitively ascribe causality and can only assert that our evidence is consistent with our prediction, but not conclusive. We also acknowledge our study examines only a subset of content on SA which was accessible to users free of charge during our sample period.

These caveats notwithstanding, we provide new evidence regarding the role of social media in equity markets. Our evidence suggests that financial analysis on social media can help reduce the information processing disadvantage some investors face when significant information, like earnings news, is released. This complements research studying the dissemination of earnings announcement news on social media (e.g., Blankespoor et al. 2014) and research studying whether financial analysis on social media provides price-relevant information (e.g., Chen et al. 2014; Campbell et al. 2019). Blankespoor et al. (2020) comment that "as technological solutions to information frictions become more prevalent, there is continued need to assess how technologies affect different investor groups (p. 74)." Addressing our research question provides evidence on the ability of original financial analysis on social media (a technological solution) to reduce the information processing disadvantage some investors have at EAs (an information friction between different investor groups).[4]

[4] Blankespoor et al. (2020) suggest that to process a disclosure, investors must (1) be aware of the disclosure, (2) acquire the disclosure, and then (3) integrate the disclosed information with other private information to make a trading decision. Prior work primarily focuses on how information intermediaries can reduce investors' (1) awareness and (2) acquisition costs (e.g., Bushee et al. 2010; Blankespoor et al. 2014; Blankespoor et al. 2018). Although SA content likely reduces investors' awareness and acquisition costs of an upcoming earnings announcement, SA also likely reduces less-informed investors' future integration costs

We also provide evidence of a factor that helps retail investors (i.e., less-informed investors) make better trading decisions in response to earnings news. Prior research suggests retail investors do not effectively incorporate earnings news into their trading decisions (e.g., Lee 1992). Our evidence suggests financial analysis on social media prior to an EA helps retail traders more effectively process earnings news.

Finally, our results add to the ongoing policy debate about social media in financial markets. To date, the SEC has largely focused on the risks of relying on opinions on social media (e.g., SEC 2015) and other regulatory bodies have implemented regulations surrounding social media (FINRA 2017). While not conclusive, we view our evidence as consistent with benefits of social media. Our evidence suggests social media sites that sponsor original financial analysis, although relatively unregulated, provide an important service to less-resourced, informationally-disadvantaged investors and represent an important benefit to be weighed in future deliberations.

II. BACKGROUND AND PREDICTIONS

Earnings Announcement Information Asymmetry

Kim and Verrecchia (1994, 1997) predict a brief increase in information asymmetry immediately after an earnings announcement because EAs "stimulate informed judgments among traders who process public disclosure into private information" (Kim and Verrecchia 1994, p. 44). Accordingly, information asymmetry between investors increases following an EA because more-informed traders are better equipped than less-informed traders to process earnings news into actionable information. Although Kim and Verrecchia (1994) and Amiram et al. (2016) suggest the post-EA increase in information asymmetry should last only one or two days, it is economically

of disclosures because the articles we examine are posted in advance of the EA and focus on original analysis.

important. The increase in information asymmetry results in an increase in bid-ask spread, which increases trading costs. The combination of increased trading costs and high trading volume on those two days results in approximately 10.8% of all a quarter's trading costs occurring in this two-day period.[5]

Prior work that examines information intermediaries' influence on EA information asymmetry primarily focuses on dissemination of earnings news and concludes that dissemination by the business press (e.g., Bushee et al. 2010; Blankespoor et al. 2018) and through Twitter (Blankespoor et al. 2014) reduces information asymmetry at EAs.[6] Although we study information asymmetry around EAs, our focus is not on dissemination of earnings news, but on whether financial analysis on social media can prepare less-informed traders to better process upcoming earnings news, and thereby reduce the post-EA increase in information asymmetry. Accordingly, the social media activity we examine (on SA) occurs in the weeks before announced earnings, unlike prior research on dissemination, where the social media activity (e.g., business press articles and Tweets about announced earnings) occurs immediately after the EA. This allows us to provide insight into whether financial analysis can give less-informed investors the tools to better prepare for, interpret, and process earnings disclosures into actionable information.

The Rise of Financial Analysis on Social Media

Contributors to financial social media and crowdsourced platforms (e.g., SA, Estimize, Stocktwits) have emerged as important information intermediaries. Like other intermediaries, these contributors are generally third parties who often disseminate existing news (similar to the

[5] We estimate trading costs as the product of bid-ask spreads and volume, both of which are elevated at the EA. Specifically, we find that 10.8% of trading costs occur on the day of and day following the EA (i.e., an average of 5.4% per day during the two-day EA window). Compared to median trading costs during the quarter of 1.9% per day, this suggests EA trading costs are approximately 2.84 times greater during the EA window relative to other days (i.e., 5.4% / 1.9% = 2.84x).

[6] Financial analysts are another important information intermediary. Prior research generally finds no relation between analyst coverage and EA information asymmetry (e.g., Blankespoor et al. 2014, Bushee et al. 2010, Yohn 1998).

business press) or analyze public information and provide original thoughts or opinions (similar to analysts and business press editorials).

Existing research on social media and crowdsourced platforms mostly focuses on price relevance and forecasting issues. For instance, news coverage on various social media sites improves price formation (Drake et al. 2017), average Twitter sentiment relates to future earnings and sales (Tang 2017; Bartov et al. 2018), and crowdsourced earnings forecasts on Estimize are incremental to analyst forecasts in predicting future earnings surprises and have a disciplining effect on analysts (Jame, Johnston, Markov, and Wolfe 2016; Jame, Markov, and Wolfe 2021). This stream of research suggests that information on social media is largely informative, incremental to other sources, and therefore likely price relevant.

The focus of our study is on whether financial analysis on social media, specifically Seeking Alpha, can reduce less-informed investors' disclosure processing costs. To measure financial analysis activity on social media, we use articles on SA for many reasons. Like some other venues, SA provides individuals a platform to share their investment analyses and opinions, but SA's editorial staff curate content to ensure a minimum level of quality, defined as articles which are "convincing, well-presented, and actionable" (Seeking Alpha 2018). SA content is also low cost; the content we downloaded was free during our sample, though SA has moved to a subscription-based model (first referred to as "essential α" and now simply "premium"). Even under this structure, users can access recent content for stocks in their portfolio. The subscription begins at around $30 per month, which is less costly than purchasing sell-side research or subscribing to multiple business press outlets. This combination of low cost and high-quality results in wide readership. SA boasts over 20 million monthly users (Seeking Alpha 2019). Article authors include buy-siders, industry experts, investment managers, analysts, and individual investors, all of whom are interested in building a reputation in the investment community and conveying value relevant information to accelerate price formation (Campbell et al. 2019).

Prior research utilizing SA content generally concludes the content is informative and price relevant. Chen et al. (2014) find that negative sentiment in SA articles relates to future abnormal returns and earnings surprises, Campbell et al. (2019) find short-window price responses to SA articles, and Drake et al. (2023) suggest SA articles preempt information in analyst reports. However, prior research has not addressed whether financial analysis content on SA affects the relative abilities of different investors to process new information, such as earnings news.[7]

Hypothesis Development

The increase in information asymmetry at EAs occurs because certain traders face lower disclosure processing costs and more quickly process public disclosure into actionable information (Kim and Verrecchia 1994; Blankespoor et al. 2019, Blankespoor et al. 2020). More-informed traders are more aware of, can more quickly acquire, and can more efficiently integrate significant news with their private information (Blankespoor et al. 2020), placing less-informed traders at an information disadvantage following significant disclosure events (Rogers, et al. 2017; Lev 1988). We expect financial analysis on social media can reduce disclosure processing costs for less-informed investors, allowing them to better convert EA news into actionable information, reducing the spike in information asymmetry at EAs.

To add context to this, we focus on one specific earnings announcement by Alphabet (GOOG). While large and well-covered, Alphabet is a complex business. We expect that SA coverage during the quarter (i.e., in advance of the EA) can mitigate the information gap between investors in Alphabet at the EA by increasing otherwise less-informed investors' ability to process

[7] Farrell et al. (2022) find evidence of profitable retail trading following the publication of SA articles, but do not consider EA outcomes.

the earnings news into actionable information. First, many SA articles explicitly discuss key indicators in upcoming earnings news or industry-specific nuances, providing readers with a detailed analysis of current performance and clarifying expectations about metrics that help investors interpret the upcoming EA. This provides otherwise less-informed investors with sharper expectations that they can use to put disclosed numbers into context when making trading decisions. Second, SA articles can give readers an understanding of fundamentals, especially about harder to understand aspects of the business.

To illustrate, consider this excerpt from an article posted on SA on September 5, 2016, 22 days before Alphabet's earnings press release:[8]

> *What does the company (Alphabet) have to show for all of its efforts? Potentially around 100k subscribers, much lower than management forecasts by this point. The company makes sweeping projections of reaching 2.4 million homes by 2018, which is nothing special when taking into account Comcast's 23 million subscribers.*

The author is referring to the Google Fiber portion of Other Bets, a segment holding experimental investments in a variety of technologies that is likely less understood by the general public than Google's core search/advertising business. The information summarized in the article (e.g., number of subscribers, company projections, competitor subscribers) can help investors interpret the statements related to Other Bets in Alphabet's upcoming EA.

With this in mind, consider the subsequent earnings press release on September 27, 2016.[9] Quoting Ruth Porat, CFO of Alphabet, the press release reads:

> *We had a great third quarter, with 20% revenue growth year on year, and 23% on a constant currency basis. Mobile search and video are powering our core advertising business and we're excited about the progress of newer businesses in Google and Other Bets.*

The Alphabet EA then reports basic GAAP and non-GAAP information for the entire entity and

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[8] See https://seekingalpha.com/article/4004104-alphabets-core-business-shines-bets-continue-flop. Another example of an SA article by a different author expressing similar skepticism of Alphabet's Other Bets segment can be found at https://seekingalpha.com/article/4003841-google-bet-major-flop.

