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Skin in the game: personal stock holdings and investors' response to stock analysis on social media

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Abstract
Motivated by concerns that financial positions impair analyst objectivity, we examine investor perceptions of the financial positions of nonprofessional analysts (hereafter NPAs) writing on the social media outlet Seeking Alpha. We find that NPA positions contribute directly to short-window returns surrounding the article's publication, holding constant the information in the article as well as contemporaneously issued news from professional analysts, managers, and the business press. Contrary to concerns that stock positions are associated with biased analysis, we find no evidence that NPA positions reduce investor responses to the tone of the article. In fact, our evidence suggests that holding a position *magnifies* investor responses to both positive and negative tone, although this effect is limited to tone that is contrary to the NPA's stock position. Overall, our findings suggest that, contrary to regulators' concerns, NPA stock positions do not decrease the credibility and informativeness of their analyses.

Keywords Analysts · Social Media · Conflicts of Interest · Disclosure

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1 Introduction

A large body of research establishes that professional financial analysts play a valuable role in the capital markets by providing both new information and

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interpreting previously released information (e.g., Womack 1996; Asquith et al. 2005; Bradshaw 2011; Bradshaw et al. 2017; Brown et al. 2015, 2016; among others). In addition, over the last decade, access to financial information has exponentially increased, leading to the proliferation of nonprofessional analysts (hereafter, NPAs) on social media (Chen et al. 2014; Drake et al. 2017) that has led some in the industry to question whether the role of professional financial analysts will eventually become obsolete (Dediu 2011; Chernova 2014). However, a challenge to the use of nonprofessional analysis by investors is the lack of regulation: unlike professional analysts, NPAs face little regulatory oversight, leading to the potential for market manipulation.[1]

We examine the information conveyed by analysis posted to the social media site Seeking Alpha (seekingalpha.com, hereafter, SA)[2] to evaluate whether perceived credibility (i.e., investor response to analysis) varies with an NPA's personal stock position in firms about which he or she writes. On the one hand, practitioners and regulators have expressed concern that stock positions may impair the objectivity of financial statement analysis. For example, the Securities and Exchange Commission (SEC) argues that stock positions "can create pressure on …independence and objectivity," although "the existence of these relationships does not necessarily mean …bias" (SEC 2016). On the other hand, NPAs with personal stock positions have a vested interest in the stocks about which the write, which may enhance the quality, rigor, and timeliness of their analysis.

We examine two specific research questions. First, does an NPA's financial position convey information incremental to the content of their analysis? If so, the direction of that position could reveal the NPA's private information to investors. However, if a financial position indicates bias on the part of the author, then investors would not find the position to be incrementally informative. Second, do investors find the tone in an NPA's analysis to be more credible when the author has a financial position (i.e., the author has "skin in the game")? If holding financial positions increases the quality of the NPA's analysis, investors may respond more strongly. Conversely, if investors perceive NPA's with personal stakes to be biased, we may observe a weaker response to the analysis.

Seeking Alpha (SA) requires NPAs to include position disclosures in the articles they write. Using 104,952 SA articles from 2006 to 2015, we find that these disclosures contribute directly to short-window returns surrounding the article's publication, after controlling for the content of the article (i.e., tone, length, rigor, numerical content, etc.) as well as contemporaneously issued news (i.e., from professional analysts, managers, and the business press). In terms of economic significance, we find that the disclosure of a long (short) position by

[1] Unlike professional analysts or firm insiders, NPAs publishing on sites like Seeking Alpha do not face legally enforced "blackout periods" that limit trading activity around the publication of their reports. However, they are still subject to US laws regarding market manipulation (15 U.S. Code § 78i).

[2] There are a number of social media venues considered by prior research, such as Motley Fool, Estimize, StockTwits, Yahoo! Finance, and online stock message boards. We focus on Seeking Alpha because (1) it requires contributors to provide written, edited analysis (suggesting a certain level of rigor and sentiment, or tone), and (2) it requires contributors to disclose whether they have a financial position in the firms about which they write. Chen, De, Hu, and Hwang (2014) find that Seeking Alpha content represents value-relevant information. Additionally, Drake, Thornock, and Twedt (2017) identify Seeking Alpha as a credible internet-based information intermediary.

an NPA corresponds to a two-day return of 0.4% (−1.2%).[3] These findings suggest that investors view a position disclosure as an information signal in its own right, presumably about the NPA's private information that is not included in the article.

Next, we find no evidence that NPA positions reduce investor responses to the tone of the article, again challenging the view that the effect of analyst stock positions is to produce biased analysis. Instead, our evidence suggests that these positions, if anything, make the analysis *more* credible. Specifically, we find that NPA positions appear to *magnify* investor responses to tone. Additional analysis suggests this result is primarily driven by tone contrary to an NPA's position (i.e., short positions magnify the response to positive tone, and long positions magnify the response to negative tone). In that sense, investors find the NPA to be most credible when they provide information about a firm that goes against their personal financial interests. However, it is important to note that tone that is directionally consistent with an NPA's position is not discounted, relative to analysis by NPAs with no positions, again inconsistent with financial positions inducing credibility-reducing bias. Overall, our results suggest that investors find position disclosures credible and useful for assessing the NPA's private information and that NPA positions increase the credibility and informativeness of their analyses rather than constituting conflicts of interest.

In additional analyses, we perform several tests to mitigate the likelihood that our results are attributable to other major events occurring concurrent to each article's publication. First, we restrict our sample to articles published in the early trading hours of the equity market. As we explain in Section 5.1, SA's editorial process makes it virtually impossible for early-morning articles to be written about events occurring on the same day as the article's publication. Results in this subsample are identical to those previously discussed, mitigating the concern that our results are due to investor reaction to an event other than the article release. Second, we test whether the reaction to an NPA's position strengthens with article length, rigor, and numerical content. Consistent with this expectation, we show that the positive (negative) association between long (short) position disclosures and returns strengthens with the length of the article. We also find some evidence that numerical content strengthens investor reactions to disclosure of short positions. These results suggest an interactive effect between the effort put forth by the NPA and the information conveyed by their stock position. Third, we examine whether the first-time disclosure of a position is more informative than subsequent disclosures and find that the reaction to both short and long disclosures is significantly stronger the first time an NPA discloses a position.[4]

We offer two important caveats for our findings. First, we are not aware of any mechanism through which SA obtains information about an NPA's investment portfolio, so they cannot audit an NPA's position disclosures. Therefore an author could intentionally mislead investors with his or her position disclosures. For that reason, we

[3] Based on data provided by George Moriarty, SeekingAlpha's editor, SA is used by both institutional and retail investors. His data suggests that the professional investors that use SA control \$15 trillion in managed assets (from both institutions and high net-worth clients) and retail investors report \$1.3 trillion in savings and investments. Thus, if SA position disclosures are informative, users of the information have the purchasing power to significantly move stock prices.

[4] We expect first-time disclosures to be most informative because they indicate new information about an author's position that may be value relevant. However, repeat disclosures indicate a continued commitment to the position and likely still provide information.

examine whether the contemporaneous reaction to a position disclosure is met with a subsequent reversal of that reaction, which one would expect if manipulation drove some of our earlier results. We find no evidence of a reversal of investors' initial responses, which is inconsistent with position disclosures being untruthful. In fact, we find that short positions are associated with continuing *negative* returns over the 60 days following the disclosure (i.e., a drift rather than a reversal).

Second, all archival studies in this area face the concern that social media activity is nonrandom (i.e., NPAs choose the firms that they follow as well as when to write an article). Of specific concern to our study is the possibility that a significant corporate event precipitates the article and that the event directly affects both the NPA's decision to write an article as well as investor reaction to that article. We attempt to mitigate the likelihood that our results are due to other corporate events through a number of research design choices, including using a return window of [0, +1] and controlling for a litany of identifiable contemporaneous events (e.g., business press articles, analyst reports, earnings announcements, etc.). Furthermore, our results *strengthen* in subsamples less likely to be confounded by other news (i.e., articles published in relatively quiet periods) and hold on a subset of articles that were written by NPAs on the day *prior* to its posting on SA (when the articles could not relate to events that are announced during our return window). Nonetheless, we cannot rule out the possibility that a simultaneous corporate news event has at least some impact on the economic significance of our empirical results.

Our study provides several contributions to the accounting and finance literatures. First, we contribute to the literature on the informativeness of crowd-sourced, peer-based advice (e.g., Chevalier and Mayzlin 2006; Liu 2006; Chen and Xie 2008; Zhu and Zhang 2010; Jame et al. 2016; Drake et al. 2017; Tang 2017). Through an examination of SA articles, Chen et al. (2014) takes a first step toward addressing the question of whether crowd-sourced financial statement analysis on social media conveys credible and value-relevant information or if instead such analysis represents noise or even an attempt to mislead. They find that, on average, these articles provide value-relevant information that is incremental to traditional information sources, such as the business press and professional financial analysts. Because SA is not directly regulated and NPAs, unlike financial journalists, lack established rules of conduct, these findings suggest that users of social media must find alternative mechanisms for assessing the credibility of information.[5] Consistent with this supposition, Chen et al. (2014) also find that investors perceive the information in SA articles to be more credible when NPAs have an established record of providing value-relevant analysis. We identify a credibility-enhancing signal that can vary by NPA: investors perceive NPAs as more credible if they hold a position in the firm's stock, thus aligning their personal incentives with either long or short traders. Furthermore, we find no evidence that NPAs exploit investors' trust, on average, despite no enforcement mechanism to ensure that they report their positions honestly, suggesting that social and reputational pressures motivate honest reporting.

Second, we contribute to research on analysts' conflicts of interest. Much of this research finds that analysts have significant conflicts of interest placed on them by their

[5] As previously mentioned, US law may provide an enforcement mechanism for truthful reporting of positions: while SA cannot observe the portfolios of its NPAs, the SEC certainly can. However, because NPAs are often writing about their own analysis and opinion, readers of SA articles must still pay attention to their credibility.

firms (e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dechow et al. 2000; Daniel et al. 2002; Bradshaw et al. 2006; Ke and Yu 2006). In a review of this literature, Bradshaw (2011) notes that one of the most prevalent beliefs in the capital markets is that analysts' behavior is dominated by conflicts of interest. SEC rules not only require analysts to disclose their positions but also impose strict rules on the timing and nature of those positions to mitigate conflicts of interest.[6] Consistent with these regulations, laboratory studies suggest that investors find analysts to be *less* credible when they have "skin in the game" (Taha and Petrocelli 2014; Marley and Mellon 2015; Elliott et al. 2018). In contrast, prior archival literature suggests that "paid-for" analysts, or those hired by the firm under scrutiny, produce informative reports, despite the inherent conflict of interest (Kirk 2011; Billings et al. 2014). More recently, Chan et al. (2018) examine the effects of long positions (i.e., stock ownership) on professional analysts' buy, hold, and sell recommendations; earnings forecasts; and target prices. They find some evidence that buy and sell recommendations of analysts owning stock are perceived as more credible but fail to find similar evidence for earnings revisions or price targets, the latter of which appear to be less credible. Possible reasons for this mixed evidence include professional analysts' heavily regulated environment, a low base rate of ownership (i.e., only 2.6% of all analyst reports disclose an ownership position), and the difficulty in disentangling the various signals issued in an analyst report (Bradley 2018). Using SA NPAs whose trading is not restricted and who, as a result, more frequently own the stocks they analyze (i.e., 27% of our SA articles disclose an author position), we find that investors perceive NPAs to be more credible when they hold positions in the firms about which they write. Thus our study should be of interest to regulators in evaluating what informational and regulatory restrictions should be placed on financial analysts and other information intermediaries.

Third, we contribute to the literature on the role of the business press in financial markets by investigating how NPA financial positions affect investors' use of information. Research examines various aspects of how the financial press contributes to a firm's information environment (Davies and Canes 1978; Barber and Loeffler 1993; Huberman and Regev 2001; Busse and Green 2002; Miller 2006; Tetlock 2007, 2010; Bushee et al., 2010; Engelberg and Parsons 2011; Dougal et al., 2012; Gurun and Butler 2012; Bradshaw et al. 2015; Li 2015; Blankespoor et al., 2018). Collectively, this research suggests that the financial press plays an important role in both the origination and dissemination of information but does not consider whether journalists' positions in the firms they cover affect this process. We contribute to this research stream as the first to examine whether these stock positions impart incremental information to investors and whether they enhance or impair credibility.

2 Background, prior literature, and hypothesis development

2.1 Personal stock positions and credibility

Whether personal holdings affect the credibility of opinions disseminated by nonprofessional analysts is an empirical question. Research identifies two primary sources of

[6] The current analyst disclosure rules were initially developed by the New York Stock Exchange (NYSE) and the Financial Industry Regulatory Authority (FINRA) and then adopted by the SEC in 2002 (SEC 2016).

conflicts of interest for professional analysts that may impair the credibility of their work. Specifically, there are *firm-related conflicts*, such as the generation of investment banking fees, trading commissions, trading gains/losses, etc. (e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dechow et al., 2000; Daniel et al. 2002; Bradshaw et al. 2006; Jacob et al. 2008) as well as *personal conflicts*, such as their compensation structure, long-term reputation, job security, need to ingratiate themselves with managers and powerful investor groups, and personal trading gains and losses (Ke and Yu 2006; Bradshaw 2011).

Regulators worry that stock positions of analysts could create an additional bias, impairing the credibility of their reports and recommendations (SEC 2016), and experimental research provides evidence consistent with this concern. Specifically, Taha and Petrocelli (2014) and Marley and Mellon (2015) directly investigate conflicts of interest arising from analysts' personal financial positions and find evidence that analysts with stock positions are *less* credible. However, both experiments use a single-period game in a laboratory setting, which removes any possible effects of analyst reputation. Most relevant to our setting, Elliott et al. (2018) suggest that experimental investors perceive social media participants with stock positions as less credible than those without. In archival settings, Bradshaw et al. (2014) find that analysts' conflicts of interest contribute to forecast bias in an international setting. Recently, Chan et al. (2018) provide mixed evidence on whether professional analysts' personal holdings affect their credibility. Specifically, their results suggest that analysts with ownership positions appear to issue (1) more informative buy, hold, and sell recommendations; (2) earnings forecasts that are no more informative; and (3) target prices that appear to be biased upwards. Bradley (2018) provides a full discussion on the implications of their study. Further complicating the inferences that can be drawn from the work of Chan et al. (2018) is the fact that professional analysts face regulatory scrutiny and trading restrictions on any ownership positions, and, as a result, most professional analysts do not take such positions (Bradley 2018). This fact is supported by Table 1 of Chan et al., which reports that only 2.6% of analysts' reports convey that the analyst holds an ownership position (Column 4). That is, there might be a selection problem associated with those professional analysts who choose to take ownership positions, despite the associated regulatory scrutiny and trading restrictions, and this problem could make their results difficult to generalize.[7]

There is also research on whether stock positions impact investors' perceptions of disclosures provided by other investors, such as firm-insiders (managers). To alleviate conflicts between managers and shareholders, 92% of firms adopt some type of policy regarding insider trading (i.e., blackout periods) (Bettis et al., 2000), whereby insiders are prohibited from trading during the trading days surrounding an earnings announcement. Bettis et al. (2000) present evidence that blackout periods on manager trading reduce adverse selection costs, suggesting that, when firms impose trading prohibitions on insiders, investors perceive the information as more credible. Furthermore, insiders

[7] Bradley (2018) argues that the most "interesting, controversial, and convincing evidence" in Chan et al. (2018) is the evidence in their Table 7 showing that, in 424 instances, analysts appear to sell their ownership positions while maintaining a buy recommendation, an act that is generally prohibited by law. However, this activity is exceedingly rare, as it represents 0.06% of all buy recommendations in the sample (i.e., 424 out of 749,606 buy recommendations). Importantly, this evidence does not conflict with our finding that, *on average*, position disclosures appear to enhance analysts' credibility.

are often privy to substantial value-relevant information not possessed by the market as a whole (Jaffe 1974; Seyhun 1986). As such, it seems natural that investors would want to observe their portfolio positions and changes in these positions. Indeed, recent studies suggest that timely information about manager purchases convey information to market participants (Fidrmuc et al., 2006; Brochet 2010).

