Crowdsourced Financial Analysis and Information Asymmetry at Earnings Announcements

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Abstract:

Prior research suggests that less sophisticated investors are at a significant information disadvantage during earnings announcements. We investigate whether a relatively new phenomenon, crowdsourced financial analysis, can mitigate this information asymmetry problem. We use the platform Seeking Alpha to measure crowdsourced financial analysis, and offer three main findings. First, more crowdsourced financial analysis during the weeks before an earnings announcement mitigates information asymmetry between investors at the earnings announcement. This suggests that crowdsourced analysis preceding earnings announcements equips less-sophisticated investors to more efficiently process earnings news. Second, this effect is significantly greater for firms operating in poorer information environments. This suggests that the crowds play a more important role for stocks when sophisticated investors' information advantage is most acute. Third, this effect is stronger for earnings announcements where management did not previously provide an earnings forecast. This suggests that crowdsourced financial analysis is more useful to investors in the absence of firm-initiated disclosure. Additional analyses reinforce our primary inferences by 1) confirming that crowdsourced financial analysis is most useful to less-sophisticated investors, and 2) showing that pre-announcement crowdsourced financial analysis reduces opinion divergence at earnings announcements. Overall, our evidence suggests the crowds play an important role in leveling the playing field among investors.

1. Introduction

Vast literatures in accounting and finance confirm that information in capital markets is of considerable value. As such, it is not surprising that some investors expend considerable resources attempting to gain an information advantage, and the consequences are costly to investors and generally viewed as socially undesirable. The friction between the better and lesser informed (i.e., the information asymmetry problem) increases the cost of trading and the cost of capital (e.g., Easley and O'Hara 2004; Hughes, Liu, and Liu 2007). While the information asymmetry problem is pervasive in capital markets, it becomes particularly acute during significant information events like earnings announcements. However, in recent years, social media platforms have drastically reduced the costs of producing, disseminating, and acquiring information. While early research suggests that crowdsourced "analysis" on internet bulletin boards is mostly noise (e.g. Antweiler and Frank 2004), more recent research suggests that crowdsourced information is value relevant (Chen et al. 2014; Jame et al. 2016; Tang 2017; Campbell, DeAngelis, and Moon 2018; Hales, Moon, and Swenson 2018; Bartov, Faurel, and Mohanram 2018). Given the proliferation and relative ease with which anyone can acquire crowdsourced financial analysis, including less sophisticated investors who lack the information acquisition and processing resources of more sophisticated investors, we ask whether crowdsourced financial analysis helps alleviate the information asymmetry problem at earnings announcements. We find that the answer is "yes".

To investigate this question, we measure the extent of firm-level crowdsourced financial analysis using data from Seeking Alpha (SA). SA is a social media platform that provides individuals the opportunity to make public their own analyses and opinions. Prior research suggests that contributors to SA are credible, producing value relevant information predictive of future performance (Chen et al. 2014; Campbell, DeAngelis, and Moon 2018). We expect crowdsourced financial analysis published on SA in the months preceding earnings announcements to be particularly useful to less-informed investors during the periods of heightened information asymmetry at earnings announcements.[1]

We focus on social media rather than news sources because content on social media is widely accessible, including to individual and likely informationally-disadvantaged investors.[2] We use SA rather than other social media outlets because SA articles often contain in-depth analyses useful for understanding earnings, and prior research suggests that this content constitutes value-relevant information (Campbell, DeAngelis, and Moon 2018; Chen et al. 2014).[3] Additionally, SA boasts both a vast following of more than four million users and unparalleled coverage, including under-covered stocks that receive little attention from professional analysts thus "unlock[ing] the world's investing insight and mak[ing] it accessible to anyone seeking new ideas" (Seeking Alpha 2017a). This final point is especially important, as we expect more sophisticated investors' information advantage is most acute for firms operating in relatively poorer information

[1] We use the terms "informed" and "sophisticated" interchangeably, though we recognize that prior research often associates these characterizations with specific criteria. We use the term "more sophisticated investor" to refer to investors that have either better access to information or better skill at analyzing information at a particular earnings announcement. Our predictions (which we describe later) do not require that less sophisticated investors be unsophisticated or financially ignorant. Our predictions only require that, for a particular earnings announcement for a specific firm, some investors have access to better information or have better information analysis skills than others.

[2] The notion that crowdsourced financial analysis is likely important to non-institutional investors is supported by descriptive data on SA's subscribers (provided to us by SA). Each user provides a "vocation" upon registering for an account. Nearly 39% of users classify themselves as "occasional investors" vs. less than 16% identifying as financial professionals (e.g., analysts, fund managers). Another 16% classify themselves as "full-time investors". Remaining categories include education (6%), retirees (11%), executives (3%), and various other categories (9%).

[3] Note that evidence suggesting SA is relevant to predicting earnings does not make its relation to the information asymmetry spike at earnings announcements obvious. In order for SA reports to mitigate more sophisticated investors' information processing advantage, they must provide the same information to unsophisticated investors that sophisticated investors use to gain an information processing advantage. For example, an SA report providing information about future cost-of-goods-sold likely only aids a less sophisticated investor in processing news about COGS. Sophisticated investors may still be able to gain an advantage by processing news about revenues or by converting the COGS portion of earnings news into private information about revenues. Additionally, evidence in Amiram, Owens, and Rozenbaum (2016) highlights how different types of earnings-relevant news events have differing effects on information asymmetry. Finally, a wealth of prior research suggests professional analyst forecasts provide information relevant to predicting earnings, yet Yohn (1998) fails to find evidence that analyst coverage mitigates the information asymmetry spike at earnings announcements.

environments. We study earnings announcements because they precipitate high information flow during a short time period, and prior research suggests some traders gain an information advantage at this time (Kim and Verrecchia 1994; Yohn 1998; Amiram, Owens, and Rozenbaum 2016). Further, research indicates information flows at earnings announcements have increased over time (e.g., Francis, Schipper, and Vincent 2002; Collins, Li, and Xie 2009; Beaver, McNichols, and Wang 2018), suggesting the potential for a worsening of the information asymmetry problem during these significant market events.

We test three hypotheses. First, we predict that crowdsourced financial analysis published *during the weeks before an earnings announcement* (*not* in the days surrounding the earnings announcement) mitigates the well-documented spike in information asymmetry at the earnings announcement. Theory and empirical evidence suggest information asymmetry increases at the earnings announcement because more sophisticated investors more efficiently process new information (Kim and Verrecchia 1994; Lee, Mucklow, and Ready 1993; Yohn 1998; Amiram, Owens, and Rozenbaum 2016). We predict that crowdsourced financial analysis in the weeks before an earnings announcement helps less sophisticated investors interpret the upcoming earnings announcement, thereby reducing the ability of more sophisticated investors to process earnings announcement information into private information. In other words, crowdsourced financial analysis helps less sophisticated investors process earnings announcement information more like more sophisticated investors. In this sense, analysis published on SA helps get investors "on the same page" and reduces sophisticated investors' information advantage.

Second, we predict that the effects of SA vary with the extent of coverage by more traditional information intermediaries, such as professional analysts and the business press. Specifically, firms with lower coverage from traditional information intermediaries (e.g.

professional analysts and financial news outlets) should have more of an information asymmetry problem in general (e.g., Muller, Riedl, and Sellhorn 2011; Kelly and Ljungqvist 2012; Yohn 1998) and thus should benefit most from crowdsourced analysis. We expect that crowdsourced financial analysis serves a greater role in mitigating information asymmetry at the earnings announcement when the firm's information environment is of lower quality.

Our third hypothesis involves the interplay between crowdsourced financial analysis and voluntary disclosure. Prior research suggests that voluntary disclosures help investors to develop expectations of future earnings (e.g., Ajinkya and Gift 1984). Further, prior work links voluntary disclosure to reduced information asymmetry and lower cost of capital (Verrecchia 2001; Baginski and Rakow 2012). As such, in the absence of firm-provided voluntary disclosures, we expect SA to play a more important role in helping investors interpret earnings announcement news. Using management earnings forecasts as our proxy for firm-initiated voluntary disclosures, we predict that crowdsourced financial analysis serves a greater role in mitigating information asymmetry at earnings announcements for firms that do not provide management forecasts.

To test these predictions, we utilize 116,346 articles about 4,426 unique firms from SA published between 2006 and 2014. Consistent with a long line of prior research, we proxy for information asymmetry among investors using bid-ask spreads (e.g., Welker 1995; Blankespoor, Miller, and White 2014; Amiram, Owens, and Rozenbaum 2016). To test our first hypothesis, we examine the association between SA reports issued in the three months prior to the earnings announcement and changes in bid-ask spreads in the day of and day following the earnings announcement. All our analyses control for the potential information asymmetry effects of traditional professional analysts and business press articles and, most importantly, include firm fixed effects to isolate time-invariant, firm-specific determinants of spreads.

Our results generally support our predictions. Consistent with our first hypothesis, we find a significantly smaller increase in information asymmetry at earnings announcements when a firm receives relatively greater SA coverage, measured by the number of articles about a firm appearing on SA during the weeks preceding the earnings announcement. The effects are economically meaningful. Moving from the lowest to highest decile of SA coverage attenuates the spread increase at the earnings announcement by approximately 18 percent.[4] Our results are consistent with the notion that SA coverage reduces more sophisticated investors' information advantage by improving less sophisticated investors' access to information about a firm.

To test our second hypothesis (that SA coverage is more important when traditional financial intermediary coverage is low) we split our sample into firms receiving relatively higher versus lower levels of coverage by more traditional intermediaries (analysts and, separately, the business press), indicative of variation in the quality of the firms' information environments. Consistent with our predictions, we find that the information asymmetry reducing benefits of crowdsourced analysis around earnings announcements are significantly stronger when firms receive relatively less coverage by professional analysts or the business press. This evidence suggests that information asymmetry benefits of SA coverage are most pronounced in firms where the discrepancy in information quality between more and less sophisticated investors is likely most acute.

To test our third hypothesis, we split our sample into firms that did and did not provide a management forecast for the earnings announced. As we predict, we find that the effect of SA on information asymmetry at the earnings announcement is significantly stronger for firm-quarters in

[4] Our estimates suggest a 9.7 basis point increase in spreads in the day of and following an earnings announcement (i.e., day 0 and day +1 relative to the earnings announcement). Moving from the lowest to highest decile of SA coverage (measured by number of articles) reduces this increase to 8.03 basis points, an 18 percent decrease.

which no management earnings guidance was provided. Our management forecast results suggest that crowdsourced analysis can help offset the information asymmetry consequences of less voluntary disclosure.

We supplement our primary analyses with two additional analyses that help corroborate our primary inference. First, because our motivation for and interpretation of our primary tests relies on SA being more useful to less than more sophisticated investors, we conduct an analysis of spreads at SA report release dates. Amiram, Owens, and Rozenbaum (2016) note that results from several studies suggest sophisticated investors already know the content of professional analyst reports prior to analysts making the reports public.[5] As a result, they predict and find that, unlike earnings-related disclosures by management, public release of analyst reports precipitate a reduction in spreads, consistent with the notion that professional analyst reports reveal new information primarily to less sophisticated investors. Similarly, we expect a decline in spreads immediately following SA article publication because the article should provide new information primarily to less sophisticated investors. As we expect, we find a sharp decline in spreads on the day of and following SA article publication.