[9] See https://www.sec.gov/Archives/edgar/data/1652044/000165204416000035/0001652044-16-000035-index.htm.

separately for the Google and "Other Bets" segments. Investors who are more-informed likely have private information and resources available to process the impact of the press release data on firm value. For example, with respect to the disclosed 20% growth in revenue for the company as a whole, more-informed investors likely have a better idea of what expected revenue growth was, and thus how to put the 20% growth in context. With respect to results from the Other Bets segment, this is perhaps particularly difficult for less-informed investors to process efficiently, because they have less private information and fewer resources. To the extent that more-informed investors understand the implications for future cash flows of the new information in Alphabet's EA better than less-informed investors, the EA exacerbates the information gap between more- and less-informed investors.

We suspect that the previously referenced SA article helps investors process news in the EA beyond Google's core advertising. In this case, understanding the Other Bets segment is particularly important in understanding Alphabet's earnings because the earnings press release reports nearly 40 percent growth in Other Bets revenue and a 12 percent reduction in Other Bets' operating loss. In the absence of the SA article, we expect that obtaining and analyzing this type of information is particularly costly for less-informed investors since they often lack resources to conduct their own information search.

In summary, we predict that financial analysis on social media reduces less-informed investors' disclosure processing costs at EAs by providing them with better expectations about key metrics and the tools to process EAs more efficiently. If SA helps less-informed investors better process earnings news, we should observe a reduction in the magnitude of the post-EA spike in information asymmetry. We formally state this in our hypothesis as follows:

Hypothesis: The magnitude of the spike in information asymmetry at the EA relates negatively to the level of Seeking Alpha coverage during the quarter preceding the EA.

This prediction is not without tension. First, although prior work suggests SA articles are priced (Campbell et al. 2019), it is less clear whether these same articles provide information relevant for processing *future* earnings news. An article having information content is not a sufficient condition for that same article to help interpret other (not yet disclosed) news in the future. Second, it is possible that all investors (i.e., both less- and more-informed) benefit similarly from SA content. If so, more-informed investors may still realize an earnings announcement processing advantage relative to less-informed investors, in which case we would not find a smaller spike in EA information asymmetry in the presence of more SA articles during the quarter.

III. SAMPLE AND RESEARCH DESIGN

Sample

We use a series of Python scripts to identify, download, and parse all SA articles published between January 1, 2006, and December 31, 2014. Our first script cycles through all pages of articles to identify individual links, and then a second script downloads the full-HTML page at each link. We do not collect SA *news* articles (https://seekingalpha.com/news) because these generally represent dissemination of news rather than original content (though we control for SA news content as discussed below). We download 445,674 articles as HTML-encoded webpages. We parse the article header information to identify the firms (tickers) mentioned in the article and the publication date. SA uses two types of tags to identify stocks that are the subject of the article: (1) “about” and (2) “primary”. The former includes tickers mentioned but not the focus of an article, and the latter includes firms that are the primary focus of the article.

Our principal source of SA article sample attrition is that we delete 262,202 articles that do not designate a primary ticker. We delete these articles because we cannot link them to a specific firm and because they typically discuss macroeconomic trends, commodity markets, or general investment patterns. However, we caveat that if these articles benefit a different subset of investors in ways different from the firm-specific articles that we retain in our analyses, this limits the generalizability of our findings.

We delete another 14,858 articles that we cannot link to Compustat and 5,267 we cannot match to CRSP. We then delete 1,600 articles about firms with a share price below $1 and another 6,444 articles where the primary ticker lacks Trade and Quote (TAQ) data. Finally, we drop 38,957 articles for which we are missing any control variable, leaving us with 116,346 SA articles. Panel A of Table 1 describes our sample attrition. Our sample construction ensures every sample firm has at least one SA article during the sample period, which equates to 4,277 unique firms, indicative of SA's vast coverage.

Research Design

To test our prediction that the spike in EA information asymmetry is smaller in quarters when firms receive greater SA coverage, we follow a design similar to Amiram et al. (2016). Specifically, we estimate the following model:

$$\begin{aligned} Spread \; = {} & \alpha_0 + Day^{0,+1}(\beta_0 + \boldsymbol{\beta_1 SAarticlesQtr_R} + \textstyle\sum Firm\ Characteristics + \\ & \textstyle\sum Information\ Events + \sum EA\ Controls) + Day^{-4,-1}(\gamma_0 + \gamma_1 SA + \\ & \textstyle\sum Firm\ Characteristics + \sum Information\ Events + \sum EA\ Controls) + \\ & \alpha_1 SAarticlesQtr_R + \textstyle\sum Firm\ Characteristics + \sum Information\ Events + \\ & \textstyle\sum EA\ Controls + \sum Firm\ Fixed\ Effects + \epsilon \end{aligned} \tag{1}$$

Following Amiram et al. (2016), we estimate equation one at the firm-day level, focusing on the 21-day period centered on each EA. Because we have 30,500 firm-quarters in our sample, this translates to 640,500 observations in our main analyses (i.e., 30,500 EAs x 21 days). Note that Amiram et al. (2016) consider a variety of specifications, but we choose to follow their Table 3 and Figure 1 design to better isolate the short-run spike in information asymmetry. Evidence in Amiram et al. (2016) suggests spreads increase as early as 4 days prior to the EA and are highest on the day of and day following the EA. We define $Day^{0,+1}$ and $Day^{-4,-1}$ to capture these two periods. $Day^{0,+1}$ captures the post-EA effect, or the increase in spread on the day of and following the EA relative to the benchmark period, which is days -10 to -5 and +2 to +10. Although not the focus of our study, we also include $Day^{-4,-1}$ to control for the pre-EA effect, driven by traders who are endowed with better knowledge about the stock (Amiram et al; 2016; Kim and Verrecchia 1994).

Following prior research (e.g., Rogers et al. 2017; Amiram et al. 2016; Blankespoor et al. 2014; Lee et al. 1993) we use bid-ask spread to proxy for information asymmetry. *Spread*, which is our dependent variable, is the firm's average quoted bid-ask spread on a given day obtained from the NYSE Trades and Quotes (TAQ) database. For each quote, we compute the raw spread (bid-price minus ask-price) and scale the raw spread by the quote midpoint. We then average the scaled spreads across all of the firm's quotes for that day.[10]

Our variable of interest, $SAarticlesQtr_R$, captures the level of financial analysis appearing on SA for a given firm during a quarter (i.e., prior to the EA). We first count the number of articles about the firm published on SA between the previous and the current EA. For a given EA, we count SA articles beginning ten days after the prior EA and ending five days before the current EA. To facilitate coefficient interpretation, we then rank the number of SA articles for each firm (by quarter) into deciles and scale the resulting ranks to between 0 and 1. We label the resulting

[10] To mitigate the effects of outliers, we apply the Holden and Jacobsen (2014) procedure for cleaning MTAQ data. This procedure removes abnormally large spreads as well as crossed, one-sided, and withdrawn quotes (which may skew estimates).

variable *$SAarticlesQtr_R$*, denoted with an "R" subscript to indicate is it a ranked variable.[11] The coefficient on *$Day^{0,+1}$* should be positive, consistent with a spike in information asymmetry immediately after the EA. Our coefficient of interest is on the interaction of *$SAarticlesQtr_R$* and *$Day^{0,+1}$* (i.e., β_1). If the post-EA spike in information asymmetry is smaller in quarters where firms receive greater SA coverage, we expect a negative estimate for β_1.

We estimate equation one as a fully interacted model because limiting interactions to terms of interest can produce correlated-omitted variables problems (deHaan et al. 2023). We estimate equation one both with and without controls (Whited et al. 2022). First, we estimate the regression with only fixed effects and our variables of interest. Second, we add controls, which consist of firm characteristics, information events, and EA controls. These controls address factors that likely determine both bid-ask spreads and SA authors' incentives to cover firms, such as its pre-article visibility and investor demand for information (e.g., Gu et al. 2023; Koenraadt 2023).[12] *Firm Characteristics* includes institutional ownership (*InstOwn*), firm size (*Size*), average share turnover (*Turnover*), volatility (*Volatility*), and complexity (*FileSize*). *Information Events* captures other sources of news during the quarter that could also contribute both to the likelihood of SA coverage and EA information asymmetry. These are business press coverage (*$DJarticlesQtr_R$*), analyst forecasts (*$AnalystForecastsQtr_R$*), firm disclosures (*$MgmtForecastQtr_R$, $8KsQtr_R$*), and SA news articles (*$SAnewsQtr_R$*). We decile rank these variables (denoted with the "*R*" subscript), similar to *$SAarticlesQtr_R$*, to compare the effects of these information sources on the EA spike in asymmetry EA. We also include stock returns during the quarter (*ReturnQtr*) to capture other news

[11] Our inferences are unchanged if we instead measure *$SAarticlesQtr_R$* using (1) raw number of articles, (2) number of unique authors writing about a firm in a quarter, or (3) logged values of *SAarticlesQtr*.

[12] Seeking Alpha now offers incentives for authors to write about smaller firms receiving little coverage. For example, Gu et al. (2023) examine a June 2013 change in which Seeking Alpha began compensating authors for writing articles about small-cap firms. Koenraadt (2023) examines a modification to this program in November 2017 (after our sample ends in 2014) to further encourage high-quality articles for firms receiving little coverage.

sources. Finally, *EA Controls* captures aspects of the EA and factors that vary daily. Although these controls are not pre-determined with respect to $SAarticlesQtr_R$ (potentially making them inappropriate based on Whited et al. (2022)), we include them to verify our results are not mediated by other outcomes of $SAarticlesQtr_R$. Specifically, we include news events and both analyst and management forecasts (*SAarticlesEA*, *SAnewsEA*, *DJarticlesEA*, *AnalystsForecastsEA*, *MgmtForecastsEA*) occurring contemporaneous to the EA. We also include stock characteristics (*CAR*, *Price*, *Depth*, and *Volume*).