With respect to professional investors, the literature suggests that institutional investors try to withhold private information. For instance, Agarwal et al. (2013) find that, when hedge funds ask the SEC to keep their ownership levels confidential, these positions are associated with information-sensitive events and higher information asymmetry. They conclude that stock positions of hedge funds convey information about their private information. Similarly, Aragon et al. (2013) conclude that hedge fund managers seek confidentiality to protect proprietary information.

NPAs publishing on SA share attributes with many of these groups. They are very similar to professional analysts (because they publicly provide detailed analyses about firm value) and investors (because they describe themselves as active investors). While not insiders, SA contributors may also have an information advantage over other investors because of unique access to management (Seeking Alpha, 2017).[8] However, there are also important differences between SA NPAs and these groups. The former *voluntarily* disclose their private information and face no trading restrictions (i.e., blackout periods) or enforcement (i.e., no portfolio audits). Thus, NPAs could either immediately trade out of a position after publishing an article or provide a false disclosure in an attempt to manipulate price (e.g., falsely disclose a short position prior to purchasing a stock). However, while strategies such as this are possible, they are unlikely to be sustainable in a multi-period setting without anonymity, and, in egregious cases, NPAs may face market manipulation charges from the SEC for providing false disclosure. We think it is more likely that NPAs provide credible private information to bolster their reputations in the investing community, providing opportunities to sell their analysis to others and to accelerate price discovery for their stock positions (Pasquariello and Wang 2018; Ljungqvist and Qian 2016). In the latter case, personal stock holdings could enhance credibility if it implies that the NPA is confident enough in their information set to "put their money where their mouth is."

2.2 Social media and investor-sourced stock opinions from SeekingAlpha

Social media allows investors to supplement information from traditional sources by communicating directly with one another.[9] Although the method of information sharing makes a difference, with some venues (e.g., internet stock message boards) seeming to produce mostly noise and confusion (Antweiler and Frank 2004; Das and Chen 2007), recent research suggests that social media can produce and disseminate value-relevant information. For instance, both Chen et al. (2014) and Jame et al. (2016) find evidence

[8] According to SeekingAlpha's website, one benefit of being a contributor is "access to company management" (https://seekingalpha.com/page/become-a-seeking-alpha-contributor). There, the publication mentions that "[c]ompanies pay close attention to what is written about them on SA. Some companies also contribute via articles and comments. Many contributors have been given exclusive access to company executives to get their side of the story."

[9] A related stream of literature examines how firm insiders, such as managers or employees, communicate with market participants via social media (e.g., Blankespoor et al. 2014; Hales et al. 2018).

that social media (i.e., SA and Estimize, respectively) communicates new information to the market. The latter study finds that crowd-sourced earnings estimates are as accurate as professional analyst forecasts for some horizons, lending credence to speculation that the role of the paid professional financial analyst might eventually become obsolete (Dediu 2011).[10] Using Twitter, research similarly links aggregated sentiment to both future sales and earnings announcement news (Tang 2017; Bartov et al. 2018). Finally, Drake et al. (2017) identify the internet as a new important information intermediary and suggest that content published on sites like SA improves price efficiency.

One of the largest social media platforms, SA has become a popular venue for both professional and nonprofessional investors to share the results of their analyses of financial securities. SA is rapidly becoming one of the most referenced sources for financial news and analysis. Investopedia.com ranks it third, behind only Google Finance and Yahoo! Finance, and users of "the top tens" rank SA first, ahead of both the *Wall Street Journal* and *Financial Times*.[11] Citing Chen et al. (2014), the *Wall Street Journal* even speculates that NPAs publishing on sites like SA could replace professional financial analysts (Chernova 2014). SA reports an average of 7 million unique visitors per month and states its mission is to provide "opinion and analysis rather than news…written by investors…rather than journalists" (Seeking Alpha 2016). SA users are also influential: according to the website's editor, George Moriarty, the publication's subscribers control more than $16 trillion in investable assets, the large majority of which are controlled by institutional investors.

SA publishes an average of 200 to 250 articles per day, which, given their subscription base, corresponds to 200 million email or mobile alerts going out each month. SA does not generally solicit opinions or content but does pay contributors based on the number of users accessing their content. Importantly, authors are not permitted to publish the content of their articles elsewhere. Chen et al. (2014) suggest that the long form of SA articles, combined with the curation of content by SA's editorial board, results in the identification of NPAs with something valuable to say and an opportunity for them to say it. Consistent with this suggestion, they find that the fraction of negative words in an SA article is negatively associated with both stock returns over the following three months and subsequent earnings surprises.

In addition to its broad and influential readership, SA is unique from other social media platforms in that the articles provide substantial, edited analysis, which may include a formal "recommendation."[12] Platforms like Estimize (Jame et al. 2016; Da and Huang 2017) provide an earnings estimate without any analysis. Stock message boards and Twitter allow any user to post information without quality control. SA articles, and in particular the long form articles we sample, provide in-depth analysis that is edited to ensure quality control.

In conclusion, research establishes that, on average, social media represents an important and emerging venue for value relevant news and SA articles, in particular,

[10] The passage of MiFID II in Europe has also led some to predict the demise of sell-side analysts (e.g., Morris 2017, Armstrong 2018), further suggesting platforms like SA will be important sources for investment news.

[11] See http://www.investopedia.com/articles/investing/112514/top-sites-latest-stock-market-news.asp and http://www.thetoptens.com/financial-news-websites/. Both sites accessed in Summer 2017.

[12] As a rule, SA articles themselves do not uniformly include an author's recommendation, though the author's analysis may come with in implicit recommendation to buy or sell a stock. In addition, SA uses keyword algorithms to generate categories of stock analysis, and two of those categories are "long ideas" or "short ideas." However, not all articles by long (short) authors are tagged as "long (short) ideas," and not all authors writing a long and short idea have a position in the stock they recommend. Note that our sample begins with all SA articles (which have many different categories, including long and short ideas, among others).

provide information that predicts a firm's future earnings and future stock prices (Chen et al. 2014). However, while this evidence suggests that these articles represent credible sources of information, no study has examined how personal financial incentives of social media participants (i.e., NPAs' financial positions) affect contemporaneous reaction to these articles.

2.3 Hypotheses

We expect that NPA stock positions could increase investor response for at least three reasons. First, these NPAs likely conduct more diligent and careful research to form their opinions because they have a personal financial stake in the firm. Second, when expressing their opinions, NPAs with personal positions may withhold at least a portion of their private information, thus making the act of disclosing a stock position a signal in its own right, similar to professional analysts' stock recommendations accompanying their detailed analysis. Finally, investors with personal holdings have incentives to accelerate price formation to realize profits on their investment positions in a more timely fashion (e.g., Pasquariello and Wang 2018; Ljungqvist and Qian 2016).

As previously discussed, Chen et al. (2014) finds that negative tone in a SA article is associated with lower returns over the following 60 trading days, implying that investors react to the information conveyed by the articles. This is consistent with SA's own claim that its "articles frequently move stocks" (Seeking Alpha 2016). Therefore our first hypothesis tests whether an NPA's stock position is a signal about the NPA's beliefs regarding the valuation of the company (i.e., like an analyst's buy or sell recommendation or a manager's forecast) that is incremental to the other information conveyed in the article. We expect the stock price to contemporaneously increase for the disclosure of long positions and to decrease for the disclosure of short positions, controlling for other information conveyed by the article (i.e., tone, length, rigor, numerical content, etc.).

H1: Investors respond to the disclosure of stock positions by NPAs.

If stock positions induce bias into these articles, however, we do not expect to find support for H1.

Our next question is whether the credibility of NPA's voluntary disclosure is impaired or enhanced when he or she has a financial position. As previously discussed, if the NPA has a financial position in the firm written about, this suggests "skin in the game" and thus might be more credible. If this is the case, we expect a *stronger* reaction to an NPA's tone when that NPA has a stock position (i.e., there is enhanced credibility). Our second hypothesis follows.

H2: Investors respond more strongly to tone in SA articles authored by NPAs with stock positions than by those with no stock positions.

On the other hand, investors could perceive that a stock position creates a conflict of interest. For example, NPAs could provide analysis that is intentionally biased in either positive or negative direction, and, if it generates trading in the same direction, the NPA could personally profit from it. In addition, NPAs could report a position disclosure that they do not actually hold to move the market and profit from the movement. For example, they could report a short position that they do not have, expecting a short-term negative price response, and then purchase the stock at an artificially deflated price. In this case, the reaction to an NPA's tone should be *weaker*, as investors discount the tone of the information, compared to when the NPA takes no position.

We test each hypothesis using short-window returns surrounding the release of each SA article, as we discuss in the next two sections. However, in additional analyses, we also examine long-window returns (60 trading days), as do Chen et al. (2014), to assess whether any short-window effects persist or reverse. We discuss these results in Section 5.2.

3 Data and research design

3.1 Seeking Alpha data

We obtain news content from Seeking Alpha by systematically downloading all content published before July 7, 2015 (the date we performed the query). To ensure that we capture new analysis provided to the markets, we download "articles" (available at seekingalpha.com/article) rather than "news" (available at seekingalpha.com/news). The former represents long-form analysis whereas the latter represents shorter news-flash-like content. Table 1 describes this beginning sample and sources of data-loss. In total, we obtain 487,197 SA articles.[13] We then parse each article to identify the article title, timestamp, referenced stocks (tickers), article content, authoring NPA, and position disclosure, each clearly delineated with specific HTML tags. The header information of the articles identifies tickers for referenced companies in two categories, "Primary" and "About." Primary tickers are only identified when a company is the focus of the article and analysis, and the "About" tickers capture other mentioned companies. We exclude articles without a "Primary" ticker, as these articles often contain news summaries across the market or within a particular industry, rather than substantive analysis regarding an individual firm. Excluding these summaries reduces our sample by 280,219 articles. Because our primary interest relates to the price effects of NPA positions, we delete another 58,378 articles with no position disclosure.[14]

Disclosures generally, though not universally, follow the same basic format. At the beginning or end of each article, the NPA includes a statement such as "I am/we are long XXX," "I/we have no positions in any stocks mentioned, and no plans to initiate any positions within the next 72 hours," or "I am/we are short XXX." However, in

[13] During our sample period, SA offered a "pro" subscription that gave subscribers early access to content selected by editors. Per our discussion with the SA editor, this access lasted 24 h after which the article is made public for 30 days. After that period, the article is archived behind a paywall and available only to pro subscribers. Due to our sampling procedures, we did download a limited number of pro articles that were published in the 30 days preceding our query of SA, but these articles were not accessible when we extracted comments at a later date and are therefore excluded from our final sample. Thus, our sample is fully comprised of articles which were available to the public on the timestamp appearing in the article. Note that, as of mid 2018, this process appears to have changed. Immediate access to articles is limited to tickers included in a user's portfolio, and access to archived content requires a pro subscription.

[14] Disclosures of positions were relatively rare until 2012 (no more than 20% each year), when SA started requiring these disclosures. In more recent years, most (over 90%) of articles with a primary ticker designation include disclosures.

Table 1 Sample attrition

Seeking Alpha articles downloaded as of July 7, 2015	487,197
Articles missing primary ticker designation	(280,219)
Articles missing position disclosure	(58,378)
Articles with ambiguous position disclosure	(246)
Articles with successfully coded disclosures	148,354
Articles not linked to CRSP	(21,124)
Articles missing other controls	(11,358)
Articles missing returns for any period	(10,920)
Total articles in sample	104,952
Unique Firm-day combinations	86,741

other instances positions are less clear, as the NPA may disclose complex option holdings or multiple positions in different stocks (i.e., long XXX and short YYY). Therefore we use a two-stage procedure to code all disclosures.

First, we identify long positions by searching for the terms "long," "hold," or "own stock/shares." We then capture the text following those words, stopping when a period or the word "may" or "short" is encountered. The latter two words indicate the beginning of a new position disclosure (i.e., "I am long … and may…"). We repeat this procedure for possible short positions, looking for the word "short" and then capturing tickers until the word "long" or "may" or a period. Note that, for both long and short positions, we do not allow negating or qualifying words (no, not, none, neither, never, nobody, may, or plan) to occur within the five words preceding the position indicator. Finally, we search for cues that the NPA holds no position in any stocks. These include the terms "No Position," "None," or "May."

Inspection of results suggests these search procedures are relatively accurate, but we do encounter complex disclosures that yield multiple classifications (i.e., long, short, and/or no position) or instances where we fail to identify any of the three positions. Further, disclosure of long or short positions could be in reference to stocks other than the stock about which the article is primarily written. Therefore we further refine our disclosure coding as follows. First, to confirm a long or short position, we require the primary ticker of the article to match one of the tickers identified in the position disclosure. If the tickers do not match, we code the disclosure as "no position." Second, inspection of disclosures where we fail to identify long, short, or no position cues suggests these are almost universally no-position disclosures, so we code them as such. Finally, we manually inspect 370 disclosures that our procedure tagged as both long and short. Based on this inspection, we code 80 of these articles as long and 44 as short. The remaining 246 disclosures correspond to unclear positions, usually involving both equity and option positions (i.e., own stock in X and short calls in X). We drop those from our sample, leaving 148,354 coded articles.[15]

We next attempt to match the primary tickers to the CRSP and Compustat header and history files. Approximately 4700 tickers fail to match these header

[15] For brevity, we refer to articles authored by investors with long (short) positions as "long articles" ("short articles") and to those holding no position as "no position articles."

files. Manual inspection of the data suggests that the majority of these relate to ETFs or REITs, but we also fail to match a few large companies, such as Alphabet and Under Armour, due to minor differences in tickers reported by SA and other data sources (e.g., GOOG vs. GOOGL). Therefore we manually investigate each unmatched ticker that corresponds to at least 20 articles (approximately 200 stocks corresponding to 14,000 articles) and identify a link to CRSP and Compustat where possible. In total, we lose 21,124 articles for stocks where we cannot identify a CRSP identifier (i.e., permno) upon which to merge. Finally, we lose another 11,358 articles that are missing any one of our basic control variables and 10,920 with missing returns for any measurement window. This leaves us with a final sample of 104,952 articles. In most of our analyses, we collapse this dataset down to 86,741 unique firm-trading day combinations.[16]

3.2 Descriptive information on SA NPAs

Before moving to our research design and results, we first present some basic descriptive information about NPAs who write for SA. We obtain this data from two sources. First, upon request, SA's executive editor provided us with basic demographic information they collect about their universe of NPAs. To supplement this data, we use a series of Python scripts to analyze the biographies posted on SA for the NPAs in our sample. We present the SA provided information (the information we generated) in Panel A (Panel B) of Table 2.