Second, Kim and Verrecchia (1994) argue that certain investors' valuation judgments following earnings announcements are superior to others. This disparity in valuation judgments can be characterized as differential interpretation of earnings news, or opinion divergence (Kandel and Pearson 1995; Garfinkel 2009). As mentioned previously, we expect that one mechanism by which SA reduces sophisticated investors' information processing advantage is by getting less

[5] For instance, research suggests that institutions trade on information in analyst reports before analysts release those reports (Irvine, Lipson, and Puckett 2007; Kadan, Michaely, and Moulton 2017) and short-sellers trade before analyst downgrades (Christophe, Ferri, and Hsieh 2010). However, we also note that survey evidence suggests many professional analysts regularly access SA, suggesting news on SA may be useful to more than just less sophisticated investors. If crowdsourced financial analysis on SA represents "new" information to all investors, it likely increases information asymmetry upon publication.

sophisticated investors more "on the same page" as more sophisticated investors, which is a reduction in opinion divergence. Therefore, we test whether SA coverage reduces opinion divergence at earnings announcements. Using standardized unexpected volume (SUV), a proxy for opinion divergence developed in Garfinkel (2009), we first document significantly higher opinion divergence at earnings announcements. More importantly, we find that SA coverage significantly reduces opinion divergence at earnings announcements. Moving from the lowest to the highest decile of SA coverage attenuates the earnings announcement-induced increase in opinion divergence by 17 percent. This evidence is consistent with SA coverage helping less sophisticated investors interpret earnings news more like more sophisticated investors.

We make several contributions to the accounting and finance literatures. First, we contribute to a growing literature on social media, crowdsourced information, and nontraditional information intermediaries. To date, research suggests analysis produced on crowdsourced platforms provides value relevant information about firms (e.g., Chen et al. 2014; Jame et al. 2016; Campbell, DeAngelis, and Moon 2018; Tang 2017; Bartov, Faurel, and Mohanram 2018), plays an important role in information dissemination (Blankespoor, Miller, and White 2014), and, depending on the source, improves price efficiency (Drake, Thornock, and Twedt 2017). All of this research focuses on the basic notion that crowdsourced information can help improve properties of price formation. Our results suggest a new and distinct benefit of crowdsourcing more related to the "second moment" of price formation. Namely, we show that the level of crowdsourced analysis can mitigate adverse selection risk and disagreement in periods of heightened information flow.

Second, less sophisticated investors' disadvantage at earnings announcements represents a fundamental concern of the SEC, who desire a level-playing field among all investors. We view mitigating information asymmetry between informationally advantaged and disadvantaged investors as directly consistent with a primary mission of the SEC, making our evidence especially pertinent to regulators. Additionally, to date, the SEC has largely focused on potential risks of relying on crowdsourced analysis (e.g., SEC 2015) and other regulatory bodies have begun to implement regulations surrounding social media (FINRA 2017). Our evidence that crowdsourced financial analysis provides an important service to informationally disadvantaged investors represents an important benefit to be weighed in future deliberations.

Finally, knowledge of factors mitigating information asymmetry is important to both managers and investors because, while not without controversy, extensive research suggests information asymmetry contributes directly to the cost of capital (Diamond and Verrecchia 1991; Leuz and Verrecchia 2000; Easley and O'Hara 2004; Bhattacharya et al. 2012). While prior research suggests broader news dissemination during earnings announcements can reduce information asymmetry by mitigating sophisticated investors' information *acquisition* advantages (Bushee et al. 2010; Blankespoor, Miller, and White 2014; Blankespoor, deHaan, and Zhu 2018), our paper documents the first information asymmetry-decreasing 'force' that mitigates the superior *processing* advantage of more-sophisticated investors during earnings announcements.

2. Background and prior research

2.1 Information asymmetry and public releases of information

Both researchers and regulators have long been interested in information asymmetry in capital markets. Strong regulator interest is evidenced by the numerous regulations aimed at reducing information asymmetry and its consequences (e.g. Regulation FD, insider trading laws, etc.). Information asymmetry exists among investors because some investors (generally referred to as more sophisticated investors) either have access to information that other investors do not (e.g., access to individuals with inside information) or because they are more skilled at interpreting and using information (Lev 1988; Kim and Verrecchia 1994). Like much prior research (e.g., Amiram et al. 2016, Bartov et al. 2000, Doyle et al. 2009, Tov 2017), we refer to investors with superior (inferior) information as more (less) sophisticated investors.[6]

Information asymmetry becomes particularly acute around major news events, like earnings announcements. Kim and Verrecchia (1994) model a setting where earnings announcements provide a noisy signal that more-sophisticated investors are better able to understand and process. Kim and Verrecchia (1994) predict an increase in information asymmetry at earnings announcements because the more sophisticated investors are able to process the announced earnings information (which is available to everyone) into private information.[7] Empirical evidence supports the Kim and Verrecchia (1994) prediction, as several studies find evidence of higher bid-ask spreads (a theoretically supported measure of information asymmetry, e.g. Amihud and Mendelson 1986) at earnings announcements (Amiram et al. 2016, Lee et al. 1993, Yohn 1998).

In part because of the significant adverse consequences of information asymmetry (higher trading costs, increased cost of capital, etc.), prior research addresses various factors that affect information asymmetry. A long line of research suggests higher quality accounting information and higher quality and quantity of disclosure reduce long-run information asymmetry (e.g., Botosan 1997, Botosan and Plumlee 2002, Healy and Palepu 2001, Heflin and Shaw 2005, Heflin

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[6] For our purposes, it is not necessary that less sophisticated investors be unsophisticated in the use of financial information. Rather, less sophisticated investors simply have less information for a particular informational event for a particular firm. At other informational events or for other firms, those same investors could be the more sophisticated investors because they have access to inside information for that firm or are more familiar with that firm's industry, etc.

[7] Kim and Verrecchia (1994) also suggest that the anticipation of an earnings announcement causes more-sophisticated investors to increase their private information search, resulting in an increase in information asymmetry *before* an earnings announcement. We control for this effect in all of our analysis and discuss this issue more in Section 4.

et al. 2016, Welker 1995) and lowers the cost of capital, presumably by lowering information asymmetry (Botosan and Plumlee 2002, Kothari et al. 2009). Blankespoor et al. (2014) study Twitter posts ("tweets") by technology firms disseminating their earnings news. They find firms using Twitter in this way experience reduced information asymmetry, and this result is most pronounced for firms with otherwise low visibility.

A large body of research also suggests professional analysts reduce information asymmetry. Easley and O'Hara (2004) argue that increased analyst coverage improves the precision of information about a firm, thus reducing information asymmetry among investors. Kelly and Ljungqvist (2012) find information asymmetry increases when analyst coverage declines. Amiram et al. (2016) argue that analyst reports primarily inform only less sophisticated investors and their evidence suggests information asymmetry declines when analyst earnings forecasts become public. Yohn (1998) addresses analysts and information asymmetry at earnings announcements. She finds that analyst coverage is associated with lower information asymmetry in the week before and week after an earnings announcement. However, she finds either no association or a weakly *positive* association between analyst coverage and information asymmetry *at the earnings announcement*.

With respect to earnings announcements and the business press, Bushee et al. (2010) find that wider *dissemination* of earnings news by the business press reduces information asymmetry at earnings announcements, but that *analysis* by the business press has either no effect or increases information asymmetry.[8] Although he does not analyze traditional measures of information

[8] A possible explanation for the Bushee et al. (2010) result that business press analysis increases information asymmetry at earnings announcements is that business press analysis provides new information to both more and less sophisticated investors, and not just wider dissemination of existing information. Evidence consistent with this explanation is in Li (2015), who finds that Wall Street Journal articles by experienced journalists are predictive of future earnings and forecast errors, suggesting the insights provided by experienced journalists contain new information.

asymmetry (such as bid-ask spread) Guest (2017) finds that Wall Street Journal coverage of earnings announcements that include more “original analyses” increase trading volume and improve price discovery, both of which can reflect a reduction in information asymmetry. Also, regarding the business press and earnings announcements, research finds that business press coverage increases investors’ response to earnings news (Li, Ramesh, and Shen 2011; Blankespoor, deHaan, and Zhu 2018), helps reduce mispricing of earnings information (Drake, Guest, and Twedt 2014), and speeds up incorporation of management forecasts into prices (Twedt 2016).

2.2 Social media and financial markets

Recent research suggests that social media plays an increasingly important role in financial markets. For instance, research finds that Twitter content helps disseminate value relevant news (Tang 2017; Bartov, Faurel, and Mohanram 2018). Jame et al. (2016) find that crowdsourced earnings forecasts available on Estimize.com are incremental to analyst forecasts in predicting future earnings surprises. Evidence in Hales, Moon, and Swenson (2018) suggests that employee outlook, available from employer reviews posted on Glassdoor.com, accurately predicts future firm disclosures. As we mention in the prior section, Blankespoor et al. (2014) find that tech firms using Twitter to disseminate earnings news experience reduced information asymmetry.

Three papers study SA and financial markets. Chen et al. (2014) find that negative sentiment in SA articles is associated with lower future abnormal stock returns and negative earnings surprises. Campbell, DeAngelis, and Moon (2018) document short-window price responses to SA articles and that the stock positions of SA contributors convey information to investors and increase investors’ perception of the credibility of SA authors. Drake, Thornock, and

Twedt (2017) suggest that news coverage by "semi-professional" internet sources, including SA, improves properties of price formation.[9]

Our paper differs from existing research in the following ways. First, we differ from existing social media research, and research addressing SA in financial markets in particular, in that we investigate the effect of crowdsourced financial analysis on the information asymmetry problem at earnings announcements, and not the value relevance of crowdsourced financial analysis or its effect on price formation. We also differ from prior research on the information environment and information asymmetry. With respect to earnings announcements, we study pre-announcement analysis (i.e., analysis during the periods between earnings announcements) by external parties (i.e., the crowds) and not dissemination of earnings news by the firm or the business press. With respect to analysts, we study the ability of analysis to reduce more sophisticated investors' ability to process public information into private (specifically earnings announcement information), as opposed to general, non-event related information asymmetry, and we focus on crowdsourced analysis and not analysis sold by professional firms.

3. Hypothesis development

3.1 Background on Seeking Alpha

Founded in 2004, SA is an investments website that provides a central repository for a variety of information useful to the investing public, including conference call transcripts, news "flashes", earnings announcement calendars, and, most relevant to our study, a crowdsourced analysis platform allowing contributors to share their own ideas, opinions, and analyses.[10] SA

[9] Specifically, they examine how coverage by various types of "information intermediaries" relates to price responsiveness and volume during earnings announcements as well as intraperiod timeliness following the earnings announcement. They do not examine how these intermediaries influence information asymmetry.