Sample Descriptives

Table 2 reports descriptive statistics. We report raw (i.e., before decile ranking) statistics for *SAarticlesQtr*. The median of 1.0 suggests over half of firm-quarters in our sample have at least one article, while the standard deviation of 4.69 suggests substantial variation in the distribution. Our sample firms also average 6.6 analyst forecasts, 3.7 business press articles, and 1.8 8-Ks. The median market cap (*Size*) is approximately $2.9 billion (*exp(7.96)*) and institutions (*InstOwn*) own about half the shares (mean = 0.51). Bid-ask spreads (*Spread*) average approximately 82 basis points during the 21-day period we examine.

IV. EMPIRICAL RESULTS

Primary Results

We first discuss basic univariate evidence. Figure 1 plots bid-ask spreads during the non-EA period (lined bars) and during the EA (solid bars) by SA coverage quintile. For comparison, we also examine spreads by quintile of analyst and business press coverage. The non-EA period is the average spreads on days -10 to -5 and +2 to +10 relative to the EA. The EA period is the average spread on days 0 and 1, similar to our research design in equation one. For all three intermediaries, non-EA spreads decline monotonically across quintiles, with analysts and the business press having a stronger relation with non-EA spreads than SA. The dramatic difference in spreads across quintiles reinforces the importance of controlling for other factors influencing spreads and using firm fixed effects. Consistent with our prediction, the size of the solid orange bar (incremental increase in spread at the EA) is significantly larger in the lowest quintile of SA coverage than in the others and the increase is smallest in quintile 5.

Next, we consider regression analysis. Table 3 reports results from estimating equation one. Column 1 includes only fixed effects and variables of interest. Column 2 adds controls. For brevity we only tabulate coefficient estimates for $Day^{0,+1}$ and each independent variable's interaction with $Day^{0,+1}$, though we include all main effects and interactions with $Day^{-4,-1}$ and present these full results in our online appendix. Consistent with prior work, we find a significantly positive coefficient on $Day^{0,+1}$, which reflects the post-EA increase in information asymmetry.

Regarding our primary interest, recall that we predict a smaller spike in post-EA information asymmetry for EAs with more SA articles about the firm during the weeks preceding the EA. Consistent with our prediction, the coefficient on $SAarticlesQtr_R \times Day^{0,+1}$ is negative and statistically significant in both columns, suggesting the post-EA spike in spread is smaller in quarters where the firm receives greater SA coverage.[13] This effect is economically meaningful. Moving from the lowest to highest decile of SA coverage attenuates the increase in EA spreads by between 29 and 44 percent.[14] Table 3 suggests that financial analysis on social media in the weeks before an EA provides analyses that helps prepare less-informed investors to process earnings disclosures.

[13] Prior work also predicts an increase in bid-ask spreads in the days leading up to the EA due to certain investors superior information endowments. Consistent with this, we find a positive and significant coefficient on $Day^{-4,-1}$ (not presented in Table 3 for brevity). However, we do not find that SA moderates the pre-EA effect (i.e., the coefficient on $SAarticlesQtr_R \times Day^{-4,-1}$ is insignificant).

[14] We also consider overall trading costs to further quantify economic magnitude. We measure trading costs on each day as raw bid-ask spread multiplied by daily trading volume. We find that firms receiving SA coverage during the quarter incur approximately 9.6% of their quarterly trading costs in the two-day EA window, compared to 16.6% for firms without SA coverage.

Regarding control variables, we observe larger post-EA spikes in spreads for firms with more institutional owners, potentially because institutional owners are better able to process earnings news and gain an information advantage over less-informed investors. We also observe larger spread spikes for EAs that are more complex (*FileSize*), consistent with Blankespoor et al. (2020) in that disclosure complexity increases disclosure processing costs. The coefficient on $DJarticlesQtr_R \times Day^{0,+1}$ is negative, suggesting business press articles also reduce EA information asymmetry. Interestingly, we find firms issuing more 8-Ks experience larger increases in post-EA spreads, consistent with the notion that 8-K disclosure captures another dimension of information complexity (Guay et al. 2016).

As a sensitivity check, we consider two alternative research designs that change the benchmark period for the EA spread window. In our primary analysis, we choose to use the 21-day period in Amiram et al. (2016) to provide a long benchmark against which to compare the "event period" spreads. If we used a shorter window like the 4-day period surrounding the event (i.e., days -2 to +1), similar to other specifications in Amiram et al. (2016), it would not allow us to control for the pre-EA run up in spreads (i.e., $Day^{-4,-1}$) and would result in us comparing the post-EA days to the pre-EA run up in spreads rather than to a benchmark period. Nonetheless, our inferences are unchanged if we use the shorter 4-day window (untabulated).

Some studies use an "abnormal spread" approach in which the change in spreads at the EA is computed by subtracting the average spread from the entire quarter preceding the EA from EA period spreads. Such an approach has at least two limitations in our context. First, the length of the non-announcement benchmark window increases the risk that non-EA spreads are contaminated by other significant information events. Second, additional analyses (not tabulated) suggest that bid-ask spreads during the quarter are smaller on days corresponding to SA article publication.

This could create a correlation between abnormal spread and our variable of interest. Nonetheless, we calculate abnormal spread by subtracting the average spread during the quarter from the average spread over days 0 and 1 relative to the EA, and regress abnormal spread on $SAarticlesQtr_R$ and controls. We find a significantly negative coefficient on $SAarticlesQtr_R$ (not tabulated).

Exogenous Author Departures

One possible concern with our primary results is that the content of SA articles reflects or disseminates content from other sources of information about earnings (e.g., the business press, professional analyst reports). Our primary analyses include control variables for information from other sources of earnings information, but the possibility remains those variables do not fully control for correlation between SA content and content from other information sources. In this section, we more directly address potential omitted correlated variable bias by exploiting plausibly exogenous reductions in SA coverage. We identify SA authors that write about multiple firms, but then stop writing for the duration of our sample period. Since these authors write about multiple firms, it is unlikely that events pertaining to any one firm drove their decisions to stop contributing to SA. Further, the departures are staggered across time, which minimizes the risk that contemporaneous events confound our inferences. We isolate the four quarters centered on the author's departure (the last two quarters with articles by that author and the first two quarters following the departure) and estimate equation one, replacing $SAarticlesQtr_R$ with *Post*, an indicator variable equaling one if the quarter occurs after the SA author departure. We expect a positive coefficient on the interaction between *Post* and $Day^{0,+1}$, indicating that spreads at the EA increase following author departures.[15]

We present the results in Table 4, Panel A. In column 1, we require the author to have written articles about more than two unique firms in the prior year, which corresponds to 204 total departures. Column 1 reports a significantly positive coefficient on $Post \times Day^{0,+1}$, suggesting a larger spike in EA spreads after the author departure. As the level of a pre-departure production by an author increases, the likelihood the author's departure is related to any specific firm declines. Therefore, in column 2, we restrict departures to those by authors writing about at least five unique firms (114 departures) in the previous year. We again observe a significantly positive coefficient on $Post \times Day^{0,+1}$. The remaining columns in Table 4, Panel A split the sample at the median level of pre-departure SA coverage, as we expect firms with less coverage to be more affected by the loss of an author. Columns 3 and 4 suggest this is the case, as we observe significantly positive coefficients on $Post \times Day^{0,+1}$ that are roughly twice as large as in columns 1 and 2. For above-median pre-shock SA coverage (columns 5 and 6), where the departure of one author is likely less important, we do not find evidence that the departure impacts EA spreads.

Panel A tests the effects of the author departures as an event study, allowing each firm to serve as its own control. In Panel B, we implement a difference-in-differences test by including control firms unaffected by the loss in coverage (i.e., firms not covered by the departing author) but affected by the same macroeconomic events. We identify control firms by propensity-score matching on pre-treatment levels of size, spread, and SA coverage, using a caliper of 0.003

[15] The median (average) decrease in SA coverage for firms experiencing exogenous departures is 1 (0.20). While the median decrease of 1 is intuitive, the average decrease of less than 1 may seem surprising. We believe it is likely driven by the increase in SA coverage over time. We compared this to research using sell-side analyst brokerage house mergers and closures, which find a median (average) decrease of 1.5 (1.06) (see Chen et al. 2018, p. 804). Their finding of a drop in analyst coverage of more than 1 is also likely driven by the sharp *decrease* in headcount of sell-side analysts over time. For example, see Drake et al. (2023) Figure 1 (2) for evidence of sharp increases (decreases) in SA authors (sell-side headcount) over time.

(Shipman et al. 2017) and we confirm there are no statistically significant differences in pre-treatment variable means between the two groups. We interact all terms with *Treat* which equals one for the firms with author departures. We expect $Treat \times Post \times Day^{0,+1}$ to be positive, suggesting a larger post-departure increase in EA spreads for treatment firms than control firms. Panel B supports this prediction and provides inferences similar to Panel A. Additionally, coefficients on $Treat \times Post$ and $Treat \times Day^{0,+1}$ are both insignificant. In sum, these results provide support that our evidence is likely driven by SA coverage rather than other correlated events.

Seeking Alpha and Other Information Intermediaries

In this section, we consider SA relative to other intermediaries, specifically professional equity analysts and the business press. We first compare the timing of publications during the quarter for SA, analyst reports, and the business press. Figure 2 plots the cumulative frequency across time of SA articles, business press articles (from Dow Jones newswire), and professional analyst forecasts. Figure 2 reveals that professional analyst forecasts are disproportionally released immediately after the EA. In contrast, SA and business press articles come out relatively consistently during the quarter. This descriptive evidence suggests that, relative to professional analysts, SA and business press articles likely have more potential to prepare investors to process upcoming earnings news than professional analyst reports, which occur primarily after the EA.