SA NPAs appear to largely consist of independent investors who are interested in establishing, building, and maintaining reputations within the investment community. Based on the descriptive data, 75% of SA NPAs reveal their name and place of employment, suggesting that a majority of NPAs face reputational concerns not only online but also in their "day jobs." SA pays each an average nominal wage of $33.30 per month based on the number of page-views. Thus, for most NPAs, monetary rewards do not appear to be the primary driver of producing high quality content. SA also reports that 27% of its nonprofessional analysts have their own independent investment blog, suggesting a substantial portion of them invest significant time in the investment community beyond SA.[17] Taken together, these results suggest that, on average, SA NPAs seek to establish a reputation within the financial community or to accelerate stock price formation rather than to earn money directly from their SA analyses.

[16] While the sample attrition in Table 1 may at first glance appear dramatic, the majority of sample attrition is due to (1) the removal of SA articles that do not relate to one specific ticker symbol (i.e., that are industry or macroeconomy articles), (2) the requirement to disclose whether the NPA holds a position, and (3) the ability to match the identified ticker symbol with a firm listed in CRSP and Compustat. Thus, when put in context, our sample attrition is largely driven by factors that are necessary to answer our questions of interest. Given our research design, we do not believe these data restrictions induce any systematic biases in our sample.

[17] SA prohibits authors from publishing the full content of their analysis in other locations. Therefore it is unlikely articles written by authors with their own blogs could be published in advance of clearing the publication's editorial process. Nonetheless, in a sensitivity analysis, we exclude articles written by authors appearing to have personal website. All of our results are quantitatively and qualitatively unchanged.

Table 2 Nonprofessional analyst (NPA) characteristics

PANEL A: NPA Characteristics As Described By Seekingalpha

	# of NPAs	% of Total
Total NPAs	13,680	
NPAs with independent blogs	3711	27.13%
Anonymous NPAs	3358	24.55%
Financial Professionals	4891	35.75%
Students (Young Investors)	1056	7.72%
Company Executives/C-Level	748	5.47%
Monthly Average Payment to NPAs in 2016	$33.30	

Panel B: NPA characteristics collected from biographies

Characteristic	Total	Position = −1	Position = 0	Position = 1
Individual NPA	56.16%	60.51%	53.03%	63.53%
Company NPA	16.37%	8.89%	19.27%	9.88%
Anonymous NPA (alias)	27.47%	30.60%	27.70%	26.59%
	100.00%	100.00%	100.00%	100.00%
Includes "Analyst" in bio	14.28%	16.11%	14.51%	13.52%
References blog or website (other than LinkedIn)	42.06%	41.04%	42.07%	42.12%
Mentions "MBA" in bio	8.76%	16.67%	8.74%	8.03%
Mentions "CFA" in bio	6.62%	7.00%	7.26%	4.97%
Followers at time bio page was downloaded (mean)	4486	3850	4487	4547

Table 2 reports descriptive statistics for NPA characteristics. Panel A reports information provided by Seeking Alpha, and Panel B reports information pertaining to articles in our sample. For Panel B, we downloaded each NPA's bio from Seeking Alpha (http://seekingalpha.com/author/...) and used hand-coding or textual analysis to collect select information. We manually coded each NPA as an individual, a company, or an alias. Remaining information was systematically extracted from each bio page

Panel B provides the information we collected and coded for all NPAs in our sample as well as descriptive statistics by position (Short, No Position, Long). We first manually code each NPA as an individual, a company (a private investment firm, advisor, etc.), or anonymous. Similar to Panel A, approximately 27% of NPAs use an alias while the remaining 73% identify themselves. These statistics are similar across positions, except that NPAs we identify as companies more frequently disclose no positions. We also search for certain keywords in contributor biographies and find approximately 14% mention "Analyst," 9% mention "MBA" (Masters degree in Business Administration), and 7% mention "CFA" (Chartered Financial Analyst). These references are also similar across all positions, except that short-position NPAs appear twice as likely to have MBAs. Finally, SA reports followers for each contributor, much like Facebook or Twitter, and these followers are notified when contributors publish new content. In our sample, the average nonprofessional analyst has a following of about 4500 accounts, suggesting fairly wide dissemination of new content.

3.3 Empirical models

To test our hypotheses, we regress short-window abnormal returns on NPA position and a series of controls as presented below in (1) (*i* and *t* denote firm and time subscripts, respectively, and "*[]*" signifies a multi-day range):

$$\begin{aligned} &AbRet_{i,[t,t+1]} = a_0 + a_1 Long_{i,t} + a_2 Short_{i,t} + a_3 NegPct_{i,t} + a_4 PosPct_{i,t} + a_5 CogProc_{i,t} + \\ &a_6 Numbers_{i,t} + a_7 lWordCount_{i,t} + a_8 ComNegPct_{i,[t,t+1]} + a_9 ComPosPct_{i,[t,t+1]} \\ &+ a_{10} DJPosPct_{i,t} + a_{11} DJNegPct_{i,t} + a_{12} IDJ_{i,t} + a_{13} Upgrades_{i,t} + \\ &a_{14} Downgrades_{i,t} + a_{15} ReviseUps_{i,t} + a_{16} ReviseDowns_{i,t} + a_{17} PosES_{i,t} + \\ &a_{18} NegES_{i,t} + a_{19} Guidance_{i,t} + a_{20} PosGuidance_{i,t} + a_{21} NegGuidance_{i,t} + \\ &a_{22} Edgar8K_{i,t} + a_{23} Volatility_{i,t} + a_{24} AbRet_{i,[t-60,t-3]} + a_{25} AbRet_{i,t-2} + \\ &a_{26} AbRet_{i,t-1} + a_{27} Size + a_{28} BTM_{i,t} + a_{29} InstOwn_{i,t} + a_{30} AnalystFollowers_{i,t-2} \\ &+ a_{31} SAFollowers_{i,t-1} + \Sigma\gamma Industry_i + \Sigma\delta Year{-}Month + e_{i,t} \end{aligned} \tag{1}$$

The dependent variable in (1) is the firm's return measured over the two days starting on the day the article was published, adjusted by a matching size, market-to-book, and momentum portfolio return over the same period. If the article was published after-hours, on a weekend, or a holiday, we begin our return window on the first trading day following the article's release.

In some cases, a stock has multiple articles written about it on the same day. If so, we follow Chen et al. (2014) and collapse the SA-derived data into firm-day observations to avoid including these firm-day combinations multiple times in our models. For instance, we compute *Long* and *Short* as the average number of articles on a given day that disclose long and short positions, respectively.[18] To measure article tone, we count the number of positive and negative words, classified using word lists from Loughran and McDonald (2011), in all articles corresponding to a given trading day and divide each count by the total word count across articles, yielding *PosPct* and *NegPct*, respectively.[19]

Based on H1, we expect a positive (negative) coefficient on *Long* (*Short*). To test H2, we estimate (1) separately for four different cross-sections, which we denote with *Position*. *Position* equals 0 if both *Long* and *Short* equal 0 on a given trading day. *Position* equals −1 (1) if *Short* exceeds *Long* (*Long* exceeds *Short*) on day *t*. If *Short* and *Long* are equal and nonzero, we exclude these days from our sample. H2 suggests that investors respond more strongly to tone expressed by NPAs with skin in the game. Specifically, H2 predicts that the coefficient on both *NegPct* and *PosPct* exhibits stronger significance (in the expected direction) in partitions where NPAs hold a financial position (*Position* is nonzero).

Our control variables attempt to isolate other news that may affect current period returns and SA article content.[20] First, we control for the volume and rigor of analysis,

[18] We provide detailed variable definitions in Appendix 1.

[19] Following Loughran and McDonald (2011), we do not code words as positive if they are preceded by a negating word (no, not, none, neither, never, or nobody).

[20] The long-form nature of SA articles makes it unlikely that an event on day *t* leads to an article written on day *t*. Furthermore, discussions with an editor at SA suggest that the editorial process can be lengthy—as long as 12 h in some cases. This delay makes it unlikely that reactions to content reflect contemporaneously issued news. Nonetheless, we control for several aspects of contemporaneous news in our models, and we conduct additional analyses in Section 5 to rule out the alternative explanation that contemporaneous events explain our findings.

as an NPAs' personal financial position might simply reflect the depth of his or her analysis. Specifically, we include the proportion of words reflecting higher cognitive effort from James Pennebaker's LIWC package. Per Pennebaker and Francis (1996), words such as "believe," "cause," and "consider" reflect a higher degree of cognitive engagement with written material. We also include the number of numbers in the article, scaled by article length, to capture the degree of specificity of the analysis (*Numbers*), and the natural log of the total number of words in the article (*lWordCount*) in case there is asymmetry in how investors respond to length. Second, we control for other news appearing alongside the SA article. Chen et al. (2014) find that comments following SA articles provide value-relevant information. Therefore we separately download comments for each article in our sample and code positive and negative linguistic tone for comments (*ComPosPct* and *ComNegPct*), using the same procedure as *PosPct* and *NegPct*. We restrict our comment sample to those posted between the date of the article and the second trading day in our return window. We also control for the tone of the business press, using news disseminated by the Dow Jones newswire (*DJPosPct* and *DJNegPct*) as well as an indicator, *IDJ*, equal to 0 on days where there is no Dow Jones content (*DJPosPct* and *DJNegPct* set to 0 on these days).

We also control for the presence of several other significant news events in the four-day window ending on the day of the article's publication. Specifically, we control for analyst upgrades, downgrades, and forecast revisions (*Upgrades*, *Downgrades*, *ReviseUps*, and *ReviseDowns*) and positive and negative earnings surprises (*PosES* and *NegES*). Furthermore, we control for the presence or absence of management guidance (*Guidance*) as well as its sign (*PosGuidance* and *NegGuidance*) and for the presence or absence of an 8-K filing. Finally, we control for several return-based measures of news and uncertainty. Specifically, we compute pre-disclosure volatility (*Volatility*), which captures uncertainty in the calendar month preceding the article's release, and pre-article stock performance over three separate windows (day *t-60* to *t-3*, day *t-2*, and day $t-1$). In addition to these determinants, we include controls for firm size (*Size*), growth (*BTM*), institutional ownership (*InstOwn*), and following by both professional analysts and SA readers (*AnalystFollowers* and *SAFollowers*).[21] Finally, all models include year-month and industry fixed effects.

3.4 Descriptive Statistics

Table 3 presents descriptive statistics for our 86,741 firm-day observations. Variables marked with "*" are scaled by 100 to facilitate presentation of descriptive statistics. Means and medians for each return metric (*AbRet*) are all near 0, suggesting fairly symmetric return distributions. Statistics for *Short* (*Long*) suggest that approximately 2 (27) percent of articles are authored by NPAs with a short (long) position. Our tone measures (*PosPct* and *NegPct*) suggest that NPAs use only about 1.3 (1.5) percent of negative (positive) words in articles. Chen et al. (2014) report similar statistics for negative words. (They do not report statistics for positive words.) We observe similar

[21] We include *SAFollowers* to control for the author's reputation, ability, or both. Our results are unchanged if, in addition to *SAFollowers*, we also include as control variables (1) a measure of the number of prior posts, (2) the number of prior posts about the target firm, (3) the author "track record," following Chen et al., and (4) whether the author is deemed a "financial professional" (coded as 1 if the author mentions "analyst" or "CFA" in his or her bio or if the account name appears to be a business).

Table 3 Descriptive Statistics

Variable	n	Mean	Std. Dev	25%	50%	75%	Position = −1		Position = 0		Position = 1		Tests of Differences		
							Mean	50%	Mean	50%	Mean	50%	-1 vs. 0	-1 vs 1	0 vs. 1
$AbRet_{i,[t,t+1]}$*	86,741	0.11	3.62	−1.26	0.02	1.35	−1.11	−0.61	0.03	−0.02	0.39	0.12	0.00	0.00	0.00
$AbRet_{i,[t+3,t+60]}$*	86,641	−0.56	16.45	−8.77	−0.63	7.34	−1.79	−1.75	−0.47	−0.58	−0.66	−0.64	0.00	0.01	0.12
$AbRet_{i,[t-2]}$*	86,741	0.02	2.39	−0.88	−0.02	0.86	−0.10	−0.14	0.02	−0.01	0.02	−0.01	0.06	0.08	0.65
$AbRet_{i,[t-1]}$*	86,741	0.05	2.79	−0.89	−0.01	0.91	−0.10	−0.12	0.04	−0.01	0.08	0.00	0.08	0.02	0.05
$AbRet_{i,[t-60,t-3]}$*	86,741	0.30	18.37	−8.87	−0.53	7.78	3.23	0.44	0.17	−0.43	0.32	−0.83	0.00	0.00	0.29
Position	86,741	0.27	0.51	0.00	0.00	1.00	−1.00	−1.00	0.00	0.00	1.00	1.00	.	.	.
Short	86,741	0.02	0.15	0.00	0.00	0.00	0.88	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long	86,741	0.27	0.43	0.00	0.00	0.67	0.00	0.00	0.00	0.00	0.90	1.00	0.00	0.00	0.00
*NegPct**	86,741	1.33	0.87	0.69	1.18	1.79	2.09	1.93	1.32	1.16	1.28	1.16	0.00	0.00	0.00
*PosPct**	86,741	1.47	0.75	0.94	1.38	1.90	1.03	0.96	1.49	1.40	1.46	1.39	0.00	0.00	0.00
*CogProc**	86,741	9.10	3.35	7.30	9.41	11.33	10.86	11.41	8.78	9.08	9.64	9.90	0.00	0.00	0.00
*Numbers**	86,741	4.54	3.17	2.37	3.90	5.89	4.12	3.53	4.59	3.91	4.45	3.92	0.00	0.00	0.00
lWordCount	86,741	6.76	0.63	6.36	6.74	7.13	7.07	7.08	6.67	6.69	6.93	6.88	0.00	0.00	0.00
$ComPosPct_{i,[t,t+1]}$*	86,741	1.02	1.19	0.00	0.91	1.53	0.90	0.92	0.97	0.73	1.16	1.13	0.00	0.00	0.00
$ComNegPct_{i,[t,t+1]}$*	86,741	1.00	1.08	0.00	0.89	1.63	1.49	1.55	0.93	0.64	1.09	1.12	0.00	0.00	0.00
$ComPosPct_{i,[t+3,t+60]}$*	86,741	0.59	1.19	0.00	0.00	0.87	0.71	0.47	0.52	0.00	0.74	0.00	0.00	0.15	0.00
$ComNegPct_{i,[t+3,t+60]}$*	86,741	0.59	1.11	0.00	0.00	0.96	1.18	0.99	0.50	0.00	0.74	0.00	0.00	0.00	0.00
*DJPosPct**	86,741	0.67	0.99	0.00	0.00	1.24	0.72	0.00	0.66	0.00	0.68	0.00	0.01	0.08	0.01
*DJNegPct**	86,741	0.51	0.71	0.00	0.00	0.96	0.52	0.00	0.51	0.00	0.51	0.00	0.36	0.57	0.37
IDJ	86,741	0.57	0.49	0.00	1.00	1.00	0.56	1.00	0.56	1.00	0.58	1.00	0.85	0.19	0.00
Upgrades	86,741	0.10	0.34	0.00	0.00	0.00	0.12	0.00	0.10	0.00	0.09	0.00	0.02	0.01	0.55

Table 3 (continued)