[10] This latter category refers to any article (excluding conference call transcripts) with a URL beginning seekingalpha.com/article/.

contributors publish analyses and opinions on over 7,000 stocks: from firms with market caps of $50 million to more than $200 billion. Unlike other social media platforms, 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).[11] These articles garner wide readership; SA boasts an active user base of over four million users (Seeking Alpha 2017). SA authors, which consist of analysts, buy-siders, industry experts, investment managers, and individual investors, are interested in building a reputation in the investment community and conveying value relevant information to accelerate price formation (Campbell, DeAngelis, and Moon 2018).[12]

3.2 Effect of Seeking Alpha on earnings announcement information asymmetry

Both theory and empirical evidence suggest that information asymmetry increases at earnings announcements. To illustrate how earnings announcements can increase information asymmetry, consider the Alphabet Inc. (GOOG) earnings press release on September 27, 2016.[13] Quoting Ruth Porat, CFO of Alphabet, the headline of 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.

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[11] This process is not perfect. The SEC recently charged several companies and individuals with failing to disclose a pay-to-write relationship with certain SA contributors. The indicted companies compensated authors to write and publish positive articles on SA and failed to disclose this arrangement (Flood 2017). However, existing evidence examining SA suggests this is rare (Chen et al. 2014; Campbell, DeAngelis, and Moon 2018; Drake, Thornock, and Twedt 2017).

[12] While the pool of SA authors likely includes some "analysts" as typically defined by prior research (i.e., sell-side analysts tracked by IBES), inspection of a sample of articles suggests they make up only a small fraction. Authors self-identifying as analysts more frequently associate with buy-side activities (e.g., working for investment bank, managing small investment funds, providing investment advice). Additionally, SA prohibits authors from posting analysis both on SA and through another venue, so sell-side analysts could not re-publish their formal reports on SA.

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

The press release next reports basic income statement information for its core business and "Other Bets," which represents experimental investments in a variety of technologies. Compared to relatively less sophisticated investors, more sophisticated investors likely have far more private information related to this performance data and resources available to evaluate its impact on firm value, particularly with respect to "Other Bets" which is mentioned in the headline yet likely less understood by the general public.

Many Seeking Alpha articles explicitly discuss upcoming earnings news, providing readers with a detailed analysis of current performance and suggesting metrics to help interpret the upcoming earnings announcement. For example, two of the articles SA published (each by different authors), in the two weeks prior to Alphabet's Q3 2016 earnings announcement specifically address Google's "Other Bets" business. The two headlines, "Alphabet's Core Business Shines While Other Bets Continue to Flop" and "This Google Bet Is A Major Flop" both imply skepticism of the very line of business that Alphabet's CFO cites as having "great progress."[14] This could be especially important because the financial results in Alphabet's press release report nearly 40 percent growth in "Other Bets" revenue and a 12 percent reduction in the operating loss on that business. The SA articles provide additional context for interpreting those reported numbers.

Another example is Costco's Q1 2018 earnings announced on December 16, 2017. On December 11, an SA contributor posted an article titled "Setting Up for Costco Earnings". [15] The article contains information about the quarter's sales (some of which was already public) and an extensive discussion of factors that investors might consider when understanding the upcoming

[14] See https://seekingalpha.com/article/4004104-alphabets-core-business-shines-bets-continue-flop and https://seekingalpha.com/article/4003841-google-bet-major-flop.

[15] See https://seekingalpha.com/article/4130855-setting-costco-earnings.

earnings announcement, such as the section, "What should we look for in Q1", in which the author discusses factors potentially affecting Costco's margins, how to interpret a change in revenues, and how a change in one component of revenue should be interpreted relative to a change in another. The author of the Costco article clearly intends that the article will influence and facilitate a reader's interpretation of Costco's upcoming earnings announcement.

While several theoretical papers address information asymmetry in capital markets, the model most directly related to our setting is Kim and Verrecchia (1994). As we note in Section 2.1, they specifically model information releases, such as earnings announcements, where some investors are, at a cost, able to process publicly released information into private information. We posit that crowdsourced financial analysis has the potential to reduce the earnings announcement information processing advantage of more sophisticated investors by providing to less sophisticated investors the tools to interpret earnings announcements in a manner more similar to more sophisticated investors. In fact, some features of the Kim and Verrecchia (1994) model point to our prediction. For example, their model predicts that earnings announcement liquidity increases as public information increases because more public information reduces the number of more sophisticated investors (Proposition 1). As our examples above illustrate, crowdsourced financial analysis on SA makes public information that is potentially useful in interpreting earnings announcement information. Additionally, although their model leaves ambiguous the relation between earnings announcement liquidity and more sophisticated investors' cost of processing public information into private, their model at least raises the potential that, as the cost increases, liquidity improves because the number of more sophisticated investors falls. Crowdsourced financial analysis on SA likely increases the cost of using earnings announcement information to become privately informed because, with more interpretation tools made public, more sophisticated investors would have to work harder to develop an insight from the earnings announcement that others cannot.

To summarize, we expect crowdsourced financial analysis reduces the ability of more sophisticated information processers to turn earnings announcement information into private information because it makes available to all investors some of the processing tools and information that otherwise only more sophisticated investors would use. In other words, crowdsourced analysis on SA likely gets individual, less sophisticated investors more "on the same page" with respect to how to interpret earnings as more sophisticated investors. This should yield a negative relation between SA coverage in the weeks preceding an earnings announcement and information asymmetry at the earnings announcement. Thus, our first hypothesis is as follows:

H1: SA coverage prior to an earnings announcement mitigates the increase in information asymmetry at earnings announcements.

3.2 Effect of Seeking Alpha and coverage by other intermediaries

One benefit of SA is its vast coverage, which includes many small firms that tend to operate in relatively poorer information environments. Often these smaller firms receive relatively little coverage from more traditional intermediaries, such as professional analysts and the business press, which yields a poorer information environment and more acute information asymmetry problem. We posit that crowdsourced financial analysis before an earnings announcement can mitigate some of the consequences of a poorer information environment by providing less sophisticated investors with some of the information to interpret the earnings announcement that might otherwise be provided by other information intermediaries. Therefore, our second hypothesis predicts that the mitigation of earnings announcement information asymmetry provided by crowdsourced financial analysis is more pronounced for firms operating in poorer information environments. As we explain in the next section, we measure the information environment with the extent of (1) professional analyst coverage and (2) Dow Jones News coverage during the quarter.

> *H2:* *SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement more for firms with poorer information environments (lower analyst coverage or business press coverage).*

3.3 Effect of Seeking Alpha and firm-initiated voluntary disclosure

Prior research suggests that management earnings forecasts help investors develop expectations about future earnings (e.g., Ajinkya and Gift 1984). Further, prior work links voluntary disclosure to reduced information asymmetry among investors (e.g., Verrecchia 2001; Easley and O'Hara 2004). Accordingly, we posit that, in the absence of firm-provided earnings guidance, the information disadvantage of less-sophisticated investors during earnings announcements is more acute. Thus, similar to H2, we expect SA serves a greater role in aiding less sophisticated investors in interpreting earnings announcement news in the absence of firm-provided earnings guidance.

> *H3:* *SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement more when there is less firm-initiated voluntary disclosure.*

Note that evidence consistent with H3 would rule out a possible alternative explanation for the relation we hypothesize in H1. Namely, more management forecasts could attract more SA articles and increase the quality of those articles. Because management forecast can reduce information asymmetry (Coller and Yohn 1997), we may erroneously attribute the effect of management forecasts on information asymmetry to SA coverage. Finding that the effect of SA coverage is stronger in the absence of management forecasts would be inconsistent with a management forecast explanation for evidence supporting H1.

4. Research design and sample

4.1 Research design

Recall that H1 predicts that SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement. To test this prediction, we estimate the following model using daily data:

$$\begin{aligned} Spread = {} & \varphi_0 + \alpha_1 SA + \alpha_2 Day^{-4,-1} + \alpha_3 Day^{0,+1} + \textstyle\sum_k \gamma_k Controls_k + \beta_1 SA * Day^{-4,-1} + \\ & \beta_2 \boldsymbol{SA} * \boldsymbol{Day^{0,+1}} + \textstyle\sum_k \delta_k Controls_k * Day^{-4,-1} + \sum_k \omega_k Controls_k * Day^{0,+1} + \\ & \textstyle\sum_j \theta_j Firm_j + \epsilon_{i,d} \end{aligned} \qquad (1)$$

We suppress subscripts for firm and day for parsimony. Similar to Amiram, Owens, and Rozenbaum (2016), we estimate equation (1) for 30,541 firm-quarters in our sample using the 21 days centered around each earnings announcement (641,361 observations in our main analyses). Consistent with a long line of prior research, we proxy for information asymmetry among investors using the bid-ask spread (Welker 1995; Blankespoor, Miller, and White 2014; Amiram, Owens, and Rozenbaum 2016). *Spread* is firm *i*'s average quoted bid-ask spread on a given day. For each quote, we compute the raw spread (bid price minus ask price). We then scale the raw spread by the quote midpoint and average, across all of the firm's quotes for that day, the scaled spreads. We obtain quote data from the NYSE Trades and Quotes (MTAQ) database (through Wharton Research Data Services).

SA captures the level of crowdsourced financial analysis appearing on SA focused on firm *i* for quarter *q*.[16] We measure *SA*, referred to as "Seeking Alpha coverage," as the number of articles about firm *i* published during the quarter. We define quarter *q* as the period beginning ten days after the prior earnings announcement (or the *q-1* earnings announcement) to five days before the current earnings announcement (the day quarter *q*'s earnings are announced). We use this

[16] We use the metadata accompanying SA articles to identify the "primary" ticker about which the article is written.

definition for two reasons. First, our hypothesis predicts that SA coverage helps less sophisticated investors interpret earnings news. To help investors interpret the current quarter's earnings news, the information from SA must be available to investors before the current quarter earnings announcement. Second, measuring SA coverage prior to the quarter *q* earnings announcement ensures our results are not driven by dissemination of the firm's earnings announcement news via SA. To facilitate coefficient interpretation, we rank *SA* into deciles and scale deciles such that they fall between 0 and 1.[17]

To test our hypotheses, we define $Day^{0,+1}$ as an indicator variable equaling 1 on the day of and day following the earnings announcement (event days "0" and "+1"). Prior research suggests that this term should be positive, consistent with short-term increases in information asymmetry during the earnings announcement (e.g. Lee et al. 1993; Amiram et al. 2016).[18] Our term of primary interest (in bold in equation (1)) is the interaction between *SA* and $Day^{0,+1}$. The coefficient on this interaction (β_2) measures the effect of *SA* on the increase in information asymmetry during the earnings announcement. H1 predicts that $\beta_2 < 0$. Note that we also define a second indicator variable, $Day^{-4,-1}$, equal to one in the 4 days preceding the earnings announcement. Since research suggests a gradual run up to the spike in information asymmetry at the earnings announcement (e.g., Yohn 1998), we include $Day^{-4,-1}$ its interaction with all control variables so that $Day^{0,+1}$ measures the change in information asymmetry relative to periods other than this run up.

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

[18] Kim and Verrecchia (1994) also suggest that the anticipation of an earnings announcement may also cause more-sophisticated investors to increase their private information search, resulting in an increase in information asymmetry *before* an earnings announcement. Thus, we also include a pre-EA event window indicator variable $Day^{-4,-1}$ to control for this potential effect. We use a two-day (four-day) period to capture the announcement (pre-announcement) increase in information asymmetry based on Figure 1 in Amiram, Owens, and Rozenbaum (2016).