Next, we explore whether the relation between SA coverage and EA spreads varies with how much coverage the firm receives from analysts and the business press. On the one hand, greater coverage from other intermediaries, like the business press or sell-side analysts, provides a richer information environment from which SA contributors could benefit from when preparing their analyses. For instance, it is possible that SA authors read and rely on the information in business press articles and analyst reports that they use when developing their own SA article content. On the other hand, greater coverage could provide less of an opportunity for SA contributors to produce content that is new and useful to other investors. If SA content is useful primarily because SA authors benefit from other intermediaries, then SA articles will help less-informed investors more in the presence of greater coverage by other intermediaries. In contrast, if SA articles fill information gaps for less-informed investors, then SA articles will help less-informed investors more when coverage by other intermediaries is lower.

We estimate equation one for firms that receive below versus above median coverage from both the business press and analysts. We present the results in Table 5. We continue to present results without and with control variables, but show only variables and interactions of interest, along with interactions for other intermediary interactions for comparison. Columns 1 (no controls) and 2 (controls) reveal that, for firms with below median coverage from the business press and analysts the coefficient on $SAarticlesQtr_R \times Day^{0,+1}$ is significantly negative and between 23 and 47% larger than the estimates in Table 3 using our full sample. Columns 3 and 4 show that, for firms with above median coverage from the business press and analysts, the coefficient on $SAarticlesQtr_R \times Day^{0,+1}$ is significantly negative only with no controls. Untabulated tests confirm the coefficients in both column 1 vs 3 and column 2 vs 4 are statistically different. In summary, Table 5's results are consistent with SA coverage being especially important when information gaps exist, and less consistent with SA articles being useful primarily because SA authors benefit from information in the press and analyst reports.[16]

[16] We also consider Estimize, which aggregates crowdsourced earnings estimates that research suggests provides information incremental to analyst forecasts (Jame et al. 2016). If SA is primarily providing information similar to forecasts, then Estimize may serve the same purpose as SA. We construct $EstimizeQtr_R$, which is the decile ranked number of Estimize forecasts from 10 days after the prior EA through five days before the current EA, interact it with $Day^{0,+1}$, and estimate equation 1 including $EstimizeQtr_R \times Day^{0,+1}$. We find a significantly negative coefficient on $SAarticlesQtr_R \times Day^{0,+1}$, but not on $EstimizeQtr_R \times Day^{0,+1}$ (untabulated).

Seeking Alpha Author Characteristics

Next, we perform cross-sectional tests based on SA article and, in the next sub-section, SA author characteristics, to shed light on the characteristics of SA that make the platform more useful for processing earnings news. We first examine whether SA author credibility is associated with SA's ability to reduce the post-EA increase in information asymmetry. We scrape SA authors' biography information from SA and measure three author characteristics to proxy for credibility: (1) the number of articles written, (2) the number of followers the author has, and (3) how long the author has contributed to SA. For each proxy, we use a median split, by year, to divide $SAarticlesQtr_R$ into "high credibility" ($SAarticlesQtr_R\_High$) and "low credibility" ($SAarticlesQtr_R\_Low$). We then estimate equation 1 replacing $SAarticlesQtr_R$ with $SAarticlesQtr_R\_High$ and $SAarticlesQtr_R\_Low$. Our prediction is that articles written by authors with greater credibility better prepare investors to process EA news.[17]

Table 6 presents results. Results using articles written (author following, author tenure) are in columns 1-2 (3-4, 5-6). The coefficient on $SAarticlesQtr_R\_High$ ($SAarticlesQtr_R\_Low$) is significantly negative (statistically insignificant) in columns 1 through 6 and the difference between $SAarticlesQtr_R\_High$ and $SAarticlesQtr_R\_Low$ is statistically significant in 5 of 6 columns. The evidence in Table 6 is consistent with SA articles written by more credible authors having a larger effect on mitigating the EA increase in information asymmetry.

Seeking Alpha Article Characteristics

We next consider SA article timing and content. Regarding timing, we expect articles written closer to the EA are more relevant to processing earnings news because articles closer to

[17] Given that more articles are likely written by more prolific authors, it is possible there is little variation in the "low" groups. The mean, 1st quartile, and 3rd quartile for SA in the "low" articles written category are 1.57, 0, and 2, respectively, compared to 2.44, 1, and 3 for the "high" articles written, suggesting at least some variation within and across categories.

the EA more likely discuss the upcoming EA, and because authors writing closer to the EA have more information available on which to base their analyses. To test the effect of timing, we replace $SAarticlesQtr_R$ in equation 1 with $SAarticlesQtr_R^{-30,-5}$, $SAarticlesQtr_R^{-60,-31}$, and $SAarticlesQtr_R^{-85,-61}$ which equal the number of SA articles on days -30 through -5, -60 through -31, and -85 through -61, respectively, relative to the EA (and decile ranked between 0 and 1, similar to $SAarticlesQtr_R$).

Table 7 Panel A presents results. Consistent with our expectation, the coefficient on $SAarticlesQtr_R^{-30,-5} \times Day^{0,+1}$ is significantly negative and much larger in magnitude than the coefficient on $SAarticlesQtr_R^{-60,-31} \times Day^{0,+1}$ and $SAarticlesQtr_R^{-85,-61} \times Day^{0,+1}$, suggesting SA articles written closer to the EA are more relevant for aiding in disclosure processing.[18] The coefficient on $SAarticlesQtr_R^{-60,-31} \times Day^{0,+1}$ is negative and significant in column 1 but not column 2, and the coefficient on $SAarticlesQtr_R^{-85,-61} \times Day^{0,+1}$ is insignificant in both columns. In untabulated tests, we further separate articles written in the -30 to -5 day window into either two periods (i.e., [-15, -5] and [-30,-16]) or five periods (i.e., [-10, -5], [-15,-11], [-20, -16], [-25,-21], and [-30,-26]). We generally find significantly negative coefficients on all interactions, suggesting articles within the (-30,-5) period reduce EA spreads. However, the coefficient magnitudes do not increase further as SA articles become closer to the EA. We interpret this to suggest SA articles posted within 30 days of the EA have a significantly larger impact on EA information asymmetry than articles posted further from the EA, but articles closer to the EA within the 30 day window have little incremental effect.

Next, we examine SA article content. Objectively categorizing article content is

[18] $SAarticlesQtr_R^{-30,-5} \times Day^{-4,-1}$ is also significantly negative, suggesting coverage during this window may reduce informed investors' pre-EA information advantage (untabulated). However, we find no evidence that articles in the (-60,-31) or (-85, -61) window have a similar effect.

challenging, so we use k-means clustering, an unsupervised machine learning algorithm, to identify articles of similar type. We apply k-means clustering to the text in SA articles and identify 25 clusters. We manually aggregate these clusters into four general "topics" (e.g., Dyer, Lang, and Lawrence 2017), recognizing this procedure's subjectivity. Approximately 20 percent of articles appear related to industry-specific topics like drug trials, oil and gas production, solar energy, or banking, which we label *Industry*. Fifty-five percent focus on general stock performance, signaled by generic words like markets, shareholders, and price. We label these clusters *Stock Performance*. Twenty-one percent relate to accounting terms, signaled by words like cash or cash flows, revenues, consensus estimates, or guidance (*Accounting Performance*). Finally, four percent relate to topics that do not clearly fit one any category (*Other*). In an online appendix, we provide more detail of how we implement k-means clustering and an example of each article type.

We re-estimate equation one, separating $SAarticlesQtr_R$ into four variables, one per topic, and present results in Panel B of Table 7. The coefficient on $SAarticlesQtr_R\_Industry \times Day^{0,+1}$ is significantly negative. Ex post, we view this as intuitive, as articles in this cluster likely describe firm- and industry-relevant benchmarks useful in interpreting and integrating earnings information. For example, an article about Lululemon (see the online appendix), discusses metrics such as "new store revenue" and "average sales per square foot," data likely relevant for evaluating retail firms. The coefficient on the interaction between $SAarticlesQtr_R\_AccountingPerformance$ and $Day^{0,+1}$ is also significantly negative. As an example, an article about oil pipeline company NuStar (see online appendix) frequently references revenues, cash flow trends, and "distributable cash flows", potentially providing investors benchmark data to use in evaluating earnings.

Coefficients for *Stock Performance* and *Other* interactions are insignificant.[19] We believe these results are intuitive, as articles seemingly relevant for EAs discuss topics which should help investors process earnings news, although we stress that this analysis is descriptive and largely exploratory.

V. EARNINGS ANNOUNCEMENT TRADING PROFITABILITY

Our evidence from analyses of spreads is consistent with SA helping to reduce the information disadvantage that less-informed investors face at EAs. However, bid-ask spreads do not identify which investors are less- versus more-informed. Further, reductions in spreads do not provide evidence about whether more-informed investors obtain at least some benefit from SA because reductions in spreads only suggest a greater benefit from SA for less-informed investors relative to more-informed investors. Much research supports that institutional traders obtain information advantages that are likely difficult for retail traders to obtain (e.g., Ben-Rephael et al. 2017; Ben-Rephael et al. 2022; Blankespoor et al. 2018; Henry and Koski 2017; Puckett and Yan 2011). Accordingly, here we examine how SA coverage during the quarter relates to the profitability of trades at the EA made by retail and by institutional traders. If SA helps less-informed investors process earnings news more than it helps institutional investors, we should observe that the association between SA coverage and trade profitability at EAs is stronger for retail trades than for institutional trades.[20]

Recent research suggests trade-sized based proxies are not reliable for identifying trader

[19] The lack of significance for *Stock Performance* may seem surprising since events affecting market prices may be relevant for understanding earnings announcements. We conjecture two reasons why articles about stock performance do not affect EA information asymmetry. First, these articles often include a discussion of technical trends that the authors argue are predictive of future price movements. Such discussions may provide little information relevant to an upcoming EA Second, many of the words in these clusters are relatively generic (e.g., stock, price, value, market, etc.), while words in the "Industry" and "Accounting Performance" clusters are more firm-specific and therefore relevant to interpreting the EA.