Variable	*n*	*Mean*	*Std. Dev*	*25%*	*50%*	*75%*	*Position = −1*		*Position = 0*		*Position = 1*		*Tests of Differences*		
							Mean	*50%*	*Mean*	*50%*	*Mean*	*50%*	*-1 vs. 0*	*-1 vs 1*	*0 vs. 1*
Downgrades	86,741	0.15	0.43	0.00	0.00	0.00	0.16	0.00	0.14	0.00	0.15	0.00	0.05	0.12	0.24
ReviseUps	86,741	1.54	3.91	0.00	0.00	1.00	1.27	0.00	1.52	0.00	1.62	0.00	0.00	0.00	0.00
ReviseDowns	86,741	1.74	4.09	0.00	0.00	2.00	1.76	0.00	1.70	0.00	1.81	0.00	0.58	0.60	0.00
PosES	86,741	0.09	0.29	0.00	0.00	0.00	0.09	0.00	0.10	0.00	0.09	0.00	0.49	0.62	0.00
NegES	86,741	0.05	0.21	0.00	0.00	0.00	0.05	0.00	0.04	0.00	0.05	0.00	0.08	0.12	0.63
Guidance	86,741	0.07	0.26	0.00	0.00	0.00	0.06	0.00	0.08	0.00	0.05	0.00	0.00	0.02	0.00
PosGuidance	86,741	0.05	0.21	0.00	0.00	0.00	0.04	0.00	0.05	0.00	0.03	0.00	0.00	0.11	0.00
NegGuidance	86,741	0.03	0.18	0.00	0.00	0.00	0.03	0.00	0.04	0.00	0.02	0.00	0.87	0.00	0.00
Edgar8K	86,741	0.28	0.45	0.00	0.00	1.00	0.30	0.00	0.28	0.00	0.28	0.00	0.05	0.21	0.06
Volatility	86,741	0.02	0.03	0.00	0.01	0.02	0.03	0.02	0.02	0.01	0.02	0.01	0.00	0.00	0.00
$AbRet_{i,[t-60,t-3]}$	86,741	0.30	18.37	−8.87	−0.53	7.78	3.23	0.44	0.17	−0.43	0.32	−0.83	0.00	0.00	0.29
$AbRet_{i,[t-2]}$	86,741	0.02	2.39	−0.88	−0.02	0.86	−0.10	−0.14	0.02	−0.01	0.02	−0.01	0.06	0.08	0.65
$AbRet_{i,[t-1]}$	86,741	0.05	2.79	−0.89	−0.01	0.91	−0.10	−0.12	0.04	−0.01	0.08	0.00	0.08	0.02	0.05
Size	86,741	15.87	2.22	14.33	16.02	17.58	15.14	15.24	15.95	16.12	15.77	15.90	0.00	0.00	0.00
BTM	86,741	0.77	1.65	0.19	0.38	0.73	0.42	0.16	0.79	0.38	0.76	0.38	0.00	0.00	0.01
InstOwn	86,741	0.49	0.35	0.02	0.61	0.78	0.53	0.66	0.51	0.64	0.44	0.55	0.00	0.00	0.00
AnalystFollowers	86,741	2.51	0.94	2.08	2.77	3.18	2.30	2.48	2.54	2.83	2.45	2.71	0.00	0.00	0.00
SAFollowers	86,741	6.94	1.96	5.67	7.19	8.33	6.62	6.87	6.92	7.11	7.02	7.39	0.00	0.00	0.00

Table 3 presents descriptive statistics for primary variables used in this study. Each observation represents a unique firm-trading day combination. All variables are defined in Appendix 1. Variables marked with "*" are multiplied by 100 for presentation purposes statistics for the language used in the comments section to the articles. On average, NPAs appear to exert fairly significant cognitive effort (mean *CogProc* of 9.1%) and include a fair amount of numerical content (i.e., numbers account for about 4.5% of total words). We also find that 10 (15) percent of articles co-occur with an analyst upgrade (downgrade). Forecast revisions occur in approximately 25% of our sample and frequently come in clusters (as evidenced by means greater than 1). Furthermore, 9 (5) percent our sample corresponds to the period following a positive (negative) earnings surprise, and 7% of articles also occur near management guidance.[22] Finally, 57% of SA-article days have at least one other co-occurring news item, as tracked by the Dow Jones newswire (*IDJ*), and the use of tone-words in these articles is relatively sparse (less than 1% for both positive and negative words).

Table 4 presents correlations among our variables. Bolded correlations are significantly different from zero ($p < 0.05$). Consistent with H1, we observe a significantly positive (negative) correlation of 0.06 (−0.06) between *Long* (*Short*) and $AbRet_{i,[t,t+1]}$. We also observe positive (negative) correlations between $Abret_{i,[t,t+1]}$ and both *PosPct* and *ComPosPct* (*NegPct* and *ComNegPct*), implying market movement in the direction consistent with the tone of SA articles. The tone of Dow Jones content exhibits weaker correlations to short-window returns (−0.03 and 0.01 for negative and positive tone, respectively). Interestingly, few non-SA related variables relate significantly to *Short* and *Long*. We observe positive correlations between *Volatility* and both *Long* (0.04) and *Short* (0.09), implying that NPAs with positions more likely publish content when uncertainty is relatively high. Long and short positions also appear more likely for smaller firms (−0.09 and − 0.07) with lower institutional ownership (−0.10 and − 0.11) and analyst following (−0.05 and − 0.09), suggesting NPAs with positions target stocks in relatively poorer information environments. We also observe a correlation of 0.03 between the abnormal return over the prior quarter ($AbRet_{i,[t-60,t-3]}$) and *Short*, suggesting that past news plays, at most, a minor role in these NPAs' decisions to publish. With respect to SA-article derived variables, we find a greater (smaller) intensity of negative (positive) words for short NPAs, suggesting that they write content consistent with their positions. Interestingly, we find that *Long* NPAs use fewer negative words, though not necessarily more positive words. The tone of comments tends to follow the tone of articles, and *Short* (*Long*) NPAs tend to incite more negative and less positive (more negative and more positive) comment sentiment. We also find that long and short NPAs write articles indicating greater cognitive effort but include fewer numbers per word of text.

4 Empirical results

4.1 Test of H1

H1 predicts that there is an investor reaction to position disclosures in SA articles at the time they are published or that the disclosure of a long position (*Long*) generates a

[22] *PosGuidance* and *NegGuidance* take the value of 1 if management issues a forecast that is greater or less than the analyst consensus before the guidance is issued, respectively, while *Guidance* is equal to 1 if any forecast is issued. The sum of the mean values for *PosGuidance* and *NegGuidance* slightly exceeds the value of *Guidance* because managers may issue multiple forecasts of varying horizons in a given window with different news (i.e., *PosGuidance* and *NegGuidance* could both equal 1).

Table 4 Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	$AbRet_{i,[t,t+1]}$		0.01	**−0.01**	**−0.01**	**−0.01**	**−0.04**	**0.04**	**0.05**	**−0.05**	**0.03**	**−0.02**	**0.01**	0.00	**0.01**	**−0.02**	0.00	**−0.01**	**0.03**
(2)	$AbRet_{i,[t+3,t+60]}$	0.00		0.00	0.00	0.00	**−0.01**	**−0.01**	0.00	0.00	**0.01**	**−0.01**	**0.02**	0.00	−0.01	**−0.01**	**−0.02**	**−0.03**	**0.01**
(3)	$AbRet_{i,[t-2]}$	−0.01	0.00		0.00	**0.02**	**−0.01**	0.00	0.00	**−0.04**	**0.03**	**−0.02**	**0.01**	**−0.01**	−0.01	**−0.03**	**−0.01**	**−0.02**	**0.04**
(4)	$AbRet_{i,[t-1]}$	0.00	−0.01	**0.02**		**0.01**	**−0.01**	0.01	**0.01**	**−0.06**	**0.03**	**−0.02**	**0.01**	**−0.02**	0.00	**−0.03**	**−0.01**	**−0.02**	**0.04**
(5)	$AbRet_{i,[t-60,t-3]}$	**−0.01**	−0.01	**0.01**	0.01		**0.01**	**−0.01**	**−0.01**	**−0.13**	**0.07**	**−0.03**	**0.03**	−0.01	**−0.01**	**−0.07**	**−0.03**	**−0.05**	−0.01
(6)	*Short*	**−0.06**	**−0.01**	−0.01	**−0.01**	**0.03**		**−0.09**	**−0.33**	**0.14**	**−0.11**	**0.10**	**−0.03**	**0.10**	0.00	**0.10**	**0.07**	**0.11**	**0.01**
(7)	*Long*	**0.06**	−0.01	0.00	**0.01**	0.00	**−0.10**		**0.96**	**−0.02**	0.00	**0.11**	**0.01**	**0.12**	**0.12**	**0.08**	**0.13**	**0.12**	**−0.02**
(8)	*Position*	**0.07**	0.00	0.00	**0.01**	−0.01	**−0.41**	**0.91**		**−0.05**	**0.03**	**0.08**	**0.01**	**0.13**	**0.12**	**0.07**	**0.12**	**0.10**	**−0.01**
(9)	*NegPct*	**−0.06**	0.00	**−0.05**	**−0.07**	**−0.12**	**0.15**	**−0.05**	**−0.08**		**−0.11**	**0.20**	**−0.15**	**0.11**	0.00	**0.18**	**0.04**	**0.10**	**0.03**
(10)	*PosPct*	**0.04**	0.01	**0.03**	**0.04**	**0.06**	**−0.10**	−0.01	**0.03**	**−0.13**		**−0.12**	**−0.07**	**0.06**	**0.05**	**−0.07**	**−0.02**	**−0.06**	**0.01**
(11)	*CogProc*	**−0.02**	−0.01	**−0.01**	**−0.02**	**−0.01**	**0.09**	**0.10**	**0.07**	**0.16**	**−0.11**		**0.01**	**0.08**	**0.03**	**0.11**	**0.08**	**0.11**	**0.01**
(12)	*Numbers*	**0.01**	**0.01**	0.00	**0.01**	**0.01**	**−0.02**	−0.01	−0.01	**−0.12**	**−0.07**	**0.05**		**−0.17**	**−0.02**	**−0.07**	**−0.04**	**−0.06**	**0.02**
(13)	*lWordCount*	0.00	0.01	−0.01	**−0.02**	0.00	**0.07**	**0.08**	**0.13**	**0.06**	**0.02**	**0.04**	**−0.19**		**0.17**	**0.17**	**0.19**	**0.20**	0.00
(14)	$ComPosPct_{i,[t,t+1]}$	**0.01**	0.00	0.00	0.00	0.00	**−0.02**	**0.06**	**0.07**	**−0.04**	**0.06**	−0.01	−0.01	**0.10**		**0.49**	**0.29**	**0.27**	**0.02**
(15)	$ComNegPct_{i,[t,t+1]}$	**−0.03**	0.00	**−0.03**	**−0.03**	**−0.06**	**0.07**	**0.04**	**0.03**	**0.18**	**−0.06**	**0.08**	**−0.07**	**0.13**	**0.24**		**0.29**	**0.34**	**0.02**
(16)	$ComPosPct_{i,[t+3,t+60]}$	0.01	0.00	−0.01	−0.01	0.00	**0.02**	**0.07**	**0.07**	−0.01	**0.01**	**0.02**	**−0.02**	**0.12**	**0.15**	**0.13**		**0.66**	**−0.01**
(17)	$ComNegPct_{i,[t+3,t+60]}$	**−0.02**	**−0.02**	**−0.01**	**−0.02**	**−0.04**	**0.09**	**0.07**	**0.05**	**0.10**	**−0.05**	**0.07**	**−0.05**	**0.15**	**0.12**	**0.24**	**0.28**		**−0.01**
(18)	*Upgrades*	**0.03**	0.01	**0.03**	**0.04**	0.00	0.00	**−0.02**	−0.01	**0.03**	0.01	**0.02**	**0.01**	**0.03**	**0.01**	**0.02**	0.00	0.00	
(19)	*Downgrades*	**−0.06**	−0.01	**−0.06**	**−0.08**	**−0.02**	0.00	**−0.02**	0.00	**0.08**	**−0.02**	**0.03**	0.00	**0.05**	0.01	**0.05**	0.00	**0.01**	**0.14**
(20)	*ReviseUps*	**0.02**	**0.02**	**0.03**	**0.05**	**0.05**	**−0.02**	**−0.03**	**0.02**	−0.01	**0.05**	**−0.01**	**0.06**	**0.06**	**0.01**	0.01	**−0.02**	**−0.02**	**0.23**
(21)	*ReviseDowns*	**−0.07**	−0.01	**−0.07**	**−0.10**	**−0.09**	**−0.01**	**−0.03**	0.01	**0.12**	**−0.03**	0.00	**0.01**	**0.09**	**0.02**	**0.06**	0.00	0.00	0.18
(22)	*PosES*	**0.04**	**0.01**	**0.04**	**0.06**	**0.02**	−0.01	**−0.03**	**−0.01**	**0.01**	**0.08**	**−0.04**	**0.12**	**−0.02**	−0.01	**−0.03**	**−0.04**	**−0.05**	**0.14**
(23)	*NegES*	**−0.07**	**−0.01**	**−0.05**	**−0.08**	**−0.03**	0.01	−0.01	0.00	**0.10**	**−0.02**	0.00	**0.04**	0.00	−0.01	**0.01**	**−0.02**	**−0.01**	**0.05**

Table 4 (continued)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(24)	*PosGuidance*	**0.03**	**0.01**	**0.03**	**0.03**	0.01	**−0.01**	**−0.05**	**−0.04**	0.00	**0.05**	**−0.03**	**0.10**	**−0.04**	**−0.02**	**−0.03**	**−0.04**	**−0.05**	**0.09**
(25)	*NegGuidance*	**−0.05**	0.00	**−0.03**	**−0.06**	**−0.02**	0.00	**−0.04**	**−0.03**	**0.05**	**0.02**	**−0.02**	**0.07**	−0.01	**−0.02**	**−0.01**	**−0.02**	**−0.03**	**0.06**
(26)	*Guidance*	−0.01	**0.01**	0.00	−0.01	−0.01	**−0.01**	**−0.06**	**−0.04**	**0.03**	**0.05**	**−0.03**	**0.11**	**−0.04**	**−0.02**	**−0.03**	**−0.04**	**−0.05**	**0.11**
(27)	*Volatility*	0.00	**−0.04**	0.00	0.01	**0.03**	**0.09**	**0.04**	0.00	**0.13**	**−0.08**	**0.14**	**−0.04**	**−0.01**	**−0.02**	**0.06**	0.01	**0.06**	**0.02**
(28)	*Size*	**−0.05**	**0.05**	**−0.02**	**−0.03**	0.00	**−0.07**	**−0.09**	**−0.01**	**−0.03**	**0.05**	**−0.04**	−0.01	**0.12**	**0.07**	**0.07**	−0.01	**−0.03**	**0.07**
(29)	*BTM*	0.01	**0.03**	0.01	0.00	**0.01**	**−0.03**	0.00	0.01	**0.08**	**−0.02**	**−0.01**	**−0.02**	**−0.03**	**−0.01**	**0.02**	0.00	**0.02**	**−0.02**
(30)	*InstOwn*	**−0.01**	**0.05**	0.00	−0.01	**−0.01**	**0.01**	**−0.11**	**−0.10**	**−0.02**	**0.06**	**−0.03**	**0.08**	**−0.06**	−0.01	**−0.03**	**−0.04**	**−0.06**	**0.04**
(31)	*AnalystFollowers*	**−0.04**	**0.04**	**−0.01**	**−0.02**	**−0.05**	**−0.05**	**−0.09**	**−0.03**	**−0.01**	**0.06**	−0.01	0.00	**0.10**	**0.05**	**0.05**	−0.01	**−0.03**	**0.13**
(32)	*SAFollowers*	0.00	0.00	0.00	0.00	0.00	**−0.03**	0.00	**0.03**	**−0.06**	**−0.05**	0.00	**0.08**	**0.05**	**0.04**	**0.03**	**0.02**	**0.02**	**0.03**
(33)	*Edgar8K*	**−0.01**	0.00	0.00	−0.01	0.00	0.00	−0.01	0.00	**0.06**	**0.02**	**−0.01**	**0.08**	**−0.01**	0.00	0.01	**−0.03**	**−0.03**	**0.11**
(34)	*DJNegPct*	**−0.03**	**0.04**	**−0.02**	**−0.03**	**−0.02**	0.00	**−0.03**	0.00	**0.14**	**−0.03**	**0.06**	**−0.02**	**0.03**	0.01	**0.09**	**−0.02**	0.00	**0.09**
(35)	*DJPosPct*	0.01	**0.03**	0.00	0.00	**0.01**	0.00	**−0.03**	0.00	**0.05**	**0.03**	**0.03**	0.00	**0.03**	**0.02**	**0.04**	**−0.02**	**−0.02**	**0.08**
(36)	*IDJ*	**−0.01**	**0.04**	0.00	**−0.01**	**0.02**	**−0.01**	**−0.03**	**0.01**	**0.07**	−0.01	**0.05**	0.00	**0.02**	**0.03**	**0.06**	**−0.02**	**−0.02**	**0.10**