Controls is a vector of 12 control variables. In addition to information asymmetry, bid-ask spreads are influenced by order processing and inventory carrying costs. We follow prior literature (e.g., Huang and Stoll 1997; Coller and Yohn 1997; Amiram, Owens, and Rozenbaum 2016) and include control variables to capture variation in spreads unrelated to information asymmetry to isolate the adverse selection component of the spread. Specifically, we include *Price*, which is the firm's closing price for the day, to control for transaction processing costs (Stoll 1978). We also include the prior quarter's turnover to control for differences in liquidity, which prior literature suggests affects inventory holding costs (Demsetz 1968). For each earnings announcement, *Turnover* is the average of the monthly turnover for the three fiscal months pertaining to that earnings announcement and thus has the same value for all 21 days of an earnings announcement period.[19] Monthly turnover is the total number of the firm's shares traded during the month divided by the firm's number of shares outstanding. We also include *Size* (the natural logarithm of the firm's beginning-of-quarter market value) and *Volatility* (the standard deviation of the firm's daily stock returns during the quarter) to also help control for differences in inventory risk.

We also include daily trading volume (*Volume*) and the three-day sum of the market-adjusted returns (*CAR*) to control for both inventory risk and differences in content of earnings announcement. As an alternative protection mechanism, the market maker may adjust depth (Lee et al. 1993). Therefore, we include daily quoted depth (*Depth*), which is the sum of the number of shares quoted at the ask plus the number quoted at the bid.[20]

[19] For example, assuming a firm has a December 31 fiscal year end, for the second fiscal quarter of 2010 *Turnover* is the average of the turnovers for April, May, and June.

[20] Note that bid-ask spreads could determine depth since liquidity declines as adverse selection risk increases, suggesting it is an inappropriate control. We control for *Depth* to be consistent with Amiram, Owens, and Rozenbaum (2016) but note that our results are insensitive to its exclusion.

We also control for various, time-varying properties of firms' information environments. We control for the percent of the firm's share held by institutions (*InstOwn*) because firms with higher institutional ownership have lower levels of information asymmetry, in general (Boone and White 2015). We include *DJarticles*, which is the number of Dow Jones news articles measured over quarter *q* (the same window used to construct *SA*). To control for Dow Jones and SA news contemporaneous to the earnings announcement, we include $DJarticles^{-1,+1}$ and $SA^{-1,+1}$, respectively. The $^{-1,+1}$ superscripts indicate event days over which we measure these measures of earnings announcement news coverage. To control for information provided by professional analysts, we include *AnFollow,* which is the decile rank of the number of I/B/E/S analysts following the firm during the quarter. Most importantly, all models include firm fixed effects to control for other firm-specific, time-invariant determinants of *Spread*. All variables are defined in Appendix A.

To test H2 and H3, we again utilize equation (1) estimated using sample partitions derived from analyst coverage (H2), the business press (H2), or the presence of a management forecast (H3).

4.2 Sample

Our sample begins with data from SeekingAlpha.com. Using a series of Python scripts, we identify and download all Seeking Alpha articles (http://seekingalpha.com/articles) published as of December 31, 2014. We exclude SA news articles (http://seekingalpha.com/news), which generally represent dissemination of news rather than original content. Our collection process yields 445,674 articles. We delete 262,202 articles that do not designate a primary ticker; these articles typically discuss industry trends or commodity markets rather than specific firms. We delete another 14,858 articles that we are unable to link to a Compustat ticker and 5,267 that we cannot match to CRSP. We then delete 1,600 articles about firms with a share price below $1 and another 4,844 articles lacking Trade and Quote (TAQ) data. Finally, we drop 38,957 articles for which we are missing any one control variable. This leaves us with an initial sample of 116,346 SA articles. Panel A of Table 1 describes our sample attrition. Note that our sample construction procedure ensures that every firm in the sample is the target of at least one SA article.

Table 2 reports descriptive statistics for all variables used in this study. As noted previously, the sample size of 641,361 corresponds to 21 firm-day observations for each earnings announcement in our sample (i.e., event days "-10" to "+10"). We winsorize all continuous variables at the first and 99th percentiles.[21,22] Our mean and median values for *Spread* are approximately 82 and 32 basis points, respectively, which is comparable to the 87 and 47 basis points reported by Amiram, Owens, and Rozenbaum (2016). We report raw (i.e., before decile ranking) descriptive statistics for *SA*. The median value of 1.0 suggesting more than half of the firms in our sample have at least one article per quarter, while the standard deviation of 4.78 suggests substantial deviation in the upper half of the SA distribution. In general, our remaining statistics reflect a sample skewed towards larger firms. For example, the median market cap is nearly $3.0 billion (*exp(7.97)*) and institutional owners own nearly half the shares in our firm.

Table 3 reports correlations among variables in our sample. Since our hypotheses predict interactive and cross-sectional results, simple correlations provide little evidence related to our main tests, but we note a few correlations of interest. *SA* is positive correlated with *Size* and

[21] We also evaluate the effects of outliers using Cooks Distance ("Cooks D"). We re-estimate all our empirical models after excluding observations in the extreme 1, 2, 3, 4, or 5 percent of Cooks D values in our sample, and all our inferences are unchanged.

[22] To further address potential outliers in our dependent variable, *Spread,* we apply the Holden and Jacobsen (2014) procedure for cleaning MTAQ data. This procedure identifies and removes abnormally large spreads as well as crossed, one-sided, and withdrawn quotes (which may also skew estimates). Professor Holden provides SAS code for this cleaning procedure on his website (https://kelley.iu.edu/cholden/).

Volume, suggesting SA authors tend to focus on larger firms with relatively greater earnings-announcement trading volume. *SAs* also correlates positively with *Anfollow* and *DJarticles*, suggesting firms targeted by SA contributors receive similar attention from more traditional intermediaries.

5. Results

5.1 Test of H1

H1 predicts that SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement. Table 4 reports our results related to this prediction. Before examining our term of interest, we note significantly positive coefficients on both $Day^{0,+1}$ and $Day^{-4,-1}$, indicating a general increase in information asymmetry immediately before and after earnings announcements, consistent with prior research. Consistent with H1, we find a statistically significant, negative coefficient on the interaction between *SA* and $Day^{0,+1}$ (coefficient = -1.744; p-value < 0.01). This estimate implies an economically meaningful attenuation in information asymmetry; moving from the bottom to top decile of SA coverage attenuates the increase in *Spread* contemporaneous to earning announcements by 18 percent (-1.744/9.773). Overall, this result is consistent with crowdsourced financial analysis mitigating more sophisticated investors' information processing advantage during earnings announcements by getting less sophisticated investors "on the same page" and aiding them in efficiently processing earnings news.

Turning to other interactions, we find several other significant terms with intuitive interpretations. For instance, we observe noticeably larger spikes in information asymmetry when earnings are relatively more informative, as the interaction *CAR* and $Day^{0,+1}$ is significantly positive. We observe larger (smaller) increases in information asymmetry for firms with larger earnings surprises (greater depth and turnover), indicated by the interaction between $Day^{0,+1}$ and

CAR (*Depth* and *Turnover*, respectively). We also observe evidence that Dow Jones coverage during the quarter similarly mitigates information asymmetry following the earnings announcement, as the interaction between $Day^{0,+1}$ and *DJarticles* is significantly negative. The magnitude of this effect is similar to that of SA, suggesting the impact of the crowds is similar to the business press. We also find a significantly positive interaction between *InstOwn* and $Day^{0,+1}$. While perhaps counterintuitive, institutional ownership reflects the overall level of investor sophistication (i.e., larger levels of institutional ownership imply greater sophistication), so the gap between less and more sophisticated investors' processing ability is likely largest for firms with higher levels of *InstOwn*.

Finally, we find a highly significant, *positive* coefficient on the interaction between *Anfollow* and $Day^{0,1}$. While unexpected, it is consistent with some of the evidence in Yohn (1998). We also highlight that studying whether professional analysts mitigate the information asymmetry problems at earnings announcements presents a significant identification challenge. Namely, analysts have access to management during conference calls, which may change the nature of any analyst-prepared news released during an earnings announcement (i.e., it may be relevant to all investors and thus increase information asymmetry). Further, as of 2014, 93% of EAs have an analyst forecast issued contemporaneously with the earnings announcement (Lobo, Song, and Stanford 2017). Thus, it is difficult to control for event-coincident forecasts by analysts.

To summarize, we find evidence consistent with H1, which suggests that the analyses produced by the "crowds" has a meaningful impact on changes in information asymmetry at earnings announcements. Our results are consistent with SA coverage mitigating information advantages exploited by sophisticated investors during important news events, likely by improving the quality and precision of less sophisticated investors' private information (Kim and Verrecchia

1991a, 1991b, 1994). We next analyze whether the effects of the "crowds" on information asymmetry vary depending on the quality of a firm's information environment.

5.2 Test of H2

H2 predicts that SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement more for firms operating in relatively poorer information environments, which we measure using coverage during the quarter by more traditional information intermediaries (professional analyst coverage Dow Jones News coverage). For each measure, we partition the sample based on the median value, re-estimate equation (1), and compare the differences in coefficients across subsamples. For brevity, we only report coefficients and interactions of interest and suppress remaining terms, but we use the same design as in Table 4. Results using professional analyst following (Dow Jones Coverage during the quarter) are presented in Panel A (Panel B) of Table 5. H2 predicts that the bolded interactions of interest will be significantly more negative in column 1 than in column 2. The third column of Table 5, denoted "Difference", reports one-tailed *p*-values signifying the significance of these tests.

Panel A of Table 5 provides evidence consistent with H2 when using analyst coverage to measure the quality of the information environment. Specifically, we observe a significantly stronger coefficient on the $SA \times Day^{0,+1}$ for firms with relatively lower analyst coverage. In fact, in the low coverage partition, moving from the lowest to highest level of SA coverage reduces the spike in information asymmetry by over 40 percent (-2.862/6.309) whereas there is no significant attenuation in the high coverage partition.[23] Panel B of Table 5 repeats these tests using Dow Jones coverage as the type of coverage. Consistent with H2, we again observe a more pronounced effect

[23] The significant difference in the main effect of $Day^{0,+1}$ across the two partitions may appear surprising, but this is consistent with results in Table 4 which revealed a significantly larger increase in *Spread* for firms with higher analyst coverage.

of *SA* in the “low coverage” partition. In the “Low” partition, moving from the lowest to highest decile of *SA* attenuates the information asymmetry spike by 37 percent (-2.481/6.616) whereas we observe no significant attenuation in the high coverage partition. However, we note that this difference is only marginally significant.

In sum, our evidence in Table 5 strongly suggests that the earnings announcement benefit of crowdsourced financial analysis is considerably stronger when firms receive relatively less coverage by traditional intermediaries. We interpret this evidence as suggesting that SA contributors play an even more significant role in the absence of information from other sources.

5.3 Test of H3

H3 predicts that SA coverage during the quarter mitigates the increase in information asymmetry at the earnings announcement more when firms provide no voluntary earnings guidance. To test H3, we bifurcate the sample into observations for which management either did or did not provide at least one earnings forecast for the given fiscal period. We report this evidence in Table 6 and again suppress all estimates but coefficients on terms of interest.