[20] Farrell et al. (2022) analyze trade profitability at the SA publication date and find that retail order imbalance following SA article publication is predictive of future returns. Our analysis differs from theirs in that (1) we examine retail trades at the EA, not the SA publication date, and (2) we consider profitability of trades by institutions.

type because informed traders frequently split orders (e.g., Campbell et al. 2009; Cready et al. 2014). Therefore, to identify retail trades we use the Boehmer et al. (2021) method which relies on off-penny and off-half-penny price improvements. We use the Lee and Ready (1991) method to identify trade direction. Trades the Boehmer et al. method identifies as retail trades are reliably initiated by retail traders, but the trades the method does not identify as retail trades are not reliably initiated by institutional traders (i.e., a high type 2 error rate). Therefore, to identify institutional trades, we use Abel Noser data, which aggregates trade-level data from their institutional clients (Bhattacharya, Cho, and Kim 2018). We caveat that the Abel Noser data only identifies a subset of trades by institutional investors (e.g., Puckett and Yan 2011), but should contain no retail trades.

We assess the extent to which the profitability of both retail and institutional trades varies with the level of SA coverage. (i.e., how strongly they predict future returns). To do so, we estimate the following empirical model:

$$AbRet^{+2,t} = \alpha_0 + \alpha_1 OIB^{0,+1} + \alpha_2 SAarticlesQtr_R + \boldsymbol{\alpha_3 SAarticlesQtr_R} \times \boldsymbol{OIB^{0,+1}} + Controls + ControlsOIB^{0,+1} + \sum Firm\ Fixed\ Effects + \epsilon \quad (2)$$

The dependent variable, $AbRet^{+2,t}$, is the abnormal return from day $d+2$, where day d is the date of the EA, through day t, which equals 2, 10, or 20. $OIB^{0,+1}$ equals either retail or institutional order imbalance, which we compute as the difference between buy-initiated and sell-initiated volume divided by total volume for the relevant group. Note that for this analysis, the unit of observation is the EA (rather than the 21 days surrounding the EA as in our prior tests). Control variables include the same (non-daily) variables as equation one, but we also add earnings surprise (*EarnSurp*), given its relation with abnormal returns following earnings announcements (Bernard and Thomas 1989). We interact all controls with $OIB^{0,+1}$, though we suppress display of their coefficient estimates for brevity. To facilitate comparison of effect sizes between retail and institutional trades, we standardize all variables to be mean zero and standard deviations of one within each type of trade. If SA coverage during a quarter improves the profitability of trading on EA information, we should observe a positive estimate for α_3.

Table 8, columns 1, 2, and 3 (2, 10, and 20 day return horizons, respectively) present results for retail trading. For all three return horizons, the coefficient on $OIB^{0,+1}$ (α_1) is insignificantly different from zero, suggesting that retail trades are, on average, not profitable when firms receive no SA coverage during the quarter. However, the coefficient on $SAarticlesQtr_R \times OIB^{0,+1}$ (α_3) is significantly positive for all three return horizons, suggesting that increased SA coverage corresponds to more profitable retail trading.

We report results for institutional trading for the three return horizons in columns 4 through 6. Since the Abel Noser data does not cover all firms, our sample size is reduced by approximately 20%. Nonetheless, the coefficient on $OIB^{0,+1}$ is positive and significant in all three columns, indicating that institutional trades are profitable even with no SA coverage. Importantly, the coefficient on the $SAarticlesQtr_R \times OIB^{0,+1}$ is insignificant, suggesting SA coverage does not improve the profitability of institutional trades. Regarding other intermediaries, the coefficient on $AnalystForecastsQtr_R \times OIB^{0,+1}$ is never significant. The coefficient on $DJarticlesQtr_R \times OIB^{0,+1}$ is negative and significant in two of three retail return horizons, potentially consistent with retail investors being more apt to buy attention grabbing stocks regardless of earnings news (Lee 1992).[21]

We view the results in Table 8 as consistent with SA's claim that financial analysis on the platform is beneficial to otherwise informationally disadvantaged investors. Namely, retail investors appear to make more profitable trades at EAs in quarters with more SA coverage, suggesting they benefit from SA. On the other hand, while our analyses only capture a subset of

[21] Similar to results on Estimize in the prior section, we fail to find evidence that Estimize forecasts during the quarter are associated with more profitable retail trades at EAs (untabulated).

trades by more-informed investors, we fail to find evidence that SA benefits at least one type of more-informed investors (institutions).

VI. CONCLUSION

Less-informed investors face greater costs of processing earnings news into actionable information. Our findings suggest that financial analysis on social media reduces less-informed investors' disclosure processing costs. Specifically, we document an attenuated spike in EA information asymmetry for quarters containing more financial analysis on social media in the weeks prior to the EA. Cross-sectional evidence suggests this finding is stronger when coverage from traditional intermediaries is lower, for financial analyses written by more credible authors, and for financial analyses that are more likely relevant to evaluating the EA. Further evidence suggests trades at EAs by retail investors, who are likely less informed than institutional traders, are significantly more profitable in quarters with greater financial analysis on social media. We find no such evidence for trades by institutional investors. Overall, our evidence suggests that financial analysis on social media plays an important role in aiding less-informed investors by helping them better process EA news.

Although we attempt to provide evidence consistent with SA helping less-informed investors process EA news, we caveat that no archival study can definitively ascribe causality. In this regard, we caution that our evidence is consistent with our prediction, but not conclusive. In addition, we acknowledge our study examines the effect of SA during a time when it was free to users, and that the effects of SA might change over time as the platform evolves. Future research is needed to further understand the impact of Seeking Alpha, as well as other social media platforms (e.g., Estimize, Stock Twits).

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APPENDIX A

Variable Definitions

Variable	Definition
AbRet(+2, t)	Buy and hold abnormal returns (using portfolio returns calculated from Daniel, Grinblatt, Titman, and Wermers 1997, and if missing, the value-weighted return from CRSP) over day +2 to day *t* relative to the earnings announcement date.
$AnalystForecastsQtr_{R}$	The number of analyst earnings per share forecasts, from the I/B/E/S detail file, for the firm from 10 days after the prior earnings announcement to five days before the current earnings announcement. In our analyses, we decile rank this variable by quarter and scale it to be between 0 and 1.
AnalystForecastsEA	The number of analyst earnings per share forecasts, from the I/B/E/S detail file, for the firm during the three-day trading window centered on the earnings announcement date.
CAR	The absolute value of the sum of the market-adjusted (using the CRSP value-weighted index) returns across the three-days centered on the earnings announcement date.
$Day^{-4,-1}$	An indicator variable identifying days -4 through -1 where day 0 is the earnings announcement date. If the earnings announcement is after trading hours, day 0 is the next trading day.
$Day^{0,+1}$	An indicator variable identifying days 0 and +1 where day 0 is the earnings announcement date. If the earnings announcement is after trading hours, day 0 is the next trading day.
Depth	The firm's average (across quotes) quoted depth for the day from TAQ. The depth for a quote is the sum of the number of shares quoted at the ask plus the number quoted at the bid.
$DJarticlesQtr_{R}$	The number of articles about the firm in the DowJones database (excluding news flashes) from 10 days after the prior earnings announcement to five days before the current earnings announcement. In our analyses, we decile rank this variable by quarter and scale it to be between 0 and 1.
DJarticlesEA	The number of articles about the firm in the DowJones database (excluding news flashes) during the three-day trading window centered on the EA date.
$8KsQtr_{R}$	The number of 8Ks (from the SEC's EDGAR system) issued by the firm from 10 days after the prior earnings announcement to five days before the current earnings announcement. In our analyses, we decile rank this variable by quarter and scale it to be between 0 and 1.
FileSize	The file size (in MB) of the firm's most recent annual earnings press release, per AuditAnalytics.
InstOIB	The firm's institutional order imbalance over the day of and day following the earnings announcement, equaling total institutional buy orders minus total institutional sell orders, scaled by total institutional volume. We use Abel Noser data to identify institutional trades and the Lee and Ready (1991) algorithm to identify buy and sell orders.
InstOwn	The percent of the firm's shares held by institutions.
MgmtForecastsQtr	The number of management earnings per share forecasts issued by the firm, per I/B/E/S Guidance, from 10 days after the prior earnings announcement to five days before the current earnings announcement.
MgmtForecastsEA	The number of management earnings per share forecasts issued by the firm, per I/B/E/S Guidance, during the three-days centered on the earnings announcement.
Price	The firm's closing stock price of the day.

RetailOIB	The firm's retail order imbalance over the day of and day following the earnings announcement, equaling total retail buy orders minus total retail sell orders, scaled by total retail volume. We use the Boehmer et al. (2021) method to identify retail trades and the Lee and Ready (1991) algorithm to identify buy and sell orders.
SAarticlesQtr$_R$	The number of Seeking Alpha articles written about the firm from 10 days after the prior earnings announcement to five days before the current earnings announcement). In our analyses, we decile rank this variable by quarter and scale it to be between 0 and 1.
SAarticlesEA	The number of Seeking Alpha articles written about the firm during the three-day trading window centered on the earnings announcement date.
SAnewsQtr$_R$	The number of Seeking Alpha News Flashes released about the firm from 10 days after the prior earnings announcement to five days before the current earnings announcement. In our analyses, we decile rank this variable by quarter and scale it to be between 0 and 1.
SAnewsEA	The number of Seeking Alpha News Flashes released about the firm during the three-day trading window centered on the earnings announcement date.
Size	The natural logarithm of the firm's market value of equity at the beginning of the quarter.
Spread	The firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points.
Turnover	The average of the monthly turnover for the three fiscal months prior to the earnings announcement, multiplied by 1000.
Volatility	The standard deviation of the firm's daily stock returns over the three months prior to the earnings announcement.
Volume	The volume of the firm's shares traded on a day, divided by 1,000,000.