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
(1)	**−0.04**	**0.02**	**−0.05**	**0.03**	**−0.05**	**0.02**	**−0.03**	0.00	0.00	**−0.02**	**0.01**	0.00	**−0.02**	0.00	0.00	**−0.01**	**0.01**	0.00
(2)	**−0.01**	**0.02**	0.00	**0.02**	**−0.01**	**0.02**	0.00	**0.02**	**−0.08**	**0.06**	**0.04**	**0.06**	**0.06**	0.01	**0.01**	**0.04**	**0.03**	**0.04**
(3)	**−0.03**	**0.03**	**−0.04**	**0.03**	**−0.04**	**0.02**	**−0.02**	0.00	**−0.02**	0.00	0.00	**0.01**	0.00	0.00	0.00	−0.01	0.00	0.01
(4)	**−0.05**	**0.03**	**−0.05**	**0.05**	**−0.06**	**0.02**	**−0.03**	0.00	**−0.01**	0.00	**0.01**	0.01	0.00	0.01	**−0.01**	**−0.01**	0.00	0.00
(5)	**−0.01**	**0.08**	**−0.11**	**0.03**	**−0.03**	**0.02**	**−0.02**	0.00	**−0.06**	**0.06**	0.00	**0.03**	0.01	**0.01**	0.00	0.01	**0.02**	**0.04**
(6)	**0.01**	**−0.02**	**−0.01**	0.00	0.01	**−0.01**	0.00	**−0.01**	**0.11**	**−0.05**	**−0.10**	**0.03**	**−0.02**	**−0.02**	**0.01**	**0.02**	**0.01**	**0.01**
(7)	**−0.01**	**−0.03**	**−0.02**	**−0.02**	0.00	**−0.05**	**−0.04**	**−0.06**	**0.06**	**−0.05**	**0.01**	**−0.11**	**−0.06**	**0.02**	0.00	**−0.01**	**−0.01**	**−0.01**
(8)	−0.01	0.00	0.00	**−0.01**	0.00	**−0.04**	**−0.03**	**−0.05**	**0.02**	−0.01	**0.04**	**−0.11**	**−0.02**	**0.04**	0.00	**0.01**	**0.01**	**0.01**

Table 4 (continued)

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
(9)	**0.07**	0.01	**0.10**	**0.01**	**0.09**	0.00	**0.05**	**0.03**	**0.15**	**−0.03**	**0.07**	**−0.03**	**0.01**	**−0.06**	**0.05**	**0.12**	**0.07**	**0.07**
(10)	**−0.01**	**0.05**	**−0.02**	**0.08**	**−0.02**	**0.05**	**0.02**	**0.05**	**−0.08**	**0.05**	**−0.02**	**0.05**	**0.07**	**−0.05**	**0.02**	**−0.02**	**0.01**	0.00
(11)	**0.03**	**−0.03**	**−0.02**	**−0.05**	**−0.01**	**−0.04**	**−0.03**	**−0.05**	**0.17**	**−0.03**	**−0.07**	**−0.04**	0.00	0.00	**−0.02**	**0.06**	**0.04**	**0.05**
(12)	**0.02**	**0.08**	**0.03**	**0.12**	**0.05**	**0.10**	**0.07**	**0.11**	**−0.05**	**−0.02**	**0.03**	**0.08**	**−0.02**	**0.07**	**0.09**	**−0.02**	**−0.01**	0.00
(13)	**0.01**	**0.02**	**0.05**	**−0.03**	−0.01	**−0.04**	**−0.01**	**−0.04**	**−0.04**	**0.11**	**−0.06**	**−0.07**	**0.11**	**0.04**	**−0.01**	**0.03**	**0.03**	0.00
(14)	**0.02**	**0.02**	**0.04**	**−0.02**	**−0.01**	**−0.04**	**−0.03**	**−0.04**	**−0.03**	**0.11**	−0.01	**−0.06**	**0.08**	**0.06**	−0.01	**0.05**	**0.05**	**0.05**
(15)	**0.05**	**0.01**	**0.07**	**−0.04**	**0.01**	**−0.05**	**−0.02**	**−0.05**	**0.06**	**0.10**	**0.02**	**−0.07**	**0.08**	**0.05**	0.00	**0.10**	**0.07**	**0.08**
(16)	−0.01	**−0.04**	**−0.02**	**−0.06**	**−0.02**	**−0.06**	**−0.04**	**−0.07**	**0.06**	**−0.02**	**−0.01**	**−0.09**	**−0.02**	**0.04**	**−0.04**	**−0.02**	**−0.02**	**−0.03**
(17)	0.00	**−0.05**	**−0.01**	**−0.07**	**−0.02**	**−0.06**	**−0.04**	**−0.07**	**0.09**	**−0.03**	0.00	**−0.10**	**−0.03**	**0.03**	**−0.04**	**−0.01**	**−0.02**	**−0.02**
(18)	**0.12**	**0.20**	**0.16**	**0.13**	**0.05**	**0.08**	**0.06**	**0.10**	**0.03**	**0.07**	0.00	**0.05**	**0.14**	**0.03**	**0.11**	**0.10**	**0.09**	**0.10**
(19)		**0.16**	**0.23**	**0.12**	**0.10**	**0.07**	**0.11**	**0.12**	**0.03**	**0.09**	**−0.02**	**0.04**	**0.16**	**0.04**	**0.13**	**0.12**	**0.10**	**0.11**
(20)	**0.18**		**0.38**	**0.38**	**0.07**	**0.24**	**0.10**	**0.24**	**−0.07**	**0.25**	0.01	**0.12**	**0.29**	**0.08**	**0.25**	**0.21**	**0.18**	**0.18**
(21)	**0.30**	**0.24**		**0.17**	**0.22**	**0.10**	**0.18**	**0.18**	**−0.04**	**0.25**	**0.05**	**0.09**	**0.29**	**0.08**	**0.23**	**0.23**	**0.17**	**0.18**
(22)	**0.12**	**0.49**	**0.13**		**−0.07**	**0.41**	**0.24**	**0.45**	**−0.01**	**0.02**	**−0.03**	**0.07**	**0.07**	**0.06**	**0.42**	**0.13**	**0.13**	**0.10**
(23)	**0.11**	**0.01**	**0.28**	**−0.07**		**0.08**	**0.16**	**0.16**	**0.03**	**−0.05**	**0.03**	**−0.01**	**−0.03**	**0.03**	**0.24**	**0.06**	**0.04**	**0.04**
(24)	**0.07**	**0.32**	**0.08**	**0.41**	**0.08**		**0.19**	**0.81**	**−0.06**	**0.04**	**−0.07**	**0.09**	**0.05**	**0.04**	**0.29**	**0.08**	**0.09**	**0.07**
(25)	**0.12**	**0.10**	**0.27**	**0.24**	**0.16**	**0.19**		**0.65**	**−0.03**	**0.03**	**−0.07**	**0.07**	**0.07**	**0.03**	**0.25**	**0.08**	**0.07**	**0.06**
(26)	**0.12**	**0.30**	**0.22**	**0.45**	**0.16**	**0.81**	**0.65**		**−0.07**	**0.05**	**−0.09**	**0.11**	**0.08**	**0.04**	**0.36**	**0.10**	**0.11**	**0.09**
(27)	**0.02**	**−0.05**	**−0.01**	**−0.03**	**0.02**	**−0.04**	**−0.03**	**−0.05**		**−0.47**	0.00	**−0.15**	**−0.21**	**−0.09**	**−0.01**	**−0.07**	**−0.09**	**−0.09**
(28)	**0.10**	**0.19**	**0.18**	**0.03**	**−0.05**	**0.04**	**0.04**	**0.05**	**−0.34**		**−0.14**	**0.22**	**0.69**	**0.11**	**0.02**	**0.44**	**0.41**	**0.44**
(29)	**−0.04**	**−0.05**	**−0.04**	**−0.04**	−0.01	**−0.05**	**−0.05**	**−0.07**	**0.04**	**−0.14**		**−0.16**	**−0.16**	**0.04**	**−0.04**	**0.03**	**−0.02**	**−0.02**
(30)	**0.04**	**0.11**	**0.09**	**0.07**	**−0.01**	**0.09**	**0.07**	**0.11**	**−0.16**	**0.31**	**−0.23**		**0.27**	0.00	**0.09**	**0.07**	**0.07**	**0.10**
(31)	**0.15**	**0.23**	**0.24**	**0.08**	−0.01	**0.07**	**0.08**	**0.10**	**−0.19**	**0.68**	**−0.34**	**0.34**		**0.09**	**0.07**	**0.33**	**0.32**	**0.33**
(32)	**0.04**	**0.08**	**0.07**	**0.06**	**0.03**	**0.04**	**0.02**	**0.04**	**−0.05**	**0.11**	**−0.02**	0.01	**0.09**		**0.08**	**0.07**	**0.06**	**0.06**

Table 4 (continued)

	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)	(33)	(34)	(35)	(36)
(33)	**0.13**	**0.29**	**0.25**	**0.42**	**0.24**	**0.29**	**0.25**	**0.36**	0.00	**0.02**	**−0.10**	**0.10**	**0.09**	**0.07**		**0.14**	**0.14**	**0.13**
(34)	**0.13**	**0.16**	**0.19**	**0.11**	**0.06**	**0.07**	**0.08**	**0.09**	**−0.01**	**0.36**	**0.08**	**0.08**	**0.23**	**0.05**	**0.13**		**0.78**	**0.71**
(35)	**0.08**	**0.14**	**0.11**	**0.12**	**0.03**	**0.08**	**0.06**	**0.10**	**−0.05**	**0.33**	0.00	**0.10**	**0.24**	**0.04**	**0.12**	**0.47**		**0.73**
(36)	**0.12**	**0.15**	**0.14**	**0.10**	**0.04**	**0.07**	**0.06**	**0.09**	**−0.06**	**0.44**	**0.03**	**0.13**	**0.31**	**0.06**	**0.13**	**0.59**	**0.63**	

Table 4 presents correlation coefficients among variables. Spearman (Pearson) correlations are presented above (below) the diagonal. Bolded correlations are statistically significant ($p < 0.05$). All variables are defined in Appendix 1 positive abnormal return in the short-window surrounding the articles release and disclosure of a short position (*Short*) generates a negative abnormal return. We report results for these predictions in Panels A and B of Table 5 using eq. (1).[23]

Panel A presents results using the 86,741 firm-day combinations in our sample. Columns 1 through 3 present results using various sets of control variables. We begin with a baseline model in column 1 that only includes variables measured from SA articles themselves: *PosPct*, *NegPct*, *Long*, *Short*, *CogProc*, *Numbers*, *lWordCount*, *ComPosPct*, and *ComNegPct*. As presented, we find strong support for H1 as the coefficient on *Long* is significantly positive (0.431, *t*-statistic = 11.92) and the coefficient on *Short* is significantly negative (−1.045, *t*-statistic = −9.12). These coefficients imply a two-day abnormal return of approximately 18 (seven) basis points attributable to a one standard deviation increase in the percentage of articles disclosing long (short) positions on a given day. The economic magnitude of our results are in line with Chen et al. (2014), particularly in light of the fact that we are examining the immediate reaction to the news and not the subsequent drift. We also observe significant coefficients on both *PosPct* and *NegPct* (12.151, *t*-statistic = 6.27 and − 16.43, *t*-statistic = −8.52, respectively). A one standard-deviation increase in *PosPct* (*NegPct*) corresponds to a return of 10 (−10) basis points, which is not insignificant in a two-day window.

We next introduce controls for non-Dow Jones related news content (column 2), such as analyst revisions and management guidance, and Dow Jones content (column 3) and continue to find strong support for H1. Coefficients on *Long* are all near 0.4 (*t*-statistics >*10.0*), while coefficients on *Short* suggest incremental returns of similar magnitude to column 1 (*t*-statistics < −9.12). Coefficients on *NegPct* and *PosPct* also exhibit similar magnitudes to column 1. We next consider various subsamples that reduce the likelihood articles appear alongside contemporaneous news. Specifically, in columns 4 and 5, we re-estimate our full model (corresponding to column 3), after removing observations with Dow Jones content (*IDJ* = 1) and after removing observations with Dow Jones content and earnings surprises (*IDJ* = *1* or *PosES* = *1* or *NegES* = *1*). All results continue to hold and the coefficients on *Long* and *Short* exhibit noticeably larger magnitudes compared to the column 3 estimates, suggesting a greater price response to SA content on days *without* concurrent news events. Column 6 shows results, after excluding articles occurring in the three days preceding an analyst recommendation, forecast revision, earnings announcement, or management guidance, and column 7 only retains days on which a single article is published (since days with multiple articles likely correspond to significant firm events). Column 7 also simplifies economic significance interpretation of *Long* and *Short* because these variables only take a value of 0 or 1 in this sample. The coefficient estimates suggest that two-day abnormal returns are an economically significant 36 (117) basis points higher (lower) on days that long (short) authors publish articles (relative to days with articles by authors with no positions). Overall, the results presented in Table 5 provide strong support for H1, suggesting that stock positions convey information about the NPA's overall opinion of the firm and that investors perceive NPAs to be credible.

[23] In all tables, we multiply the dependent variable by 100 to facilitate presentation of coefficient estimates. All specifications also include industry and year-month fixed effects. Significance is assessed from standard errors clustered by year-month to correct for cross-sectional correlation in returns.