Our results are generally consistent with H3. Specifically, the effect of *SA* on the earnings announcement spike in information asymmetry is significantly stronger in the 62 percent of the sample pertaining to firms that do not provide earnings guidance. In the absence of a forecast, moving from the lowest to highest decile of *SA* attenuates the earnings announcement spike in information asymmetry by nearly 30 percent (-2.048/6.874) whereas we observe no significant attenuation for firms providing a forecast. As with Panel B of Table 5, the difference in estimates is marginally different across the two partitions.

As noted previously, we also highlight that this cross-sectional test provides evidence against a plausible alternative explanation for our results. Specifically, it is possible managers’ voluntary disclosures attract SA authors and allow the authors to produce higher quality analyses, thus reducing information asymmetry at earnings announcement. Supporting this notion, prior research finds that voluntary disclosures reduce information asymmetry, at least in the long-run (Coller and Yohn 1997; Balakrishnan et al. 2014). However, we find that our results are significantly *stronger* when firms do not provide a management forecast for the current period's earnings. This helps to mitigate the concern that managers' voluntary disclosure activity is driving our results.

Overall, the evidence in Table 6 suggests that the earnings announcement benefit of crowdsourced financial analysis is considerably stronger when firms provide less disclosure. This suggests that SA contributors play a more important role in the absence of information produced by the firm.

6. Additional analysis

6.1 Differential usefulness of SA Reports

Throughout the paper we assume that crowdsourced financial analysis on SA provides information more relevant to relatively less sophisticated investors but we provide relatively little evidence on whether this is the case. Therefore, in this section we provide more direct evidence related to this assumption.[24] As mentioned previously, Amiram, Owens, and Rozenbaum (2016) document a reduction in bid-ask spreads following analyst forecast revisions and conclude that,

[24] While contemporaneous work by Campbell, DeAngelis, and Moon (2018) document a short-window price response to SA article publication, this does not imply a reduction in information asymmetry. In fact, if SA article publication leads to informed trading, one could observe price movement and an increase in information asymmetry (Kim and Verrecchia 1994). Additionally, other research suggests that more-sophisticated investors incur costs to subscribe to internet sources such as news feeds in order to obtain timely information and more efficiently initiate trades (Li, Ramesh, and Shen 2011; Rogers, Skinner, and Zechman 2017; Drake, Thornock, and Twedt 2017). This further suggests that at least some of the information from sources such as SA may be new to both more- and less-sophisticated investors.

unlike public information releases (EAs or management forecasts), these forecasts represent new information only to less sophisticated investors. Therefore, we conduct a similar test using crowdsourced financial analysis on SA. Our research design for this test mirrors our prior tests except that we focus on the publication date of SA content as our "event date." Specifically, we estimate the following model:

$$Spread_{i,d} = \beta_0 + \beta_1 DAY_{i,d}^{-4,-1} + \beta_2 DAY_{i,d}{}^{0,+1} + \beta_3 DAY_{i,d}^{+2,+10} + \beta_4 CAR_{i,p} + \beta_5 Depth_{i,d} + \beta_6 DJarticles_{SA_{i,p}} + \beta_7 Institutions_{i,q-1} + \beta_8 Price_{i,d} + \beta_9 Size_{i,q-1} + \beta_{10} Turnover_{i,q-1} + \beta_{11} Volume_{i,d} + \beta_{12} Volatility_{i,q-1} + \epsilon_{i,d} \quad (2)$$

Where subscripts i, d, and q, refer to firm, day, and quarter, respectively. Equation (2) is similar in spirit to equation (1) except that "d" indexes days relative to an SA article publication date (rather than an earnings announcement) and interactions are not needed. If SA analysis is differentially useful to less sophisticated investors, we should observe a significantly negative estimate for β_2. Note that we adjust variable definitions for this test to be relative to the SA publication date as the "event-day" rather than the earnings announcement. To illustrate, $Day^{0,+1}$ equals 1 on the day of and day following an SA article publication, and $Institutions_{i,q-1}$ refers to institutional ownership as of the end of the quarter ending closest by prior to the SA publication date.

We report results from estimating equation (2) in Table 7. Columns 1 reports results for our full sample of SA articles and column 2 reports results for a reduced sample where we remove SA articles published concurrent to an analyst forecast revision or earnings announcement (described in more detail below). Our results include firm fixed effects with standard errors clustered by firm and quarter (Petersen 2009).

Consistent with our predictions, we observe a significantly negative coefficient on $Day^{0,+1}$ in column 1 (-1.213, p-value < 0.01). Economically, this effect translates to a 1.2 basis point reduction in *Spread* on days of SA article publication, which is very similar to the effect size of analyst forecast revisions documented in Amiram, Owens, and Rozenbaum (2016).

One concern regarding these results is that we are capturing the decrease in information asymmetry driven by some other contemporaneous event which also reduces information asymmetry. We do not believe this to be the case, given the long-form nature of SA reports, which include extensive analyses, tables, figures, etc. Thus, it is unlikely that SA authors are simply issuing reports in immediate reaction to some corporate event.[25,26] In addition, we control for the dissemination of news by the business press. Nonetheless, it is still possible that we are capturing the effect of some other contemporaneous information release. To alleviate this concern, we remove observations for which the SA article is released within 1) a 5-day window of a professional analyst report, or 2) a 5-day window of the firm's earnings announcement. Column 2 presents results from estimating equation 1 using this reduced sample. The coefficient on $Day^{0,+1}$ remains significantly negative (-2.578, p-value < 0.01) and the magnitude of the effect more than doubles, suggesting that any contamination of contemporaneous events likely *lessens* the influence of SA articles. This larger effect translates to a reduction in *Spread* of approximately 2.6 basis points, or 3.3 percent of the sample mean.

In sum, this evidence is consistent with crowdsourced financial analysis being more useful to informationally disadvantaged, less sophisticated investors. In addition, these results supplement prior research suggesting SA articles have a price impact (Chen et al. 2014; Campbell,

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[25] Similar to this claim, Li et al. (2015) show that professional analysts rarely "piggyback" on other news events.

[26] Campbell, DeAngelis, and Moon (2018) conduct an analysis using only articles published early in the morning after purging their returns measures of overnight returns. They find inferences similar to their main tests, suggesting that the price response in their paper to SA is unlikely driven by contemporaneous events. This adds further comfort that results in Table 7 are not attributable to some other contemporaneous event.

DeAngelis, and Moon 2018) by showing that SA articles also appear to reduce adverse selection risk.

6.2 SA Coverage and Divergent Opinions

Theory suggests that the primary mechanism leading to the increase in information asymmetry at EAs is the fact that certain (sophisticated) investors better and more accurately process and react to information than other investors (Kim and Verrecchia 1994). This combination of informed trading by more sophisticated investors and divergent opinions by less sophisticated investors contributes to increased information asymmetry and higher trading volume (Kim and Verrecchia 1994). We argue that SA coverage of a firm over a period of time helps inform less sophisticated investors, bettering their valuation judgments and lessening sophisticated investors processing advantages. If this is the case, then we should observe less opinion divergence (i.e., trading is driven more by consensus in new price than disagreement).

To test this supposition, we use "standardized-unexpected-volume" (*SUV*) to proxy for disagreement-driven trading. Prior research suggests this measure considerably outperforms other measures of disagreement (Garfinkel 2009; Bamber, Barron, and Stevens 2011). To compute *SUV*, we use the following empirical model, which is estimated by firm and calendar quarter using daily CRSP data:

$$Volume_{i,t} = \alpha_{0,i,q} + \alpha_{1,i,q}PosRet_{i,t} + \alpha_{2,i,q}|NegRet_{i,t}| + e_{i,t} \qquad (3)$$

where *Volume* equals daily share turnover (volume divided by shares outstanding) from CRSP, and *PosRet* (*NegRet*) equals the firm's daily return if the return is positive (negative) and 0 otherwise. $SUV_{i,t}$ equals the residual from equation (3) for firm *i* on day *t,* standardized by the standard deviation of all residuals from each firm-quarter estimation window. We then use *SUV* in place of *Spread* in equation (1). If SA coverage contributes to belief convergence (i.e., gets investors "on the same page") before an earnings announcement, then we expect the interaction between *SA* and $Day^{0,+1}$ to be significantly negative.

Table 8 presents the results from estimating equation (3). Consistent with differential interpretation of earnings news driving increased trading following EAs (Kandel and Pearson 1995), we observe a highly significant, positive coefficient on $Day^{0,+1}$ (0.553, p-value < 0.01). Also, consistent with our prediction, we observe a significantly negative coefficient on the interaction between *SA* and $Day^{0,+1}$ (-0.082, p-value < 0.01). Moving from the lowest to highest decile of SA coverage corresponds to a 15 percent decrease in the spike in *SUV* following the earnings announcement. Overall, this evidence corroborates our previous inferences that SA coverage aids less sophisticated investors process new information released during EAs.

7. Conclusion

We study the effects of crowdsourced financial analysis, an information source of growing importance in financial markets, on information asymmetry during earnings announcements. Prior research generally suggests that crowdsourced analysis has price ramifications, and we extend this research by showing it serves an important role during earnings announcements. Crowdsourced financial analysis appears to contribute to a "more level" playing field by better preparing less sophisticated investors for earnings announcements. Specifically, we show that higher levels of crowdsourced financial analysis during a quarter attenuate the well-documented earnings announcement spike in information asymmetry. Additionally, we predict and find that our results are most pronounced for firms operating in poorer information environments, and for firms who provide less voluntary disclosure. We provide additional evidence supporting the notion that crowdsourced financial analysis is differentially useful to less sophisticated investors and that crowdsourced financial analysis indeed gets investors "on the same page," as evidenced by less disagreement-driven volume.

Our results make several contributions to the disclosure and information asymmetry literatures. Namely, we provide, to our knowledge, the first evidence that, like the business press and professional analysts, the "crowds" can have a meaningful impact on information asymmetry. These crowds can also help mitigate sophisticated investors' information advantage around important information events (earnings announcements). For this reason, we expect our evidence to be of interest to regulators, who constantly strive to "level the playing field." To date, regulators have focused on risks associated with crowdsourcing, and we document an important benefit that should be weighed in any deliberations.

References

Ajinkya, Bipin B., and Michael J. Gift. 1984. "Corporate Managers' Earnings Forecasts and Symmetrical Adjustments of Market Expectations." *Journal of Accounting Research* 22 (2): 425–44.

Amiram, Dan, Edward Owens, and Oded Rozenbaum. 2016. "Do Information Releases Increase or Decrease Information Asymmetry? New Evidence from Analyst Forecast Announcements." *Journal of Accounting and Economics* 62 (1): 121–38. https://doi.org/10.1016/j.jacceco.2016.06.001.

Antweiler, Werner, and Murray Z. Frank. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards." *The Journal of Finance* 59 (3): 1259–94. https://doi.org/10.1111/j.1540-6261.2004.00662.x.

Baginski, S. P., and Kenneth C. Rakow. 2012. "Management Earnings Forecast Disclosure Policy and the Cost of Equity Capital." *Review of Accounting Studies* 17 (2): 279–321. https://doi.org/10.1007/s11142-011-9173-4.