Figure 1: Earnings Announcement and Non-Announcement Bid-Ask Spreads, in Basis Points, by Financial Intermediary Type

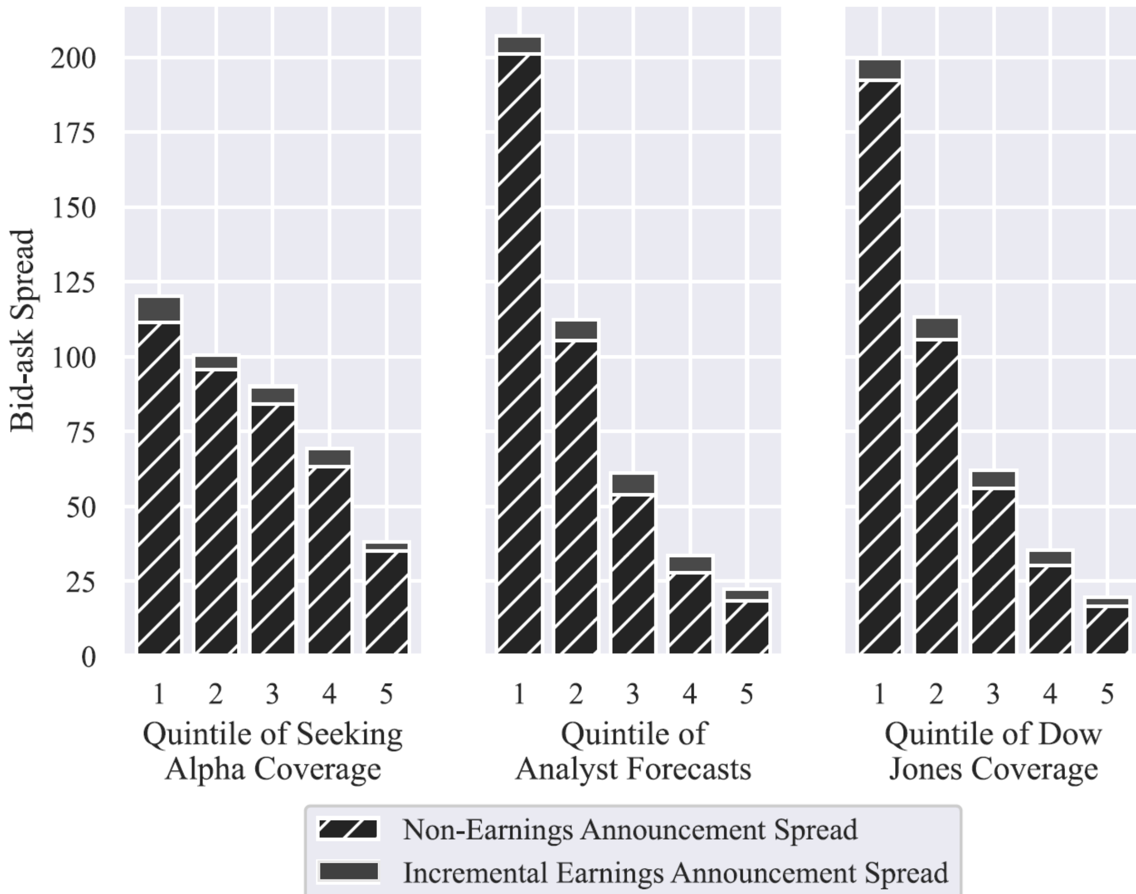

Figure 2: Seeking Alpha Articles, Business Press Articles, and Analyst Forecast Timing Relative to Earnings Announcements

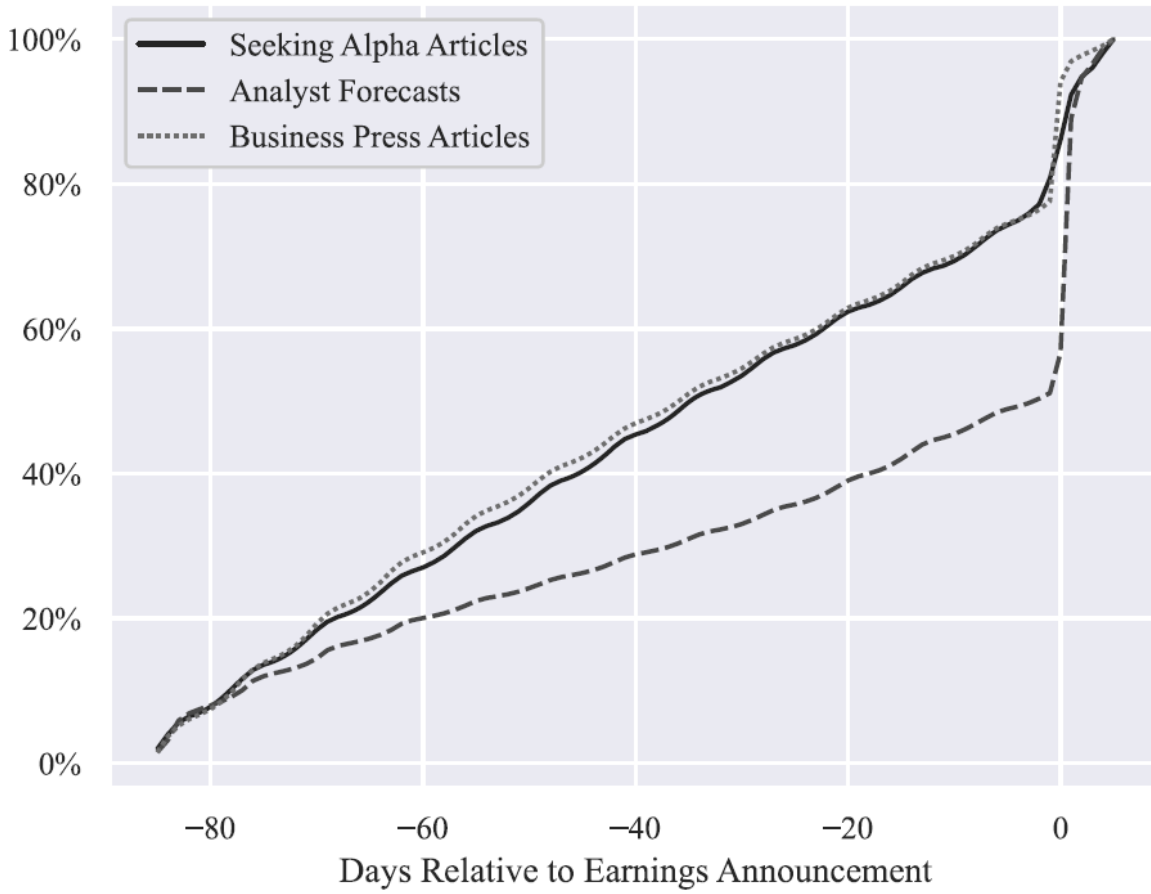

TABLE 1

Sample Attrition

Sample selection procedure	
Seeking Alpha Articles Downloaded between 1/1/2006 - 12/31/2014	445,674
Less:	
Articles with missing primary designation	(262,202)
Articles not linked to Compustat	(14,858)
Articles not linked to CRSP	(5,267)
Articles for which stock price is less than $1	(1,600)
Missing TAQ data	(6,444)
Missing necessary control variable information	(38,957)
Seeking Alpha Articles for Analyses	116,346

TABLE 2

Descriptive Statistics

Variable	**N**	**Mean**	**Q1**	**Median**	**Q3**	**Std Dev**
AnalystForecastsQtr	640,500	6.61	1.00	3.00	8.00	9.02
AnalystForecastsEA	640,500	7.19	2.00	6.00	11.00	6.70
CAR	640,500	0.06	0.02	0.04	0.08	0.06
Depth	640,500	30.59	5.20	7.80	16.45	144.53
DJarticlesQtr	640,500	3.66	2.89	3.64	4.47	1.26
DJarticlesEA	640,500	2.84	2.30	2.83	3.37	0.85
8KsQtr	640,500	1.84	0.00	1.00	3.00	2.30
FileSize	640,500	19.36	3.00	10.00	20.00	60.91
InstOwn	640,500	0.51	0.16	0.59	0.79	0.34
MgmtForecastsQtr	640,500	0.13	0.00	0.00	0.00	0.52
MgmtForecastsEA	640,500	0.41	0.00	0.00	1.00	0.69
Price	640,500	37.74	12.16	26.76	47.93	49.21
SAarticlesQtr	640,500	1.78	0.00	1.00	2.00	4.69
SAarticlesEA	640,500	0.14	0.00	0.00	0.00	0.40
SAnewsQtr	640,500	2.25	0.00	0.00	2.00	7.07
SAnewsEA	640,500	1.15	0.00	1.00	2.00	1.54
Size	640,500	7.96	6.49	7.97	9.46	2.00
Spread	640,500	82.15	14.43	31.93	83.50	128.32
Turnover	640,500	13.34	5.61	9.49	16.01	14.17
Volatility	640,500	0.03	0.02	0.02	0.03	0.02
Volume	640,500	3.87	0.32	1.13	3.47	10.33
AbRet(+2)	28,701	0.03	-1.35	-0.03	1.33	2.93
AbRet(+2, +10)	28,701	-0.04	-3.17	-0.17	2.96	6.46
AbRet(+2, +20)	28,701	-0.05	-4.76	-0.29	4.23	9.27
RetailOIB	28,701	0.06	-0.61	0.09	0.75	0.70
InstOIB	22,089	-0.02	-0.20	-0.01	0.16	0.33

The unit of observation is a firm-day, except for the abnormal return (i.e., *AbRet(+s,+t)*) and order imbalance (i.e., *RetailOIB* and *InstOIB*) variables, for which the unit of observation is an earnings announcement. For variables at the firm-day level, we use the 21 days centered on each firm's earnings announcement and primary analyses use 30,500 earnings announcements (30,500x21=640,500). For variables at the earnings announcement level, the number of observations is less than 30,500 because of limited order imbalance data. For count variables that are ranked in our analyses (denoted with an "R" subscript in our analyses), we present underlying values here, before ranking. Appendix A provides detailed definitions of all variables.