Table 5 Test of H1

Panel A: Test of H1

Variable	(1) ALL	(2) ALL	(3) ALL	(4) NO DOW-JONES	(5) NO DOW-JONES OR EARNINGS SURPRISE	(6) NO POST-ARTICLE EVENTS	(7) SINGLE ARTICLE DAYS
Short	−1.045***	−1.154***	−1.158***	−1.552***	−1.643***	−1.441***	−1.173***
	(−9.12)	(−9.73)	(−9.74)	(−9.55)	(−9.61)	(−9.47)	(−9.64)
Long	0.431***	0.373***	0.371***	0.505***	0.518***	0.512***	0.362***
	(11.92)	(11.25)	(11.27)	(9.77)	(9.95)	(11.71)	(10.76)
NegPct	−16.430***	−14.452***	−14.278***	−15.509***	−15.781***	−18.704***	−12.860***
	(−8.52)	(−7.77)	(−7.92)	(−5.75)	(−5.66)	(−7.16)	(−6.95)
PosPct	12.151***	11.197***	10.944***	12.890***	12.867***	11.725***	10.290***
	(6.27)	(5.49)	(5.38)	(4.86)	(4.88)	(4.51)	(4.89)
CogProc	−1.615***	−1.575***	−1.589***	−1.327**	−1.160**	−1.616***	−1.596***
	(−4.07)	(−3.96)	(−4.00)	(−2.24)	(−2.01)	(−3.19)	(−4.20)
Numbers	0.542	0.398	0.377	1.121	1.108	−0.010	0.547
	(1.42)	(1.01)	(0.97)	(1.51)	(1.45)	(−0.02)	(1.36)
lWordCount	0.037	0.089***	0.091***	0.150***	0.146***	0.166***	0.093***
	(1.50)	(3.63)	(3.73)	(4.01)	(3.82)	(4.98)	(3.11)
$ComNegPct_{i,[t,t+1]}$	−7.117***	−5.619***	−5.524***	−5.017***	−4.152**	−5.396***	−6.275***
	(−5.24)	(−4.26)	(−4.16)	(−2.84)	(−2.33)	(−3.04)	(−4.84)
$ComPosPct_{i,[t,t+1]}$	2.754***	3.246***	3.190***	4.058***	4.411***	4.545***	3.860***
	(2.64)	(3.18)	(3.10)	(2.73)	(2.92)	(3.52)	(3.57)
DJNegPct			−6.800***			0.237	−5.101**
			(−3.39)			(0.09)	(−2.45)
DJPosPct			17.137***			10.833***	15.512***

Table 5 (continued)

		(8.00)			(4.13)	(6.88)
IDJ		0.046			0.060	0.045
		(1.39)			(1.45)	(1.25)
Upgrades	0.528***	0.522***	0.254***	0.248**	0.445***	0.567***
	(10.66)	(10.55)	(2.76)	(2.38)	(6.94)	(10.28)
Downgrades	−0.447***	−0.446***	−0.235***	−0.151**	−0.350***	−0.463***
	(−10.94)	(−11.08)	(−4.01)	(−2.39)	(−5.47)	(−9.99)
ReviseUps	0.013***	0.013***	0.015*	0.032***	0.013*	0.019***
	(3.27)	(3.26)	(1.93)	(3.07)	(1.67)	(3.85)
ReviseDowns	−0.030***	−0.030***	−0.013*	−0.014*	−0.025***	−0.025***
	(−7.81)	(−7.71)	(−1.85)	(−1.76)	(−2.97)	(−5.43)
PosES	0.496***	0.482***	0.061		0.238*	0.408***
	(6.48)	(6.34)	(0.55)		(1.78)	(4.97)
NegES	−0.903***	−0.915***	−0.562***		−0.560***	−0.927***
	(−10.98)	(−11.05)	(−4.64)		(−3.39)	(−9.53)
Guidance	−0.088	−0.095	0.155	0.292	−0.033	−0.259
	(−0.39)	(−0.42)	(0.47)	(0.63)	(−0.12)	(−1.07)
PosGuidance	0.454**	0.452**	−0.008	−0.159	0.213	0.565***
	(2.21)	(2.20)	(−0.03)	(−0.36)	(0.80)	(2.64)
NegGuidance	−0.764***	−0.758***	−0.452*	−0.798*	−0.506*	−0.565**
	(−3.40)	(−3.37)	(−1.70)	(−1.90)	(−1.91)	(−2.56)
Edgar8K	−0.024	−0.037	0.018	−0.049	−0.053	−0.019
	(−0.63)	(−0.97)	(0.32)	(−0.95)	(−1.01)	(−0.49)
Volatility	−0.575	−0.635	−3.124***	−2.865**	−0.910	−0.657
	(−0.63)	(−0.70)	(−2.93)	(−2.57)	(−0.87)	(−0.76)

Table 5 (continued)

$AbRet_{i,[t-60,t-3]}$		−0.598***	−0.606***	−0.313**	−0.302*	−0.688***	−0.624***
		(−5.28)	(−5.35)	(−1.98)	(−1.77)	(−4.36)	(−5.89)
$AbRet_{i,[t-2]}$		−3.895***	−3.907***	−2.299**	−2.711**	−4.211***	−3.640***
		(−5.24)	(−5.26)	(−2.04)	(−2.21)	(−3.78)	(−4.19)
$AbRet_{i,[t-1]}$		−3.271***	−3.323***	−1.126	−1.607	−2.863***	−2.608***
		(−4.62)	(−4.71)	(−1.21)	(−1.44)	(−3.07)	(−3.28)
Size		−0.077***	−0.088***	−0.132***	−0.136***	−0.118***	−0.094***
		(−7.54)	(−7.25)	(−7.88)	(−7.70)	(−8.06)	(−7.67)
BTM		−0.003	−0.005	0.002	0.002	−0.008	−0.014
		(−0.37)	(−0.52)	(0.13)	(0.12)	(−0.80)	(−1.34)
InstOwn		0.032	0.029	0.033	−0.004	−0.018	−0.026
		(0.79)	(0.71)	(0.64)	(−0.08)	(−0.32)	(−0.63)
AnalystFollowers		−0.072***	−0.074***	−0.091***	−0.084**	−0.082***	−0.082***
		(−3.00)	(−3.05)	(−2.70)	(−2.42)	(−2.74)	(−3.19)
SAFollowers		0.009	0.008	0.003	−0.002	0.011	0.010
		(1.35)	(1.28)	(0.29)	(−0.22)	(1.27)	(1.55)
Observations	86,741	86,741	86,741	37,291	33,641	45,612	74,775
Adjusted R^2	0.011	0.030	0.031	0.027	0.028	0.029	0.029

Panel B: Test of H1 (Article-level, NPA Fixed Effects)

	(1)	(2)	(3)	(4)
Variable	ALL	ALL	NO DOW-JONES	NO DOW-JONES OR EARNINGS SURPRISE
Short	−0.605***	−0.609***	−0.841***	−0.982***
	(−5.03)	(−5.06)	(−4.43)	(−4.53)

Table 5 (continued)

Long	0.296***	0.295***	0.343***	0.350***
	(7.25)	(7.29)	(5.31)	(4.95)
NegPct	−16.983***	−16.349***	−15.839***	−14.781***
	(−8.70)	(−8.63)	(−5.40)	(−4.77)
PosPct	10.067***	9.627***	7.284**	8.105***
	(4.60)	(4.42)	(2.60)	(2.76)
CogProc	−1.602***	−1.586***	−1.492**	−1.226
	(−3.47)	(−3.43)	(−2.09)	(−1.64)
Numbers	0.966*	0.922*	1.561	1.546
	(1.83)	(1.75)	(1.57)	(1.44)
lWordCount	0.151***	0.153***	0.262***	0.228***
	(3.23)	(3.31)	(3.83)	(3.16)
$ComPosPct_{i,[t,t+1]}$	2.465**	2.318**	3.388**	3.215**
	(2.61)	(2.44)	(2.30)	(2.16)
$ComNegPct_{i,[t,t+1]}$	−5.963***	−5.741***	−3.458*	−2.732
	(−4.05)	(−3.91)	(−1.80)	(−1.43)
Constant	1.329	1.336	−1.257	−0.632
	(1.29)	(1.28)	(−1.07)	(−0.66)
Observations	104,952	104,952	40,293	36,005
Adjusted R^2	0.062	0.063	0.081	0.085

Table 5 presents results from estimating [1]. The dependent variable is $AbRet_{i,[t,t+1]}$, multiplied by 100 to facilitate exposition. Panel A reports results using the full sample of firm-day observations, and Panel B supplements [1] with NPA fixed effects and presents results at the article (rather than firm-day) level. Columns 1 through 3 (1 and 2) include all observations, and Columns 4 and 5 (3 and 4) exclude observations with concurrently issued Dow Jones news content and Dow Jones news content and earnings surprises in Panel A (Panel B). Columns 6 and 7 in Panel A also exclude articles with post-article information events and articles on days on which more than one article is published. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes two-tailed significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (two-tailed) assessed using *t*-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms.

One immediate concern related to these results is that NPA positions correlate with some unobserved characteristic, such as reputation or writing style, which drives the results found in support for H1 and for which we have been unable to control. To address this possibility, we supplement eq. (1) with NPA fixed effects and estimate this model at the article rather than firm-day level. Panel B reports results of this test. For brevity, we only report coefficients on SA-related variables. As presented, we continue to find strong support for H1, as both *Long* and *Short* exhibit highly significant associations (t-statistics between 4.43 and 7.29 in magnitude) with returns in the two-day window following the article's publication.[24] The coefficients in Panel B of Table 5 suggest a positive two-day return of approximately 0.3% for long positions, and disclosure of a short position corresponds to negative returns between 0.60 and 1.0% over the same period. These effects are similar, though smaller than those presented in Panel A.

4.2 Test of H2

H2 predicts that investors respond more strongly to the tone (*PosPct* and *NegPct*) of articles authored by those with stock positions compared to those with no position. We report results related to H2 in Table 6, where we use *Position* as a partitioning variable and estimate eq. (1) using four separate subsamples: (1) $Position = 0$, (2) $|Position| = 1$, (3) $Position = -1$, and (4) $Position = 1$.[25] The final four columns of Table 6 report tests of differences of coefficients across the partitions (i.e., the header "1–2" reports the significance of the difference in coefficients between columns 1 and 2).

Columns 1 and 2 present our formal test of H2. Specifically, H2 suggests that the coefficients on *NegPct* and *PosPct* should be stronger (larger in magnitude) in column 2 than in column 1. The magnitude of the coefficient on *NegPct* in column 2 (−31.925) exceeds that in column 1 (−11.696), and this difference is highly significant ($p < 0.01$). We observe a similar pattern for *PosPct*. The column 2 coefficient (23.3) significantly exceeds the column 1 value (8.862, difference significant at $p < 0.01$). While we make no predictions of how coefficient patterns differ over the remaining columns in Table 6, we present the remaining tests-of-differences for completeness. Comparing coefficient estimates in column 3 (4) to column 1 provides an indication of whether positive and negative tone by short (long) NPAs is considered more credible than those with no position. Interestingly, the magnitudes of coefficients on *PosPct* in column 3 and *NegPct* in column 4 are larger than the same coefficients in column 1, though these differences are only marginally significant (one-tailed p-values of 0.06 and 0.04, respectively). Thus positive (negative) tone in articles written by NPAs is more credible when they hold short (long) positions, suggesting that an NPA is most credible when reporting information contrary to his or her position. Comparing column 3 (short positions) to column 4 (long positions) suggests no significant differences.

[24] To the extent that the absolute (rather than signed) reaction to an author's work varies with his or her reputation, using signed returns in Panel B may not adequately control for unobserved author characteristics. Therefore, in untabulated tests, we replace the dependent variable with the natural log of 1 plus the absolute value of $AbRet_{i,[0,1]}$ and repeat tests in Panel B of Table 5. While we continue to find significant coefficients on *Short* in all specifications (t-statistics between 2.54 and 4.75), coefficients on *Long* are significant only in full-sample models.

[25] We present results for H2 using sample partitions. To assess significance, we estimate equation [1] using a series of fully interacted models. Reported significance levels reflect the significance of the interaction distinguishing the two compared columns. We report one-tailed p-values when comparing "position" articles versus no position (i.e., columns 2, 3, or 4 versus column 1) and two-tailed otherwise.

Table 6 Test of H2

Variable	(1) Position = 0	(2) |Position| = 1	(3) Position = −1	(4) Position = 1	Test of Difference 1–2	1–3	1–4	3–4
NegPct	−11.696***	−31.925***	−19.280*	−19.424***	0.00	0.24	0.04	0.99
	(−5.88)	(−9.17)	(−1.77)	(−4.91)				
PosPct	8.862***	23.300***	37.616*	12.341***	0.00	0.06	0.20	0.17
	(4.52)	(5.52)	(1.97)	(3.10)				
CogProc	−1.346***	−2.642***	−1.580	−2.429***	0.16	0.91	0.19	0.78
	(−3.18)	(−2.84)	(−0.49)	(−2.84)				
Numbers	0.854*	−0.443	−4.301	0.430	0.17	0.13	0.65	0.16
	(1.84)	(−0.57)	(−1.26)	(0.56)				
lWordCount	0.066**	0.081**	−0.385**	0.185***	0.76	0.00	0.01	0.00
	(2.12)	(2.06)	(−2.50)	(4.74)				
$ComNegPct_{i,[t,t+1]}$	−4.828***	−10.638***	4.903	−8.709***	0.04	0.36	0.17	0.22
	(−3.72)	(−3.87)	(0.45)	(−3.14)				
$ComPosPct_{i,[t,t+1]}$	1.937	8.275***	−8.084	6.358***	0.03	0.43	0.11	0.22
	(1.47)	(3.47)	(−0.64)	(2.82)				
DJNegPct	−9.387***	−1.320	−22.341*	−0.450	0.03	0.25	0.03	0.08
	(−4.16)	(−0.41)	(−1.84)	(−0.13)				
DJPosPct	16.411***	18.176***	17.408	18.205***	0.73	0.97	0.75	0.97
	(6.86)	(4.52)	(0.85)	(4.35)				
IDJ	0.048	0.020	0.080	0.042	0.75	0.89	0.98	0.89
	(1.26)	(0.31)	(0.29)	(0.62)				
Upgrades	0.535***	0.491***	0.349	0.490***	0.55	0.54	0.54	0.65
	(10.39)	(6.72)	(1.12)	(6.56)				
Downgrades	−0.434***	−0.467***	−0.710**	−0.436***	0.63	0.31	0.96	0.31
	(−8.94)	(−7.57)	(−2.56)	(−6.90)				
ReviseUps	0.012**	0.018***	−0.008	0.018***	0.51	0.63	0.45	0.52
	(2.14)	(2.78)	(−0.18)	(3.09)				
ReviseDowns	−0.027***	−0.036***	−0.087**	−0.035***	0.23	0.07	0.30	0.12
	(−5.42)	(−5.36)	(−2.54)	(−5.44)				
PosES	0.511***	0.405***	1.710**	0.314**	0.52	0.08	0.26	0.05
	(6.02)	(2.84)	(2.39)	(2.09)				
NegES	−1.090***	−0.542***	1.465**	−0.737***	0.02	0.00	0.13	0.00
	(−9.59)	(−3.20)	(2.24)	(−4.01)				
Guidance	−0.287	0.455	3.098*	−0.073	0.25	0.04	0.72	0.04
	(−1.22)	(0.78)	(1.85)	(−0.15)				
PosGuidance	0.572***	0.090	−2.512*	0.638	0.45	0.03	0.89	0.01
	(2.78)	(0.16)	(−1.71)	(1.31)				
NegGuidance	−0.660***	−1.105**	−4.733***	−0.437	0.44	0.01	0.65	0.00
	(−2.75)	(−2.12)	(−2.94)	(−1.03)				
Edgar8K	0.017	−0.138**	−0.644*	−0.091	0.04	0.07	0.21	0.15
	(0.40)	(−2.12)	(−1.78)	(−1.17)				

Table 6 (continued)

Variable	(1) *Position = 0*	(2) *|Position| = 1*	(3) *Position = −1*	(4) *Position = 1*	Test of Difference 1–2	1–3	1–4	3–4
Volatility	−1.813	0.179	−5.325*	3.229**	0.25	0.22	0.00	0.00
	(−1.60)	(0.13)	(−1.93)	(2.29)				
$AbRet_{i,[t-60,t-3]}$	−0.483***	−0.987***	−1.700***	−0.655***	0.01	0.01	0.37	0.04
	(−3.52)	(−5.93)	(−3.67)	(−3.37)				
$AbRet_{i,[t-2]}$	−4.205***	−3.587***	−12.895***	−1.872	0.76	0.03	0.24	0.00
	(−3.83)	(−2.68)	(−3.43)	(−1.31)				
$AbRet_{i,[t-1]}$	−3.549***	−3.242**	−12.769***	−2.273	0.88	0.01	0.50	0.00
	(−3.92)	(−2.31)	(−3.72)	(−1.53)				
Size	−0.051***	−0.141***	0.358***	−0.166***	0.00	0.00	0.00	0.00
	(−3.90)	(−6.85)	(3.56)	(−7.47)				
BTM	0.013	−0.020	0.066	−0.054***	0.12	0.72	0.00	0.42
	(1.15)	(−1.11)	(0.42)	(−3.41)				
InstOwn	−0.013	0.051	0.467	0.076	0.49	0.24	0.36	0.36
	(−0.27)	(0.72)	(1.11)	(0.95)				
AnalystFollowers	−0.012	−0.171***	0.430**	−0.287***	0.00	0.02	0.00	0.00
	(−0.43)	(−3.89)	(2.22)	(−6.99)				
SAFollowers	0.006	0.034***	−0.009	0.039***	0.06	0.81	0.03	0.39
	(0.71)	(2.62)	(−0.17)	(2.95)				
Observations	58,057	28,684	2431	26,253				
Adjusted R^2	0.025	0.036	0.108	0.044				

Table 6 presents results from estimating [1] separately by position and tests of differences in coefficients across the four columns. The dependent variable is $AbRet_{i,[t,t+1]}$, multiplied by 100 to facilitate exposition. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (one-tailed where a prediction is made and two-tailed otherwise) assessed using *t*-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms.