Balakrishnan, Karthik, Mary Brooke Billings, Bryan Kelly, and Alexander Ljungqvist. 2014. "Shaping Liquidity: On the Causal Effects of Voluntary Disclosure." *The Journal of Finance* 69 (5): 2237–78. https://doi.org/10.1111/jofi.12180.

Bamber, Linda Smith, Orie E. Barron, and Douglas E. Stevens. 2011. "Trading Volume Around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research*." *Contemporary Accounting Research* 28 (2): 431–71. https://doi.org/10.1111/j.1911-3846.2010.01061.x.

Bartov, Eli, Lucile Faurel, and Partha S. Mohanram. 2018. "Can Twitter Help Predict Firm-Level Earnings and Stock Returns?" *The Accounting Review* 93 (3): 25–57. https://doi.org/10.2308/accr-51865.

Beaver, William H., Maureen F. McNichols, and Zach Z. Wang. 2018. "The Information Content of Earnings Announcements: New Insights from Intertemporal and Cross-Sectional Behavior." *Review of Accounting Studies* 23 (1): 95–135. https://doi.org/10.1007/s11142-017-9417-z.

Bhattacharya, Nilabhra, Frank Ecker, Per M. Olsson, and Katherine Schipper. 2012. "Direct and Mediated Associations among Earnings Quality, Information Asymmetry, and the Cost of Equity." *The Accounting Review* 87 (2): 449–82. https://doi.org/10.2308/accr-10200.

Blankespoor, Elizabeth, Ed deHaan, and Christina Zhu. 2018. "Capital Market Effects of Media Synthesis and Dissemination: Evidence from Robo-Journalism." *Review of Accounting Studies* 23 (1): 1–36. https://doi.org/10.1007/s11142-017-9422-2.

Blankespoor, Elizabeth, Gregory S. Miller, and Hal D. White. 2014. "The Role of Dissemination in Market Liquidity: Evidence from Firms' Use of Twitter™." *The Accounting Review* 89 (1): 79–112. https://doi.org/10.2308/accr-50576.

Boone, Audra L., and Joshua T. White. 2015. "The Effect of Institutional Ownership on Firm Transparency and Information Production." *Journal of Financial Economics* 117 (3): 508–33. https://doi.org/10.1016/j.jfineco.2015.05.008.

Bushee, Brian J., John E. Core, Wayne Guay, and Sophia J.w. Hamm. 2010. "The Role of the Business Press as an Information Intermediary." *Journal of Accounting Research* 48 (1): 1–19. https://doi.org/10.1111/j.1475-679X.2009.00357.x.

Campbell, John L., Matthew D. DeAngelis, and James R. Moon. 2018. "Bias in the Crowds? An Examination of Whether Financial Positions Affect Investor Perceptions of Stock Opinions Transmitted Through Social Media." SSRN Scholarly Paper ID 2837321. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=2837321.

Chen, Hailiang, Prabuddha De, Yu (Jeffrey) Hu, and Byoung-Hyoun Hwang. 2014. "Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media." *Review of Financial Studies* 27 (5): 1367–1403. https://doi.org/10.1093/rfs/hhu001.

Christophe, Stephen E., Michael G. Ferri, and Jim Hsieh. 2010. "Informed Trading before Analyst Downgrades: Evidence from Short Sellers." *Journal of Financial Economics* 95 (1): 85–106. https://doi.org/10.1016/j.jfineco.2009.02.004.

Coller, Maribeth, and Teri Lombardi Yohn. 1997. "Management Forecasts and Information Asymmetry: An Examination of Bid-Ask Spreads." *Journal of Accounting Research* 35 (2): 181–91.

Collins, Daniel W., Oliver Zhen Li, and Hong Xie. 2009. "What Drives the Increased Informativeness of Earnings Announcements over Time?" *Review of Accounting Studies* 14 (1): 1–30. https://doi.org/10.1007/s11142-007-9055-y.

Demsetz, Harold. 1968. “The Cost of Transacting.” *The Quarterly Journal of Economics* 82 (1): 33–53. https://doi.org/10.2307/1882244.
Diamond, Douglas W., and R. E. Verrecchia. 1991. “Disclosure, Liquidity, and the Cost of Capital.” *Journal of Finance* 46 (4): 1325–1359.
Drake, Michael S., Nicholas M. Guest, and Brady J. Twedt. 2014. “The Media and Mispricing: The Role of the Business Press in the Pricing of Accounting Information.” *The Accounting Review* 89 (5): 1673–1701. https://doi.org/10.2308/accr-50757.
Drake, Michael S., Jacob R. Thornock, and Brady J. Twedt. 2017. “The Internet as an Information Intermediary.” *Review of Accounting Studies* 22 (2): 543–76. https://doi.org/10.1007/s11142-017-9395-1.
Easley, David, and Maureen O’Hara. 2004. “Information and the Cost of Capital.” *The Journal of Finance* 59 (4): 1553–83.
FINRA. 2017. *Regulatory-Notice-17-18.Pdf. 17-18*. https://www.finra.org/sites/default/files/notice_doc_file_ref/Regulatory-Notice-17-18.pdf.
Flood, Chris. 2017. “Fake News Infiltrates Financial Markets.” Financial Times. May 5, 2017. https://www.ft.com/content/a37e4874-2c2a-11e7-bc4b-5528796fe35c.
Francis, Jennifer, Katherine Schipper, and Linda Vincent. 2002. “Earnings Announcements and Competing Information.” *Journal of Accounting and Economics* 33 (3): 313–42. https://doi.org/10.1016/S0165-4101(02)00058-7.
Garfinkel, Jon A. 2009. “Measuring Investors’ Opinion Divergence.” *Journal of Accounting Research* 47 (5): 1317–48. https://doi.org/10.1111/j.1475-679X.2009.00344.x.
Guest, Nicholas M. 2017. “Do Journalists Help Investors Analyze Firms’ Earnings News?” SSRN Scholarly Paper ID 3067387. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=3067387.
Hales, Jeffrey, James R. Moon, and Laura A. Swenson. 2018. “A New Era of Voluntary Disclosure? Empirical Evidence on How Employee Postings on Social Media Relate to Future Corporate Disclosures.” *Accounting, Organizations and Society*, New Corporate Disclosures and New Methods, 68–69 (July): 88–108. https://doi.org/10.1016/j.aos.2018.04.004.
Heflin, Frank L., James R. Moon, and Dana M. Wallace. 2015. “A Re-Examination of the Cost of Capital Benefits of Higher Quality Disclosures.” *Journal of Financial Reporting* Forthcoming.
Holden, Craig W., and Stacey Jacobsen. 2014. “Liquidity Measurement Problems in Fast, Competitive Markets: Expensive and Cheap Solutions: Liquidity Measurement Problems in Fast, Competitive Markets.” *The Journal of Finance* 69 (4): 1747–85. https://doi.org/10.1111/jofi.12127.
Huang, R. D., and H. R. Stoll. 1997. “The Components of the Bid-Ask Spread: A General Approach.” *Review of Financial Studies* 10 (4): 995–1034. https://doi.org/10.1093/rfs/10.4.995.
Hughes, John S., Jing Liu, and Jun Liu. 2007. “Information Asymmetry, Diversification, and Cost of Capital.” *The Accounting Review* 82 (3): 705–29. https://doi.org/10.2308/accr.2007.82.3.705.
Irvine, Paul, Marc Lipson, and Andy Puckett. 2007. “Tipping.” *Review of Financial Studies* 20 (3): 741–68.
Jame, Russell, Rick Johnston, Stanimir Markov, and Michael C. Wolfe. 2016. “The Value of Crowdsourced Earnings Forecasts.” *Journal of Accounting Research*, April, n/a-n/a. https://doi.org/10.1111/1475-679X.12121.
Kadan, Ohad, Roni Michaely, and Pamela C. Moulton. 2017. “Trading in the Presence of Short-Lived Private Information: Evidence from Analyst Recommendation Changes.” SSRN Scholarly Paper ID 2427282. Rochester, NY: Social Science Research Network. https://papers.ssrn.com/abstract=2427282.
Kandel, Eugene, and Neil D. Pearson. 1995. “Differential Interpretation of Public Signals and Trade in Speculative Markets.” *Journal of Political Economy* 103 (4): 831.
Kelly, Bryan, and Alexander Ljungqvist. 2012. “Testing Asymmetric-Information Asset Pricing Models.” *Review of Financial Studies* 25 (5): 1366–1413.
Kim, Oliver, and Robert E. Verrecchia. 1991a. “Trading Volume and Price Reactions to Public Announcements.” *Journal of Accounting Research* 29 (2): 302–21. https://doi.org/10.2307/2491051.
———. 1991b. “Market Reaction to Anticipated Announcements.” *Journal of Financial Economics* 30 (2): 273–309. https://doi.org/10.1016/0304-405X(91)90033-G.
———. 1994. “Market Liquidity and Volume around Earnings Announcements.” *Journal of Accounting and Economics* 17 (1): 41–67. https://doi.org/10.1016/0165-4101(94)90004-3.
Kothari, S. P., X. Li, and J. E. Short. 2009. “The Effect of Disclosures by Management, Analysts, and Business Press on Cost of Capital, Return Volatility, and Analyst Forecasts: A Study Using Content Analysis.” *The Accounting Review* 84 (5): 1639–1670.

Lee, Charles M. C., Belinda Mucklow, and Mark J. Ready. 1993. “Spreads, Depths, and the Impact of Earnings Information: An Intraday Analysis.” *The Review of Financial Studies* 6 (2): 345–74. https://doi.org/10.1093/rfs/6.2.345.

Leuz, Christian, and Robert E. Verrecchia. 2000. “The Economic Consequences of Increased Disclosure.” *Journal of Accounting Research* 38 (January): 91–124. https://doi.org/10.2307/2672910.

Li, Congcong. 2015. “The Hidden Face of the Media: How Financial Journalists Produce Information.” https://doi.org/10.13016/M2BK78.

Li, Edward Xuejun, K. Ramesh, and Min Shen. 2011. “The Role of Newswires in Screening and Disseminating Value-Relevant Information in Periodic SEC Reports.” *The Accounting Review* 86 (2): 669–701. https://doi.org/10.2308/accr.00000023.

Li, Edward Xuejun, K. Ramesh, Min Shen, and Joanna Shuang Wu. 2015. “Do Analyst Stock Recommendations Piggyback on Recent Corporate News? An Analysis of Regular-Hour and After-Hours Revisions.” *Journal of Accounting Research* 53 (4): 821–61. https://doi.org/10.1111/1475-679X.12083.

Lobo, Gerald J., Minsup Song, and Mary Harris Stanford. 2017. “The Effect of Analyst Forecasts during Earnings Announcements on Investor Responses to Reported Earnings.” *The Accounting Review* 92 (3): 239–63. https://doi.org/10.2308/accr-51556.

Muller, III, Karl A., Edward J. Riedl, and Thorsten Sellhorn. 2011. “Mandatory Fair Value Accounting and Information Asymmetry: Evidence from the European Real Estate Industry.” *Management Science* 57 (6): 1138–53.