TABLE 3

The Effect of Social Media Financial Analysis on Earnings Announcement Information Asymmetry

Dependent Variable: *Spread*

	[1]	[2]
$SAarticlesQtr_R$*Day$^{0,+1}$	**-2.488***** **(0.001)**	**-1.674***** **(0.006)**
Day$^{0,+1}$	5.603*** (0.000)	5.714*** (0.000)
*InstOwn*Day$^{0,+1}$*		2.029*** (0.002)
*Size*Day$^{0,+1}$*		-0.146 (0.503)
*Turnover*Day$^{0,+1}$*		-0.021 (0.180)
*Volatility*Day$^{0,+1}$*		-0.133 (0.616)
*FileSize*Day$^{0,+1}$*		1.166*** (0.001)
*$DJarticlesQtr_R$*Day$^{0,+1}$*		-4.271*** (0.000)
*$AnalystForecastsQtr_R$*Day$^{0,+1}$*		0.286 (0.609)
*$SAnewsQtr_R$*Day$^{0,+1}$*		-0.613 (0.253)
*MgmtForecastQtr*Day$^{0,+1}$*		-0.849*** (0.008)
*ReturnQtr*Day$^{0,+1}$*		-2.103 (0.362)
*$8KsQtr_R$*Day$^{0,+1}$*		1.786*** (0.001)
*CAR*Day$^{0,+1}$*		13.280** (0.036)
*Price*Day$^{0,+1}$*		-0.004 (0.312)
*Depth*Day$^{0,+1}$*		-0.002 (0.218)
*DJarticlesEA*Day$^{0,+1}$*		0.184 (0.870)
*AnalystForecastsEA*Day$^{0,+1}$*		0.202 (0.698)
*SAarticlesEA*Day$^{0,+1}$*		-1.128** (0.047)
*Volume*Day$^{0,+1}$*		-0.019 (0.603)
*SAnewsEA*Day$^{0,+1}$*		0.778 (0.155)
*MgmtForecastsEA*Day$^{0,+1}$*		1.781*** (0.000)

Observations	640,500	640,500
Fixed Effects	Firm	Firm
Adjusted R^2	0.785	0.814

Table 3 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of Seeking Alpha coverage on earnings announcement spreads. The sample is at the firm-day level, and includes 21 days surrounding each of the 30,500 EAs in our sample (i.e., 30,5000 EAs * 21 days = 640,500 observations in this regression). The dependent variable, *Spread*, is the firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points. $Day^{0,+1}$ equals one for days 0 and +1 relative to the earnings announcement date. $SAarticlesQtr_R$ equals the decile rank of the number of Seeking Alpha articles during the period from day +10 of the previous earnings announcement through day -5 of the current earnings announcement. An R subscript indicates that the variable is decile ranked. Column 1 (2) presents results without (with) controls. Per equation 1, this regression includes the main effects of all variables and interactions with $Day^{-4,-1}$, but we have suppressed those results for brevity. However, we present the full set of results in our online appendix. We cluster standard errors by firm and quarter. ***, **, and * denote two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.

TABLE 4

Earnings Announcement Information Asymmetry After Losing Social Media Financial Analysis Coverage

Dependent Variable: *Spread*

Panel A: *Without Control Firms*

	Full Sample		*Below median pre-shock SA Coverage*		*Above median pre-shock SA Coverage*	
	Author > 2 firms	*Author > 5 firms*	*Author > 2 firms*	*Author > 5 firms*	*Author > 2 firms*	*Author > 5 firms*
	[1]	[2]	[3]	[4]	[5]	[6]
Post*Day$^{0,+1}$	**9.372****	**7.699***	**17.874****	**17.300****	**-1.089**	**-2.759**
	(0.031)	**(0.062)**	**(0.014)**	**(0.038)**	**(0.712)**	**(0.472)**
Day$^{0,+1}$	6.259***	4.889**	6.817**	4.954*	5.188**	1.135
	(0.009)	(0.040)	(0.042)	(0.050)	(0.034)	(0.362)
Post	15.532	6.384	32.783*	19.081	-1.481	-2.336
	(0.151)	(0.466)	(0.057)	(0.195)	(0.712)	(0.717)
Observations	17,136	9,681	9,324	4,998	7,812	4,683
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.851	0.848	0.848	0.853	0.723	0.681

Panel B: *With Control Firms*

	Author > 2 firms	*Author > 5 firms*	*Author > 2 firms*	*Author > 5 firms*	*Author > 2 firms*	*Author > 5 firms*
	[1]	[2]	[3]	[4]	[5]	[6]
Treat*Post*Day$^{0,+1}$	**13.490****	**11.950***	**24.465****	**24.426****	**1.238**	**-1.373**
	(0.030)	**(0.071)**	**(0.041)**	**(0.045)**	**(0.802)**	**(0.807)**
*Treat*Post*	16.240	13.443	25.751	21.534	3.982	4.832
	(0.174)	(0.385)	(0.175)	(0.415)	(0.753)	(0.625)
*Treat*Day$^{0,+1}$*	-1.761	-2.027	-0.164	-1.808	-2.260	-1.409
	(0.633)	(0.665)	(0.977)	(0.832)	(0.390)	(0.626)
Day$^{0,+1}$	7.950***	5.602**	8.866***	7.467***	9.263**	3.913*
	(0.000)	(0.013)	(0.000)	(0.002)	(0.042)	(0.061)
Treat	-10.089	-4.690	13.687	20.150	-1.878	-3.789
	(0.237)	(0.519)	(0.591)	(0.167)	(0.776)	(0.484)
Post	6.920	4.922	18.428	15.945	-3.569	-4.423
	(0.394)	(0.536)	(0.140)	(0.270)	(0.543)	(0.302)
Observations	17,136	9,681	9,324	4,998	7,812	4,683
Fixed effects	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.857	0.894	0.861	0.895	0.739	0.728

Table 4 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of losing Seeking Alpha coverage on earnings announcement spreads. The unit of observation is a firm day, and each estimation uses the 21 days for each firm centered on the firm's earnings announcement (day 0). The dependent variable, *Spread*, is the firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points. *Day$^{0,+1}$* equals one for days 0 and +1 relative to the earnings announcement date. *Post* equals zero (one) for the two quarters before (after) the firm loses coverage from a Seeking Alpha author. *Treat* equals one for firms losing Seeking Alpha coverage and zero for propensity score matched control firms. Estimations in the odd (even) numbered columns require the departing Seeking Alpha author to have written articles about more than 2 (5) firms prior to departure. All estimations include control variables (see equation 1) whose coefficient estimates we suppress for brevity. We cluster standard errors by firm and quarter. ***, **, and * denote two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.

TABLE 5

The Effect of Social Media Financial Analysis on Earnings Announcement Information Asymmetry, Conditional on Coverage from Other Intermediaries

Dependent Variable: *Spread*

	Low Analyst Following and Low Business Press		*High Analyst Following and High Business Press*	
	[1]	[2]	[3]	[4]
SAarticlesQtr$_R$*Day$^{0,+1}$	**-3.067****	**-2.855****	**-1.366*****	**-0.080**
	(0.027)	**(0.032)**	**(0.001)**	**(0.859)**
Day$^{0,+1}$	6.774***	13.841***	4.039***	6.519***
	(0.000)	(0.000)	(0.000)	(0.000)
SAarticlesQtr$_R$	-8.877*	-0.784	-2.607**	-0.588
	(0.069)	(0.825)	(0.013)	(0.481)
*DJarticlesQtr$_R$*Day$^{0,+1}$*		-4.011**		-0.884
		(0.020)		(0.545)
*AnalystForecastsQtr$_R$*Day$^{0,+1}$*		0.412		-0.664
		(0.793)		(0.235)
Observations	229,551	229,551	224,112	224,112
Fixed Effects	Firm	Firm	Firm	Firm
Adjusted R^2	0.736	0.785	0.493	0.542

Table 5 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of Seeking Alpha coverage on earnings announcement spreads conditional on coverage by other information intermediaries. The unit of observation is a firm day, and each estimation uses the 21 days for each firm centered on the firm's earnings announcement (day 0). The dependent variable is *Spread*, which is the firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points. *Day$^{0,+1}$* equals one for days 0 and +1 relative to the earnings announcement date. *SAarticlesQtr$_R$* equals the number of Seeking Alpha articles during the period from day +10 of the previous earnings announcement through day -5 of the current earnings announcement. An R subscript indicates that the variable is decile ranked. Columns 1 and 2 (3 and 4) present coefficients (p-values) from estimations using firms with below (above) median coverage from both professional analysts and the business press. The total amount of observations used in this table is 453,663 (229,551 + 224,112) which is less than our primary Table 3 sample of 640,500 because for the below (above) median cross-section in this table, we require the firm to be in the (above) below median portion of the sample for both analyst coverage and the business press. Columns 2 and 4 show results from estimations that include control variables (see equation 1) whose coefficient estimates we suppress for brevity. We cluster standard errors by firm and quarter. ***, **, and * denotes two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.