In sum, we find strong support for H2. Investors appear to perceive tone by NPAs holding positions to be more credible than those with no position. Additional evidence suggests that these results are primarily driven by the response to tone that is contrary with an author's position (i.e., positive tone for short authors and negative tone for long authors). Importantly, though, we find no evidence that even position-consistent tone is discounted, implying investors perceive no bias related to NPAs having skin in the game.

5 Additional analysis

5.1 Alternative explanations: Contemporaneous events leading to observed stock price reactions

A concern is that our variables of interest capture some other article attribute or contemporaneous event. We believe this is unlikely because the long-form of

SA articles, which often include tables, charts, and links to detailed analysis, makes it unlikely that a nonprofessional analyst observes an event and immediately produces such an article. In addition, SA articles undergo an editorial process which, per our discussions with an SA executive, averages 4.5 h and can take up to 12. Finally, with respect to H2, contemporaneous events would need to correlate with not only the content of the articles but also the position of the person writing the article, and an inspection of the articles reveals no systematic differences in articles authored by positioned NPAs (*Short* or *Long* equaling 1) compared to those with no position. Nevertheless, in this section, we perform several additional tests designed to mitigate the likelihood that our results are due to contemporaneous firm economic events.

5.1.1 Controlling for firm news around the SA article release date and time

Another alternative explanation for our results is that the stock returns we observe are not a reaction to the SA article but instead a reaction to contemporaneous news. In our main tests, we attempt to rule out this explanation by including a host of control variables related to contemporaneous news, including the tone of business press articles, analyst revisions and recommendations, and management guidance. To further mitigate this issue, we take advantage of the fact that the SA editorial process takes an average of 4.5 h to complete and assume that any article published before 1 pm (i.e., the first 3.5 trading hours of the day) must have been submitted to SA before the market opened for the day. We then redefine the day 0 return as (closing price – opening price) / opening price (all measured on day 0). Therefore any overnight or pre-market news impounded into the opening price is excluded from our returns.

Using this revised measure of returns and limiting the sample to articles posted in the first few hours of trading, we repeat our analyses from Table 5 and present the results in Table 7. As shown, we continue to find significant coefficients on both *Long* and *Short*, and the economic significance of these effects is relatively unchanged. While it is impossible to empirically control for all possible contemporaneous news, these results add further assurance that our stock price results are not explained by contemporaneous news events and are instead a reaction to the SA articles themselves.

5.1.2 Interactions between rigor of analysis and position

While we contend that disclosure of stock positions provides a value-relevant signal to market participants, we recognize that simply saying "I am long …" without any other support would likely garner little investor reaction. Therefore we expect that the reaction to NPA positions increases with the amount of information and quality of analysis presented alongside their position disclosure. To test this conjecture, we use cognitive effort (*CogProc*), the number of numbers (*Numbers*), and article length (*lWordCount*) as proxies for the quality and volume of information in the article and interact these variables with both *Long* and *Short* in eq. (1). We expect each interaction to load in the same

Table 7 Early Morning SA Articles

Variable	(1) ALL	(2) ALL	(3) ALL	(4) NO DOW-JONES	(5) NO DOW-JONES OR EARNINGS SURPRISE	(6) NO POST ARTICLE EVENTS	(7) SINGLE ARTICLE DAYS
Short	−1.312***	−1.398***	−1.403***	−1.896***	−2.051***	−1.385***	−1.462***
	(−6.86)	(−6.97)	(−6.99)	(−6.46)	(−6.16)	(−5.46)	(−6.89)
Long	0.371***	0.323***	0.321***	0.483***	0.524***	0.550***	0.319***
	(6.12)	(5.33)	(5.32)	(4.58)	(4.74)	(5.74)	(5.17)
NegPct	−7.247*	−6.655*	−6.692*	−15.825**	−18.039***	−15.703***	−6.413
	(−1.87)	(−1.66)	(−1.67)	(−2.51)	(−2.78)	(−2.77)	(−1.57)
PosPct	8.585**	9.181**	9.147**	15.420**	15.221**	13.485**	9.710**
	(2.31)	(2.46)	(2.44)	(2.49)	(2.43)	(2.43)	(2.60)
CogProc	−1.721**	−1.472*	−1.471*	−0.005	−0.210	−0.919	−1.475*
	(−2.29)	(−1.93)	(−1.93)	(−0.00)	(−0.18)	(−0.91)	(−1.92)
Numbers	1.275	1.259	1.250	1.314	0.945	−0.331	1.398*
	(1.58)	(1.50)	(1.50)	(0.95)	(0.66)	(−0.28)	(1.69)
lWordCount	0.097*	0.079	0.079	0.054	0.056	0.145**	0.083
	(1.86)	(1.49)	(1.51)	(0.75)	(0.74)	(2.12)	(1.53)
$ComNegPcti_{,[t,t+1]}$	−5.105**	−4.071	−3.990	−1.289	−1.113	−6.123**	−4.319*
	(−2.09)	(−1.65)	(−1.61)	(−0.37)	(−0.31)	(−2.07)	(−1.76)
$ComPosPcti_{,[t,t+1]}$	3.058	3.363	3.376*	3.679	4.080	4.909*	3.294
	(1.51)	(1.66)	(1.66)	(1.30)	(1.36)	(1.68)	(1.60)
Upgrades		0.286***	0.284***	0.174	0.297	−0.014	0.265***
		(2.90)	(2.87)	(1.00)	(1.53)	(−0.09)	(2.69)
Downgrades		−0.189**	−0.187**	−0.213	−0.124	−0.129	−0.207**
		(−2.24)	(−2.22)	(−1.53)	(−0.82)	(−0.98)	(−2.32)

Table 7 (continued)

Variable	(1) ALL	(2) ALL	(3) ALL	(4) NO DOW-JONES	(5) NO DOW-JONES OR EARNINGS SURPRISE	(6) NO POST ARTICLE EVENTS	(7) SINGLE ARTICLE DAYS
Volatility		−2.012	−2.090	1.088	0.838	−0.249	−1.700
		(−1.09)	(−1.14)	(0.48)	(0.37)	(−0.12)	(−0.92)
$AbRet_{i,[t-60,t-3]}$		−0.658***	−0.660***	−0.692**	−0.656**	−0.756**	−0.689***
		(−3.00)	(−2.99)	(−2.40)	(−2.10)	(−2.59)	(−3.09)
$AbRet_{i,[t-2]}$		−2.317	−2.325	−0.256	−2.416	−3.225	−2.289
		(−1.55)	(−1.56)	(−0.11)	(−1.01)	(−1.48)	(−1.48)
$AbRet_{i,[t-1]}$		−1.880	−1.911	−1.408	−2.485	−1.509	−1.735
		(−1.33)	(−1.35)	(−0.70)	(−1.04)	(−0.77)	(−1.20)
PosES		0.215	0.205	0.095		0.268	0.238
		(1.46)	(1.39)	(0.43)		(1.19)	(1.52)
NegES		−0.704***	−0.711***	−0.542*		−0.639**	−0.713***
		(−4.19)	(−4.26)	(−1.96)		(−2.24)	(−4.03)
DJNegPct			−1.980			−2.890	−3.075
			(−0.69)			(−0.62)	(−0.99)
DJPosPct			10.002***			4.488	11.686***
			(2.99)			(0.98)	(3.49)
IDJ			−0.008			−0.028	−0.034
			(−0.11)			(−0.28)	(−0.47)
ReviseUps		0.005	0.005	−0.001	0.003	0.013	0.010
		(0.54)	(0.54)	(−0.06)	(0.14)	(0.92)	(1.12)
ReviseDowns		0.004	0.004	0.023	0.029*	0.023	0.003
		(0.50)	(0.51)	(1.56)	(1.97)	(1.59)	(0.36)
Guidance		−0.038	−0.048	−0.129	−0.657	−0.583	−0.071
		(−0.09)	(−0.12)	(−0.26)	(−1.07)	(−1.03)	(−0.17)

Table 7 (continued)

Variable	(1) ALL	(2) ALL	(3) ALL	(4) NO DOW-JONES	(5) NO DOW-JONES OR EARNINGS SURPRISE	(6) NO POST ARTICLE EVENTS	(7) SINGLE ARTICLE DAYS
PosGuidance		0.267	0.269	−0.109	0.640	0.398	0.162
		(0.72)	(0.73)	(−0.24)	(1.07)	(0.78)	(0.42)
NegGuidance		−0.494	−0.482	0.009	0.391	0.252	−0.449
		(−1.31)	(−1.28)	(0.02)	(0.67)	(0.54)	(−1.14)
Edgar8K		−0.067	−0.076	−0.059	−0.093	−0.166	−0.058
		(−0.85)	(−0.97)	(−0.50)	(−0.78)	(−1.54)	(−0.73)
Size		−0.054***	−0.061***	−0.058*	−0.063*	−0.053*	−0.054**
		(−2.70)	(−2.81)	(−1.69)	(−1.75)	(−1.82)	(−2.46)
BTM		−0.022	−0.024	−0.016	−0.012	−0.004	−0.025
		(−1.22)	(−1.29)	(−0.56)	(−0.40)	(−0.18)	(−1.36)
InstOwn		0.170**	0.171**	0.095	0.102	0.055	0.187***
		(2.44)	(2.46)	(0.92)	(0.92)	(0.56)	(2.84)
AnalystFollowers		−0.156***	−0.156***	−0.273***	−0.267***	−0.159***	−0.165***
		(−3.16)	(−3.16)	(−4.15)	(−4.00)	(−2.73)	(−3.40)
SAFollowers		0.007	0.007	0.011	0.004	0.008	0.007
		(0.68)	(0.68)	(0.59)	(0.18)	(0.50)	(0.63)
Observations	18,782	18,782	18,782	9,042	8,218	10,259	18,141
Adjusted R^2	0.015	0.023	0.023	0.033	0.035	0.028	0.024

Table 7 presents results from estimating [1] using a sample of articles published between 9:30 am and 1:00 pm on trading days. The dependent variable is the two-day abnormal return, where the day 0 return is defined as (closing price – opening price) / opening price. The two-day abnormal return is multiplied by 100 to facilitate exposition. Columns 1 through 3 impose no additional sample screens, and Column 4 (5) [6] {7} excludes observations with concurrently issued Dow Jones news content (Dow Jones news content or earnings surprises) [post-article information events] {articles on days on which more than one article is written}. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes two-tailed significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (two-tailed) assessed using *t*-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms direction as the position (e.g., positive for *Long x lWordCount* and negative for *Short x lWordCount*).[26]

Results from these analyses are presented in Table 8. We include the same subsamples as in earlier analyses (all observations, excluding Dow Jones, excluding Dow Jones and earnings surprises, excluding post-article information events). In all four columns, coefficients on *Long* and *Short* remain significant at less than the 1% level, and magnitudes are similar to those shown in Table 5. Most importantly, we observe several significant coefficients on interactions in the expected direction. That is, in all specifications, the interaction between *Long* and *lWordCount* is significantly positive (*t*-statistics between 2.84 and 3.66), and the interaction between *Short* and *lWordCount* is significantly negative (*t*-statistics between −3.69 and − 5.85). We also find some evidence that the number of numbers (*Numbers*) increases the credibility of short positions (*t*-statistics of −2.18, −1.72 and − 1.86 in columns 1, 2 and 3, respectively. Thus investor reaction to NPA positions appears to increase with article length, as expected, and, to a lesser extent, numerical information enhances the reaction to short position disclosures. More importantly, the fact that the main effects for *Short* and *Long* continue to hold provides further evidence that NPA positions themselves convey meaningful information to readers and are not capturing dimensions of article quality.

5.1.3 First-time versus repeated disclosures

To further support that NPA positions, and not an unidentified correlated omitted variable, explains the reaction to SA content, we next examine whether the reaction to position is stronger for the NPA's first article publishing his or her stock position. Specifically, we sort our sample of SA content by firm (i.e., primary ticker), NPA, and date, and identify whether the article marks the first time an NPA discloses a position about the subject firm. We denote this article using an indicator variable, *FirstDisc.* We then estimate eq. (1), including interactions between *FirstDisc* and both *Long* and *Short.* We expect that the relations between returns and both *Short* and *Long* are stronger the first time an NPA discloses a position.[27] In addition, we include interactions between *FirstDisc* and other article attributes (*CogProc*, *Numbers*, *lWordCount*, *NegPct*, *PosPct*, *ComNegPct*, and *ComPosPct*), because relations between those variables and returns may vary depending on how often the NPA writes about a given firm. However, we make no predictions related to these interactions.

Table 9 presents results from this analysis. For brevity, we only include coefficients on the interactions between SA-related variables and *FirstDisc* and suppress tabulation of other coefficients. We include the same subsamples used throughout the paper.

[26] We center these three variables at 0 for this analysis to maintain interpretability of coefficients on *Long* and *Short*. In other words, main effects on *Long* and *Short* represent the response to position for average levels of the interacted variables. This is especially useful, as another explanation for our results related to H1 is that, for articles written by NPAs with a long (short) position, article length captures positive (negative) tone not measured in *PosPct* (*NegPct*). If this were the case, then we would observe a significant interaction between each position variable and *lWordCount* but insignificant main effects on *Long* and *Short*.

[27] One may argue that the first-time disclosure of a position should be the only time this knowledge matters. However, multiple articles disclosing the same position affirm the author's beliefs over time, similar to management affirming a previously issued forecast, thus providing additional relevant signals.