Petersen, Mitchell A. 2009. “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches.” *Review of Financial Studies* 22 (1): 435–80.

Rogers, Jonathan L., Douglas J. Skinner, and Sarah L. C. Zechman. 2017. “Run EDGAR Run: SEC Dissemination in a High-Frequency World.” *Journal of Accounting Research* 55 (2): 459–505. https://doi.org/10.1111/1475-679X.12167.

SEC. 2015. “SEC.Gov | Updated Investor Alert: Social Media and Investing -- Stock Rumors.” 2015. https://www.sec.gov/oiea/investor-alerts-bulletins/ia_rumors.html.

Seeking Alpha. 2017. “About Seeking Alpha.” Seeking Alpha. 2017. https://seekingalpha.com/page/about_us.

———. 2018. “Article Submission Guidelines.” Seeking Alpha. 2018. https://seekingalpha.com/page/article-submission-guidelines.

Stoll, Hans R. 1978. “The Supply of Dealer Services in Securities Markets.” *The Journal of Finance* 33 (4): 1133–51. https://doi.org/10.1111/j.1540-6261.1978.tb02053.x.

Tang, Vicki Wei. 2017. “Wisdom of Crowds: Cross-Sectional Variation in the Informativeness of Third-Party-Generated Product Information on Twitter.” *Journal of Accounting Research* In-press. https://doi.org/10.1111/1475-679X.12183.

Twedt, Brady. 2016. “Spreading the Word: Price Discovery and Newswire Dissemination of Management Earnings Guidance.” *The Accounting Review* 91 (1): 317–46. https://doi.org/10.2308/accr-51129.

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

Welker, M. 1995. “Disclosure Policy, Information Asymmetry, and Liquidity in Equity Markets.” *Contemporary Accounting Research* 11 (2): 801–827.

Yohn, Teri Lombardi. 1998. “Information Asymmetry Around Earnings Announcements.” *Review of Quantitative Finance and Accounting* 11 (2): 165–82. https://doi.org/10.1023/A:1008268201014.

APPENDIX A

Variable Definitions

Variable	Definition
Anfollow	The decile rank of firm i's analyst following during the quarter, as measured by I/B/E/S.
CAR	Absolute value of the sum of firm i's market-adjusted returns for the three-day trading window centered on the earnings announcement date, using the CRSP value-weighted index.
Depth	Firm i's average quoted depth from TAQ on day d, measured as the sum of the number of shares quoted at the ask plus the number quoted at the bid.
Djarticles	The natural logarithm of the number of articles in the DowJones database about firm i from day d+10 to d-5 relative to the prior and current quarter's earnings announcement, respectively.
$DJarticles^{-1,+1}$	The natural logarithm of the number of articles in the DowJones database about firm i from day d-1 to d+1 relative to the current quarter's earnings announcement.
InstOwn	The percent of firm i's shares held by institutions.
MEF	An indicator variable equal to one if firm i issued a management forecast for quarter t's earnings, and zero otherwise.
Price	The closing stock price of firm i on day d relative to the earnings announcement. For the validation test in Table 4, Price is relative to the SA article release date.
SA	The decile rank of the number of Seeking Articles of firm i from day d+10 to d-5 relative to the prior and current quarter's earnings announcement, respectively.
$SA^{-1,+1}$	The decile rank of the number of Seeking Articles about firm i from day d-1 to d+1 relative to the current quarter's earnings announcement.
Size	The natural logarithm of firm i's market value at beginning-of-the period.
Spread	Firm i's average daily bid-ask spread from TAQ on day d in basis points, scaled by the midpoint.
SUV	Standardized unexpected volume as defined by Garfinkel (2009).
Turnover	The average of the monthly turnover for the three fiscal months pertaining to that earnings announcement, multiplied by 1000.
Volatility	Firm i's volatility, measured as the standard deviation of the firm's daily stock returns during the quarter.
Volume	The volume of shares traded in firm i on day d relative to the earnings announcement. Divided by 1,000,000. For the validation test in Table 4, Volume is relative to the SA article release date.

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	(4,844)
Missing necessary control variable information	(38,957)
Seeking Alpha Articles for Main Analyses	116,346

TABLE 2

Descriptive Statistics

Variable	N	Mean	Q1	Median	Q3	Std Dev
Anfollow	641,361	10.95	4.00	9.00	17.00	8.56
CAR	641,361	0.06	0.02	0.04	0.08	0.06
Depth	641,361	30.62	5.22	7.86	16.72	140.81
DJarticles	641,361	3.66	2.89	3.64	4.47	1.26
DJarticles$^{-1,+1}$	641,361	2.84	2.30	2.83	3.37	0.85
InstOwn	641,361	0.51	0.16	0.59	0.79	0.34
MEF	641,361	0.37	0.00	0.00	1.00	0.48
Price	641,361	37.72	12.16	26.76	47.92	49.18
SA	641,361	1.76	0.00	1.00	2.00	4.68
SA$^{-1,+1}$	641,361	0.13	0.00	0.00	0.00	0.40
Size	641,361	7.96	6.49	7.97	9.46	2.00
Spread	641,361	82.18	14.44	31.95	83.53	128.35
SUV	641,361	0.14	-0.52	-0.06	0.58	1.01
Turnover	641,361	13.33	5.60	9.48	16.00	14.17
Volatility	641,361	0.03	0.02	0.02	0.03	0.02
Volume	641,361	3.86	31.91	11.25	34.64	10.32

Table 2 presents descriptive statistics. For coefficient interpretation, decile rank of *Anfollow, SA,* and *SA*$^{-1,+1}$ are used in the analyses. However, we present underlying variable values here.

TABLE 3

Correlation Matrix

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*	*(13)*	*(14)*	*(15)*	*(16)*
(1) Anfollow		-0.07	0.08	0.50	0.53	0.22	0.30	0.30	0.17	0.05	0.59	-0.45	0.05	0.10	-0.23	0.31
(2) CAR	-0.03		0.00	-0.11	0.01	0.00	0.00	-0.10	-0.02	0.06	-0.23	0.12	0.04	0.20	0.34	0.01
(3) Depth	0.12	-0.01		0.17	0.13	-0.04	-0.06	-0.09	0.18	-0.02	0.08	-0.04	0.00	0.08	0.03	0.49
(4) DJarticles	0.52	-0.10	0.34		0.71	0.13	0.16	0.21	0.21	0.03	0.71	-0.48	0.02	0.11	-0.10	0.42
(5) DJarticles-1,+1	0.56	0.01	0.25	0.73		0.11	0.24	0.21	0.18	0.08	0.66	-0.46	0.05	0.07	-0.16	0.39
(6) InstOwn	0.25	0.01	-0.11	0.13	0.09		0.13	0.15	-0.01	0.00	0.14	-0.26	0.02	0.03	-0.09	0.01
(7) MEF	0.35	0.01	-0.05	0.18	0.27	0.13		0.08	-0.02	0.08	0.21	-0.22	0.04	-0.04	-0.18	0.01
(8) Price	0.44	-0.17	-0.47	0.34	0.38	0.23	0.26		0.14	-0.01	0.41	-0.24	0.03	-0.01	-0.25	-0.03
(9) SA	0.06	-0.06	0.07	0.15	0.07	-0.01	-0.04	0.06		-0.12	0.18	-0.08	0.00	0.08	-0.01	0.24
(10) SA-1,+1	0.05	0.06	0.01	0.02	0.08	0.03	0.09	0.01	-0.46		0.03	-0.04	0.01	0.02	0.02	0.00
(11) Size	0.60	-0.22	0.15	0.71	0.70	0.12	0.21	0.66	0.12	0.01		-0.66	0.04	-0.04	-0.42	0.35
(12) Spread	-0.60	0.19	-0.33	-0.66	-0.65	-0.15	-0.24	-0.48	-0.12	-0.01	-0.83		-0.05	-0.16	0.32	-0.17
(13) SUV	0.05	0.04	0.00	0.03	0.05	0.03	0.04	0.04	0.00	0.01	0.04	-0.04		0.01	-0.02	0.16
(14) Turnover	0.28	0.23	0.19	0.20	0.17	0.18	0.06	-0.03	0.03	0.05	0.02	-0.16	0.03		0.42	0.12
(15) Volatility	-0.24	0.36	0.10	-0.15	-0.20	-0.06	-0.17	-0.49	-0.04	0.04	-0.48	0.44	-0.01	0.44		0.01
(16) Volume	0.63	-0.02	0.51	0.68	0.64	0.15	0.18	0.21	0.12	0.04	0.68	-0.73	0.23	0.41	-0.10	

Table 3 presents correlations using the sample for H1 (641,361 observations). Correlations above (below) the diagonal are Pearson (Spearman). All correlations are significant at $p<0.05$ level. Variable definitions are in Appendix A.

TABLE 4

Effect of SA Coverage on Earnings Announcement Information Asymmetry

Dependent Variable: *Spread*

	Predicted Sign	[1]
SA* Day$^{0,+1}$	**-**	**-1.744***** **(0.00)**
SA	?	-1.775 (0.28)
Day$^{0,+1}$	+	9.773*** (0.00)
Day$^{-4,-1}$	+	5.071*** (0.00)
CAR	?	5.216 (0.75)
Depth	-	0.002 (0.34)
DJarticles	-	-27.79*** (0.00)
DJarticles$^{-1,+1}$	-	-12.518*** (0.01)
InstOwn	-	-45.508*** (0.00)
Anfollow	-	-11.835** (0.02)
Price	-	0.102*** (0.00)
Size	-	-27.947*** (0.00)
Turnover	-	-1.465*** (0.00)
SA$^{-1,+1}$	?	-2.132 (0.17)
Volume	-	-0.054 (0.21)
Volatility	+	9.086*** (0.00)
CAR Day$^{0,+1}$*	+	11.755** (0.03)
Depth Day$^{0,+1}$*	-	-0.003** (0.05)
DJarticles Day$^{0,+1}$*	-	-3.517*** (0.00)
DJarticles$^{-1,+1}$ Day$^{0,+1}$*	-	1.302 (0.12)
InstOwn Day$^{0,+1}$*	?	2.269*** (0.00)
Anfollow Day$^{0,+1}$*	?	1.68** (0.01)
Price Day$^{0,+1}$*	-	-0.003

		(0.18)
Size $*$ $Day^{0,+1}$	?	-0.331
		(0.14)
Turnover $*$ $Day^{0,+1}$	?	-0.027*
		(0.08)
SAarticles$^{-1,+1}$ $*$ $Day^{0,+1}$	-	-1.252**
		(0.01)
Volume $*$ $Day^{0,+1}$	?	0.004
		(0.91)
Volatility $*$ $Day^{0,+1}$	?	-0.4092
		(0.13)
SA $*$ $Day^{-4,-1}$	-	-0.493
		(0.15)
CAR $Day^{-4,-1}$	+	14.227***
		(0.00)
Depth $*$ $Day^{-4,-1}$	-	-0.001
		(0.24)
DJarticles $*$ $Day^{-4,-1}$	-	-1.866**
		(0.02)
DJarticles$^{-1,+1}$ $*$ $Day^{-4,-1}$	-	1.487***
		(0.00)
InstOwn $*$ $Day^{-4,-1}$	?	-0.472
		(0.32)
Anfollow $*$ $Day^{-4,-1}$	?	-0.023
		(0.97)
Price $*$ $Day^{-4,-1}$	?	0.003
		(0.17)
Size $*$ $Day^{-4,-1}$	?	-0.397**
		(0.04)
Turnover $*$ $Day^{-4,-1}$	-	-0.037***
		(0.00)
SA$^{-1,+1}$ $*$ $Day^{-4,-1}$	?	-0.167
		(0.72)
Volume $*$ $Day^{-4,-1}$	?	0.003
		(0.84)
Volatility $*$ $Day^{-4,-1}$	?	-0.0932
		(0.67)
Observations		641,361
Fixed Effects		Firm
Adjusted R-squared		0.81