TABLE 6

The Effect of Social Media Financial Analysis on Earnings Announcement Information Asymmetry, Conditional on Author Characteristics

Dependent Variable: *Spread*

	Articles Written		*Author Following*		*Author Tenure*	
	[1]	[2]	[3]	[4]	[5]	[6]
SAarticlesQtr$_R$_High*Day$^{0,+1}$	**-3.089*** **	**-1.460*** **	**-2.895*** **	**-1.437*** **	**-2.212*** **	**-0.594**
	(0.000)	**(0.008)**	**(0.000)**	**(0.005)**	**(0.002)**	**(0.354)**
SAarticlesQtr$_R$_Low*Day$^{0,+1}$	**-0.062**	**0.159**	**-0.962**	**0.131**	**-0.443**	**-0.436**
	(0.913)	**(0.774)**	**(0.108)**	**(0.821)**	**(0.577)**	**(0.468)**
SAarticlesQtr$_R$_High	-7.636***	1.411	-9.111***	0.394	-2.012	1.429
	(0.000)	(0.345)	(0.000)	(0.764)	(0.190)	(0.266)
SAarticlesQtr$_R$_Low	-6.051***	0.561	-4.332***	0.435	-13.609***	-0.131
	(0.001)	(0.647)	(0.006)	(0.762)	(0.000)	(0.930)
Day$^{0,+1}$	5.603***	5.797***	5.603***	5.798***	5.603***	5.805***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
*DJarticlesQtr$_R$*Day$^{0,+1}$*		-4.524***		-4.538***		-4.600***
		(0.000)		(0.000)		(0.000)
*AnalystForecastsQtr$_R$*Day$^{0,+1}$*		0.259		0.268		0.250
		(0.640)		(0.630)		(0.652)
Test of difference for bolded coefficients:	**-3.027*** **	**-1.301** **	**-1.933** **	**-1.568** **	**-2.1677* **	**-0.158**
	(0.001)	**(0.014)**	**(0.020)**	**(0.029)**	**(0.068)**	**(0.869)**
Observations	640,500	640,500	640,500	640,500	640,500	640,500
Fixed Effects	Firm	Firm	Firm	Firm	Firm	Firm
Adjusted R^2	0.813	0.843	0.813	0.843	0.813	0.843

Table 6 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of Seeking Alpha coverage on earnings announcement spreads conditional on Seeking Alpha author characteristics. The unit of observation is a firm day, and each estimation uses the 21 days for each firm centered on the firm's earnings announcement (day 0). The dependent variable is *Spread*, which is the firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points. *Day$^{0,+1}$* equals one for days 0 and +1 relative to the earnings announcement date. We cluster standard errors by firm and quarter. *SAarticlesQtr$_R$_High* (*SAarticlesQtr$_R$_Low*) equals the number of Seeking Alpha articles written during the quarter by authors who have above (below) the median number of articles authored (columns 1 and 2), number of followers (columns 3 and 4), and tenure on Seeking Alpha (columns 5 and 6). An R subscript indicates that the variable is decile ranked. Estimations in columns 2, 4, and 6 include control variables (see equation 1) whose coefficient estimates we suppress for brevity. We cluster standard errors by firm and quarter. ***, **, and * denote two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.

TABLE 7

The Effect of Social Media Financial Analysis on Earnings Announcement Information Asymmetry, Conditional on the Article Characteristics

Panel A: *Timing of Social Media Financial Analysis*

Dependent Variable: *Spread*

	[1]	[2]
$\boldsymbol{SAarticlesQtr_R^{-30,-5}*Day^{0,+1}}$	**-3.216*** **	**-2.391*** **
	(0.000)	**(0.000)**
$\boldsymbol{SAarticlesQtr_R^{-60,-31}*Day^{0,+1}}$	**-0.944** **	**-0.308**
	(0.012)	**(0.232)**
$\boldsymbol{SAarticlesQtr_R^{-85,-61}*Day^{0,+1}}$	**-0.091**	**0.723**
	(0.868)	**(0.193)**
$Day^{0,+1}$	5.603***	5.799***
	(0.000)	(0.000)
$SAarticlesQtr_R^{-30,-5}$	-6.202***	-0.155
	(0.000)	(0.860)
$SAarticlesQtr_R^{-60,-31}$	-0.944**	-0.308
	(0.024)	(0.463)
$SAarticlesQtr_R^{-85,-61}$	-2.294*	2.086**
	(0.082)	(0.021)
$DJarticlesQtr_R*Day^{0,+1}$		-4.549***
		(0.000)
$AnalystForecastsQtr_R*Day^{0,+1}$		0.303
		(0.581)
Observations	640,500	640,500
Fixed Effects	Firm	Firm
Adjusted R^2	0.813	0.843

Panel B: *Topic of Social Media Financial Analysis*

Dependent Variable: *Spread*

	[1]	[2]
SAarticlesQtr$_R$_Industry*Day$^{0,+1}$	**-2.256*****	**-1.608*****
	(0.000)	**(0.001)**
SAarticlesQtr$_R$_StockPerformance*Day$^{0,+1}$	**-0.806**	**-0.568**
	(0.173)	**(0.317)**
SAarticlesQtr$_R$_AccountingPerformance*Day$^{0,+1}$	**-1.859*****	**-0.760****
	(0.000)	**(0.044)**
SAarticlesQtr$_R$_Other*Day$^{0,+1}$	**-0.034**	**0.215**
	(0.968)	**(0.780)**
Day$^{0,+1}$	5.603***	5.603***
	(0.000)	(0.000)
SAarticlesQtr$_R$_Industry	-4.693***	0.071
	(0.004)	(0.953)
SAarticlesQtr$_R$_StockPerformance	-6.676***	1.292
	(0.000)	(0.293)
SAarticlesQtr$_R$_AccountingPerformance	-2.230	2.125*
	(0.104)	(0.092)
SAarticlesQtr$_R$_Other	-1.394	3.736**
	(0.323)	(0.015)
*DJarticlesQtr$_R$*Day$^{0,+1}$*		-4.166***
		(0.000)
*AnalystForecastsQtr$_R$*Day$^{0,+1}$*		0.500
		(0.351)
Observations	640,500	640,500
Fixed Effects	Firm	Firm
Adjusted R^2	0.813	0.843

Table 7 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of Seeking Alpha coverage on earnings announcement spreads conditional on Seeking Alpha author characteristics. The unit of observation is a firm day, and each estimation uses the 21 days for each firm centered on the firm's earnings announcement (day 0). The dependent variable is *Spread*, which is the firm's bid-ask spread scaled by the spread midpoint, averaged across the day, and expressed in basis points. *Day$^{0,+1}$* equals one for days 0 and +1 relative to the earnings announcement date. In Panel A, *SAarticlesQtr$^{-s,-t}$* equals the number of Seeking Alpha articles written during days *-s* to *-t* relative to the earnings announcement. An R subscript indicates that the variable is decile ranked. In Panel B, *SAarticlesQtr_Industry*, *SAarticlesQtr_StockPerformance*, *SAarticlesQtr_AccountingPerformance*, and *SAarticlesQtr_Other* equal the decile rank of the number of articles written about the firm during the quarter for which the topic is "Industry", "Stock Performance", "Accounting Performance", and "other" respectively. Article topic groups are explained in an online appendix. The estimation in column 2 includes control variables (see equation 1) whose coefficient estimates we suppress for brevity. We cluster standard errors by firm and quarter. ***, **, and * denote two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.

TABLE 8

The Effect of Social Media Financial Analysis on Earnings Announcement Retail and Institutional Trading

	Retail Trading Order Imbalance			*Institutional Trading Order Imbalance*		
DV = *AbRet(+2,t)*	*(+2)* [1]	*(+2, +10)* [2]	*(+2, +20)* [3]	*(+2)* [4]	*(+2, +10)* [5]	*(+2, +20)* [6]
$SAarticlesQtr_R$*$OIB^{0,+1}$	**0.483***	**0.186****	**0.005****	**-0.147**	**-0.144**	**-0.001**
	(0.061)	**(0.037)**	**(0.041)**	**(0.491)**	**(0.425)**	**(0.491)**
$OIB^{0,+1}$	0.151	-0.048	0.002	1.021***	0.830***	0.010***
	(0.611)	(0.836)	(0.611)	(0.001)	(0.000)	(0.001)
$SAarticlesQtr_R$	-0.257	-0.164	-0.003	-0.225	-0.528	-0.002
	(0.785)	(0.818)	(0.785)	(0.818)	(0.507)	(0.818)
*$DJarticlesQtr_R$*$OIB^{0,+1}$*	-0.817**	0.105	-0.008**	-0.578	-0.407	-0.006
	(0.035)	(0.678)	(0.035)	(0.147)	(0.110)	(0.147)
*$AnalystForecastsQtr_R$*$OIB^{0,+1}$*	0.065	-0.102	0.001	-0.254	-0.125	-0.003
	(0.854)	(0.572)	(0.854)	(0.332)	(0.328)	(0.332)
Observations	28,701	28,701	28,701	22,089	22,089	22,089
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.0424	0.0357	0.0424	0.0310	0.0330	0.0310

Table 8 presents coefficient estimates and p-values (in parentheses below) from analyses of the effect of Seeking Alpha coverage on retail and institutional trading profitability at earnings announcements. The unit of observation is an earnings announcement. *$SAarticlesQtr_R$* equals the number of Seeking Alpha articles during the period from day +10 of the previous earnings announcement through day -5 of the current earnings announcement. An R subscript indicates that the variable is decile ranked. The dependent variable is *AbRet(+2, t),* where t = +2, +10, or +20. In Columns 1 through 3, *$OIB^{0,+1}$* equals retail trading order imbalance, which is total retail buy orders minus total retail sell orders over days 0 and +1 relative to the earnings announcement, scaled by total retail volume over days 0 and +1. We use the Boehmer et al. (2021) method to identify retail trades and the Lee and Ready (1991) algorithm to identify buy and sell orders. In Columns 4 through 6, *$OIB^{0,+1}$* equals institutional trading order imbalance defined as institutional buy orders minus institutional sell orders on days 0 and +1 relative to the earnings announcement, scaled by total institutional volume over that window. We use Abel Noser data to identify institutional trades. To facilitate coefficient magnitude interpretations across retail and institutional trading results, we standardize all variables to be mean zero and standard deviation of one. All estimations include control variables (see equation (2)) whose coefficient estimates we suppress for brevity. We cluster standard errors by firm and quarter. ***, **, and * denote two-tailed significance at the one, five, and 10 percent levels, respectively. Appendix A provides detailed definitions of all variables.