This table presents coefficients (p-values) from estimates of equation (1), $Spread = \varphi_0 + \alpha_1 SA + \alpha_2 Day^{-4,-1} + \alpha_3 Day^{0,+1} + \sum_k \gamma_k Controls_k + \beta_1 SA * Day^{-4,-1} + \beta_2 \boldsymbol{SA} * \boldsymbol{Day^{0,+1}} + \sum_k \delta_k Controls_k * Day^{-4,-1} + \sum_k \omega_k Controls_k * Day^{0,+1} + \sum_j \theta_j Firm_j + \epsilon_{i,d}$. Each estimation uses, for all firm-quarters, the 21 days centered on the firm's earnings announcement, clusters standard errors by firm and quarter, and includes firm fixed effects. *Spread*=the firm's daily average percentage bid-ask spread. *SA*=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. $Day^{0,+1}$ is an indicator variable equal to 1 for days 0 and +1 relative to the earnings announcement, and zero otherwise. $Day^{-4,-1}$ is an indicator variable equal to 1 for days -4 through -1 relative to the earnings announcement, and zero otherwise. *** (**, *) denotes one-tailed (two-tailed) significance at the p<0.01 (p<0.05, p<0.10) level when coefficient signs are predicted (not predicted). Appendix A provides detailed definitions of all variables.

TABLE 5

Cross-sectional Tests Based on Analyst and Dow Jones Coverage

Panel A: High vs. Low Analyst Following

Dependent Variable: *Spread*

	Predicted Sign	Low [1]	High [2]	Difference [1] - [2]
SA*Day $^{\mathbf{0,+1}}$	-	**-2.862*****	**-0.091**	**-2.771*****
		(0.00)	**(0.42)**	**(0.01)**
SA	?	-1.113	-1.869	0.756
		(0.73)	(0.13)	(0.41)
Day $^{0,+1}$	+	6.309**	19.077***	-12.768***
		(0.02)	(0.00)	(0.00)
Observations		297,864	343,497	
Fixed Effects		Firm	Firm	
Adjusted R-squared		0.79	0.663	

Panel B: High vs. Low Dow Jones Coverage

Dependent Variable: *Spread*

	Predicted Sign	Low [1]	High [2]	Difference [1] - [2]
SA* Day $^{\mathbf{0,+1}}$	-	**-2.481****	**-0.644**	**-1.837***
		(0.01)	**(0.11)**	**(0.07)**
SA	?	-0.685	-0.778	0.093
		(0.82)	(0.47)	(0.49)
Day $^{0,+1}$	+	6.616**	11.478***	-4.862*
		(0.03)	(0.00)	(0.09)
Observations		317,457	323,904	
Fixed Effects		Firm	Firm	
Adjusted R-squared		0.804	0.714	

This table presents coefficients (p-values) from estimates of equation (1), $Spread = \varphi_0 + \alpha_1 SA + \alpha_2 Day^{-4,-1} + \alpha_3 Day^{0,+1} + \sum_k \gamma_k Controls_k + \beta_1 SA * Day^{-4,-1} + \boldsymbol{\beta_2 SA * Day^{0,+1}} + \sum_k \delta_k Controls_k * Day^{-4,-1} + \sum_k \omega_k Controls_k * Day^{0,+1} + \sum_i \theta_i Firm_i + \epsilon_{i,d}$. The Low (High) column in Panel A presents results for firms with below (above) median analyst coverage during the quarter. The Low (High) column in Panel B presents results for firms with below (above) median Dow Jones coverage during the quarter. Controls are suppressed for brevity. Each estimation uses, for all firm-quarters, the 21 days centered on the firm's earnings announcement, clusters standard errors by firm and quarter, and includes firm fixed effects. *Spread*=the firm's daily average percentage bid-ask spread. *SA*=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. $Day^{0,+1}$ is a indicator variable equal to 1 for days 0 and +1 relative to the earnings announcement, and zero otherwise. $Day^{-4,-1}$ is an indicator variable equal to 1 for days -4 through -1 relative to the earnings announcement, and zero otherwise. *** (**, *) denotes one-tailed (two-tailed) significance at the p<0.01 (p<0.05, p<0.10) level when coefficient signs are predicted (not predicted). Appendix A provides detailed definitions of all variables.

TABLE 6

Forecasting Firms

Dependent Variable: *Spread*

	Predicted Sign	No Forecast [1]	Forecast [2]	Difference [1] - [2]
SA* Day $^{0,+1}$	-	**-2.048*****	**-0.475**	**-1.573***
		(0.01)	**(0.27)**	**(0.07)**
SA	?	-2.745	-1.657	-1.087
		(0.27)	(0.29)	(0.35)
Day $^{0,+1}$	+	6.874***	18.694***	-11.820***
		(0.01)	(0.00)	(0.00)
Observations		400,029	241,332	
Fixed Effects		Firm	Firm	
Adjusted R-squared		0.821	0.759	

This table presents coefficients (p-values) from estimates of equation (1), $Spread = \varphi_0 + \alpha_1 SA + \alpha_2 Day^{-4,-1} + \alpha_3 Day^{0,+1} + \sum_k \gamma_k Controls_k + \beta_1 SA * Day^{-4,-1} + \boldsymbol{\beta_2 SA * Day^{0,+1}} + \sum_k \delta_k Controls_k * Day^{-4,-1} + \sum_k \omega_k Controls_k * Day^{0,+1} + \sum_j \theta_j Firm_j + \epsilon_{i,d}$. The No Forecast (Forecast) column in Panel A presents results for firms that do not provide (provide) an earnings estimate for the quarter of interest. Controls are suppressed for brevity. Each estimation uses, for all firm-quarters, the 21 days centered on the firm's earnings announcement, clusters standard errors by firm and quarter, and includes firm fixed effects. *Spread*=the firm's daily average percentage bid-ask spread. *SA*=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. *Day* $^{0,+1}$ is a indicator variable equal to 1 for days 0 and +1 relative to the earnings announcement, and zero otherwise. *Day* $^{-4,-1}$ is an indicator variable equal to 1 for days -4 through -1 relative to the earnings announcement, and zero otherwise. *** (**, *) denotes one-tailed (two-tailed) significance at the p<0.01 (p<0.05, p<0.10) level when coefficient signs are predicted (not predicted). Appendix A provides detailed definitions of all variables.

TABLE 7

Information Asymmetry around SA Article Dates

Dependent Variable: *Spread*

	[1]	[2]
Day$^{-4,-1}$	-0.196*	-1.004***
	(0.07)	(0.00)
***Day*$^{0,+1}$**	**-1.213*** **	**-2.578*** **
	(0.00)	**(0.00)**
Day$^{+2,+10}$	-1.345***	-2.308***
	(0.00)	(0.00)
CAR	13.137*	38.377**
	(0.07)	(0.02)
Depth	0.002	-0.001
	(0.18)	(0.73)
DJarticles$^{-1,+1}$	0.364***	0.079
	(0.00)	(0.53)
InstOwn	-35.15***	-43.492***
	(0.00)	(0.00)
Price	0.048***	0.077***
	(0.00)	(0.00)
Size	-18.679***	-26.797***
	(0.00)	(0.00)
Turnover	-0.652***	-0.882***
	(0.00)	(0.00)
Volume	-0.003	-0.018
	(0.86)	(0.56)
Volatility	5.77***	6.104***
	(0.00)	(0.00)
Observations	2,443,266	840,924
Fixed Effects	Firm	Firm
Adjusted R-squared	0.82	0.836

This table presents coefficients (p-values) for tests of information asymmetry around SA article release dates. We use a window of -10 days to +10 days around the SA article (Thus, 2,443,266 observations divided by 21 days equals the 116,346 SA articles shown in Table 1). Column 1 uses the full sample of SA articles. Column 2 uses the reduced sample of SA articles, which exclude SA articles within 1) a 5-day window of a professional analyst report or 2) within a 5-day window of the firm's earnings announcement. Standard errors are clustered by firm and quarter. *Day*$^{0,+1}$ is a indicator variable equal to 1 for days 0 and +1 relative to the Seeking Alpha article release and zero otherwise. *Day*$^{-4,-1}$ is a indicator variable equal to 1 for days -4 through -1 relative to the Seeking Alpha article release, and zero otherwise. *DAY* $^{+2,+10}$ is an indicator variable equal to 1 for days +2 through +10 relative to the Seeking Alpha article release, and zero otherwise. *** (**, *) denotes two-tailed significance at the p<0.01 (p<0.05, p<0.10) level. All variables are defined in Appendix A.

TABLE 8

Effect of SA Coverage on Earnings Announcement Opinion Divergence

Dependent Variable: *SUV*

	Predicted Sign	[1]
SA* Day $^{\mathbf{0,+1}}$	**-**	**-0.082*****
		(0.00)
SA	?	-0.027***
		(0.01)
Day$^{0,+1}$	+	0.553***
		(0.00)
Observations		641,361
Fixed Effects		Firm
Adjusted R-squared		0.180

This table presents coefficients (p-values) from estimates of equation (1) with SUV as the dependent variable, $SUV = \varphi_0 + \alpha_1 SA + \alpha_2 Day^{-4,-1} + \alpha_3 Day^{0,+1} + \sum_k \gamma_k Controls_k + \beta_1 SA * Day^{-4,-1} + \beta_2 \boldsymbol{SA} * \boldsymbol{Day^{0,+1}} + \sum_k \delta_k Controls_k * Day^{-4,-1} + \sum_k \omega_k Controls_k * Day^{0,+1} + \sum_j \theta_j Firm_j + \epsilon_{i,d}$. Controls are suppressed for brevity. Each estimation uses, for all firm-quarters, the 21 days centered on the firm's earnings announcement, clusters standard errors by firm and quarter, and includes firm fixed effects. *SUV* is standardized unexpected volume as defined by Garfinkel (2009). *SA*=the decile rank of the number of Seeking Alpha articles (authors) in Column 1 (2) during the period from day +10 of the previous earnings announcement through day -5 of the current earnings announcement. *Day*$^{0,+1}$ is an indicator variable equal to 1 for days 0 and +1 relative to the earnings announcement, and zero otherwise. *Day*$^{-4,-1}$ is a indicator variable equal to 1 for days -4 through -1 relative to the earnings announcement, and zero otherwise. *** (**, *) denotes one-tailed (two-tailed) significance at the p<0.01 (p<0.05, p<0.10) level when coefficient signs are predicted (not predicted). Appendix A provides detailed definitions of all variables.