Table 8 NPA Positions and Article Length, Rigor, and Numerical Content

Variable	(1) ALL	(2) NO DOW-JONES	(3) NO DOW-JONES OR EARNINGS SURPRISE	(4) NO POST EVENTS
Short	−0.988***	−1.267***	−1.354***	−1.210***
	(−7.94)	(−7.71)	(−7.63)	(−7.49)
Long	0.368***	0.493***	0.503***	0.485***
	(11.15)	(9.51)	(9.62)	(10.63)
Short x CogProc	−1.496	0.076	0.296	−1.077
	(−0.47)	(0.02)	(0.08)	(−0.26)
Short x Numbers	−7.529**	−8.325*	−9.024*	−3.907
	(−2.18)	(−1.72)	(−1.86)	(−0.89)
Short x lWordCount	−0.899***	−0.965***	−0.977***	−0.833***
	(−5.85)	(−4.36)	(−4.41)	(−3.69)
Long x CogProc	−0.168	2.461	2.340	−1.049
	(−0.18)	(1.64)	(1.53)	(−0.69)
Long x Numbers	−0.449	−1.125	−0.731	1.512
	(−0.51)	(−0.89)	(−0.51)	(1.21)
Long x lWordCount	0.165***	0.250***	0.236***	0.264***
	(3.24)	(3.02)	(2.84)	(3.66)
NegPct	−14.400***	−15.634***	−15.829***	−19.688***
	(−7.98)	(−5.83)	(−5.70)	(−7.07)
PosPct	11.142***	13.245***	13.223***	12.963***
	(5.51)	(5.04)	(5.03)	(4.70)
CogProc	−1.448***	−1.925***	−1.740**	−0.992*
	(−3.40)	(−2.70)	(−2.56)	(−1.75)
Numbers	0.628	1.578**	1.492*	−0.130
	(1.40)	(2.01)	(1.81)	(−0.21)
lWordCount	0.072**	0.108**	0.110**	0.132***
	(2.46)	(2.25)	(2.29)	(3.21)
$ComNegPct_{i,[t,t+1]}$	−5.334***	−4.863***	−4.027**	−4.031**
	(−4.06)	(−2.76)	(−2.26)	(−2.27)
$ComPosPct_{i,[t,t+1]}$	3.108***	4.071***	4.404***	4.610***
	(3.02)	(2.73)	(2.89)	(3.56)
DJNegPct	−6.752***			1.322
	(−3.36)			(0.45)
DJPosPct	17.145***			11.803***
	(8.00)			(4.23)
IDJ	0.046			0.063
	(1.40)			(1.51)
Upgrades	0.524***	0.254***	0.248**	0.449***
	(10.56)	(2.76)	(2.37)	(6.18)
Downgrades	−0.445***	−0.231***	−0.146**	−0.313***
	(−11.05)	(−3.94)	(−2.32)	(−4.81)

Table 8 (continued)

Variable	(1) ALL	(2) NO DOW-JONES	(3) NO DOW-JONES OR EARNINGS SURPRISE	(4) NO POST EVENTS
ReviseUps	0.013***	0.015*	0.032***	0.008
	(3.23)	(1.91)	(3.04)	(0.97)
ReviseDowns	−0.030***	−0.013*	−0.014*	−0.026***
	(−7.74)	(−1.87)	(−1.78)	(−3.02)
PosES	0.483***	0.065		0.210
	(6.36)	(0.59)		(1.46)
NegES	−0.919***	−0.563***		−0.605***
	(−11.06)	(−4.62)		(−3.30)
Guidance	−0.108	0.141	0.279	0.031
	(−0.48)	(0.43)	(0.60)	(0.11)
PosGuidance	0.464**	−0.000	−0.156	0.232
	(2.28)	(−0.00)	(−0.35)	(0.88)
NegGuidance	−0.750***	−0.447*	−0.797*	−0.483*
	(−3.35)	(−1.70)	(−1.91)	(−1.93)
Edgar8K	−0.035	0.020	−0.047	−0.065
	(−0.92)	(0.36)	(−0.90)	(−1.21)
Volatility	−0.548	−3.069***	−2.806**	−1.351
	(−0.61)	(−2.89)	(−2.52)	(−1.21)
$AbRet_{i,[t-60,t-3]}$	−0.608***	−0.314**	−0.303*	−0.540***
	(−5.37)	(−1.99)	(−1.78)	(−3.23)
$AbRet_{i,[t-2]}$	−3.939***	−2.380**	−2.817**	−4.873***
	(−5.31)	(−2.11)	(−2.28)	(−4.25)
$AbRet_{i,[t-1]}$	−3.346***	−1.175	−1.650	−3.167***
	(−4.75)	(−1.26)	(−1.48)	(−3.49)
Size	−0.089***	−0.132***	−0.137***	−0.119***
	(−7.31)	(−7.85)	(−7.68)	(−8.04)
BTM	−0.006	0.002	0.002	−0.016
	(−0.59)	(0.17)	(0.17)	(−1.46)
InstOwn	0.034	0.037	−0.002	−0.011
	(0.82)	(0.70)	(−0.03)	(−0.19)
AnalystFollowers	−0.078***	−0.094***	−0.087**	−0.112***
SAFollowers	(−3.26)	(−2.82)	(−2.51)	(−3.78)
	0.008	0.004	−0.001	0.009
	(1.25)	(0.38)	(−0.13)	(0.97)
Observations	86,741	37,291	33,641	41,075
Adjusted R^2	0.032	0.028	0.029	0.031

Table 8 presents results from estimating [1] after interacting article characteristics with NPA positions. Column 1 includes all observations, and Column 2 (3) [4] excludes firm-days with contemporaneously issued Dow Jones content (contemporaneously issued Dow Jones content or earnings-surprise announcements) [post-article information events]. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (one-tailed where a prediction is made and two-tailed otherwise) assessed using t-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms

Consistent with expectations, we observe a highly significant negative coefficient on the interaction between *FirstDisc* and *Short* for first disclosures (*t*-statistics between −4.5 and − 5.8) and a significantly positive coefficient on the interaction between *FirstDisc* and *Long* (*t*-statistics between 3.11 and 3.43).[28]

5.2 SA content and long-run returns

As discussed, Chen et al. (2014) document a significantly negative return between the percentage of negative words in SA articles and returns over the subsequent quarter (approximately 60 trading days). In our main tests, we focus on contemporaneous pricing of SA content. We now repeat these analyses (Tables 5 and 6) replacing our short window return ($AbRet_{i,[t,t+1]}$) with the post-event return over the following 60 days ($AbRet_{i,[t+3,t+60]}$), following Chen et al. (2014). We also examine returns during the window three to five days after the article, three to 10 days, and three to 20 days to evaluate the exact timeframe over which any drift or reversal occurs.

Table 10 replicates Table 5 using post-event returns. We use all controls from (1) and add $AbRet_{i,[t,t+1]}$ and tone from comments over the duration of the full return window. We include the same models as in Table 5. Unlike Chen et al. (2014), we do not observe associations between *NegPct* and *PosPct* and post-event returns.[29] We do, however, find a significant negative association between 60-day returns and *Short*, suggesting that the market does not fully impound the information content of a short position. Importantly, the previously discussed results related to the pricing of position disclosures do not reverse, further supporting these disclosures as credible market signals.

5.3 NPA characteristics as alternative credibility signals

Similar to other research in the area, we focus on NPA's personal stock positions as a signal of credibility. However, there are likely many other means by which readers of SA could evaluate the credibility of NPAs, such as whether the NPA is a financial professional, has a large number of followers, or has exhibited a strong record of accurate analysis. We briefly consider some of these characteristics in untabulated analyses in this section. Specifically, we bifurcate our sample (similar to our tests of H2) based on NPA attributes and consider whether the sensitivity of returns to position disclosures and article sentiment vary across partitions.

First, we consider whether the NPA is a financial professional based on whether he or she self-reports as an analyst or CFA or whether the SA account appears to be owned by an investment firm or advisor. We find that disclosures of long positions (*Long*) are significantly more credible in this group ($p = 0.05$) but observe no other differences. Second, we consider whether author following represents a salient measure of credibility. Note that authors with more

[28] We also considered whether a change in disclosures represents a credible signal. However, this only occurs in about 8% of articles.

[29] In untabulated tests, we replicate their result using size and book-to-market matched portfolio returns as well as simple market-adjusted returns. Thus the difference in our result appears to be driven by return definition (ours corrects for momentum, theirs does not) rather than differences in sample period or control variables. Additionally, Chen et al. (2014) still provide important evidence that SA articles predict future earnings news.

Table 9 First-time vs. Repeated Disclosures of Position

Variable	(1) ALL	(2) NO DJ	(3) NO DJ OR EARN OR EARNINGS SURPRISE	(4) NO POST EVENT
FirstDisc x Short	−1.314***	−1.668***	−1.701***	−1.445***
	(−5.83)	(−4.50)	(−4.51)	(−4.96)
FirstDisc x Long	0.205***	0.312***	0.296***	0.292***
	(3.43)	(3.29)	(3.11)	(3.21)
FirstDisc x NegPct	−0.604	−4.345	−5.827	6.092
	(−0.18)	(−0.83)	(−1.14)	(1.18)
FirstDisc x PosPct	−6.992*	−6.647	−9.666*	−7.758
	(−1.81)	(−1.17)	(−1.66)	(−1.63)
FirstDisc x CogProc	2.925***	1.934	1.188	1.654
	(3.54)	(1.63)	(0.91)	(1.55)
FirstDisc x Numbers	−1.625*	−1.212	−1.528	−1.682
	(−1.68)	(−0.96)	(−1.15)	(−1.39)
FirstDisc x lWordCount	−0.086*	−0.218***	−0.204***	−0.141*
	(−1.73)	(−2.94)	(−2.64)	(−1.79)
FirstDisc x $ComPosPct_{i,[t,t+1]}$	0.833	1.989	5.135	1.084
	(0.39)	(0.58)	(1.49)	(0.35)
FirstDisc x $ComNegPct_{i,[t,t+1]}$	−0.466	−4.185	−4.286	0.668
	(−0.17)	(−1.05)	(−1.02)	(0.16)
Observations	86,741	37,291	33,641	41,075
Adjusted R-squared	0.032	0.029	0.030	0.031

Table 9 presents results from estimating [1] after including interactions between Seeking Alpha article-related variables and *FirstDisc*, an indicator equaling 1 the first time the NPA discloses a position. All other control variables from [1] are included, but coefficient estimates are suppressed to facilitate exposition. Column 1 includes all observations, and Column 2 (3) [4] excludes firm-days with contemporaneously issued Dow Jones content (contemporaneously issued Dow Jones content or earnings-surprise announcements) [post-article information events]. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (one-tailed where a prediction is made and two-tailed otherwise) assessed using *t*-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms

followers write far more articles, so we partition at the 90th percentile of following to obtain reasonable sample sizes in each partition. In this group, we find a significantly stronger coefficient on *PosPct* for articles with a high number of followers ($p < 0.01$); none of the other SA variables exhibit significant differences.[30] Finally, we consider how frequently NPAs write about a

[30] If we partition at the median following for the author population, the low (high) partition has approximately 8000 (96,000) observations. Nonetheless, we find similar evidence as that reported, except we also observe stronger responses to short position in the high-following sample ($p = 0.06$).

Table 10 NPA Position and Post-Publication Drift

Variable	(1) ALL 60 Days	(2) ALL 60 Days	(3) ALL 60 Days	(4) NO DOW-JONES 60 Days	(5) NO DOW-JONES OR EARNINGS SURPRISE 60 Days	(6) ALL Day 3–5	(7) ALL Day 3–10	(8) ALL Day 3–20
Short	−2.070***	−1.510***	−1.526***	−1.942**	−1.883**	−0.001	−0.001	−0.005
	(−3.51)	(−2.69)	(−2.72)	(−2.55)	(−2.39)	(−1.37)	(−0.62)	(−1.51)
Long	−0.282	0.005	−0.006	−0.192	−0.257	0.000	0.001	0.001
	(−1.38)	(0.03)	(−0.03)	(−0.67)	(−0.84)	(0.30)	(1.03)	(0.88)
NegPct	−4.709	−6.889	−9.599	−20.541	−17.318	0.010	−0.000	−0.039
	(−0.52)	(−0.77)	(−1.09)	(−1.54)	(−1.30)	(0.60)	(−0.02)	(−0.95)
PosPct	4.049	−3.462	−2.233	6.293	8.244	0.014	0.006	−0.017
	(0.43)	(−0.38)	(−0.25)	(0.44)	(0.55)	(0.78)	(0.20)	(−0.39)
CogProc	−3.638	−2.218	−2.387	−6.216*	−6.958**	−0.004	−0.010	−0.016
	(−1.54)	(−1.01)	(−1.09)	(−1.87)	(−2.13)	(−0.83)	(−1.29)	(−1.23)
Numbers	5.239**	3.648	3.951*	7.356**	7.239**	0.006	0.010	0.028**
	(2.19)	(1.58)	(1.71)	(2.10)	(2.01)	(1.64)	(1.28)	(2.39)
lWordCount	0.345**	0.351**	0.353**	0.428	0.449	0.000	0.001	0.000
	(2.40)	(2.49)	(2.51)	(1.63)	(1.58)	(1.17)	(1.66)	(0.54)
$ComNegPct_{i,[t,t+1]}$	4.226	2.984	2.083	−4.395	−4.871	0.000	−0.038*	−0.010
	(0.57)	(0.43)	(0.30)	(−0.42)	(−0.44)	(0.01)	(−1.67)	(−0.29)
$ComPosPct_{i,[t,t+1]}$	−6.293	−7.515*	−7.159	−2.819	−0.883	0.010	0.015	0.036
	(−1.38)	(−1.67)	(−1.59)	(−0.34)	(−0.10)	(0.88)	(0.86)	(1.25)
$ComNegPct_{i,[t+3,t+60]}$	−33.368***	−30.581***	−30.326***	−47.694***	−45.243***	−0.059***	−0.135***	−0.193***
	(−5.09)	(−4.65)	(−4.62)	(−4.42)	(−4.03)	(−4.45)	(−6.17)	(−5.75)

Table 10 (continued)

Variable	(1) ALL 60 Days	(2) ALL 60 Days	(3) ALL 60 Days	(4) NO DOW-JONES 60 Days	(5) NO DOW-JONES OR EARNINGS SURPRISE 60 Days	(6) ALL Day 3–5	(7) ALL Day 3–10	(8) ALL Day 3–20
$ComPosPct_{i,[t+3,t+60]}$	6.163	8.021*	8.208*	19.825**	24.444***	0.003	0.047***	0.068***
	(1.38)	(1.79)	(1.83)	(2.49)	(2.96)	(0.25)	(2.76)	(2.72)
DJNegPct			29.500***			−0.009	0.051*	0.088**
			(3.61)			(−0.52)	(1.79)	(2.21)
DJPosPct			−20.735**			−0.018	−0.052	−0.083
			(−2.03)			(−0.86)	(−1.62)	(−1.54)
IDJ			0.243			0.000	0.000	0.002
			(1.26)			(0.56)	(0.65)	(1.34)
Upgrades		0.104	0.084	0.457	0.351	0.000	0.000	0.000
		(0.44)	(0.36)	(1.04)	(0.62)	(0.61)	(0.30)	(0.21)
Downgrades		−0.422*	−0.451**	−0.613*	−0.877**	0.000	−0.001	−0.001
		(−1.97)	(−2.09)	(−1.72)	(−2.30)	(0.47)	(−1.46)	(−0.71)
ReviseUps		0.046*	0.045*	0.086**	0.097*	0.000	0.000	0.000
		(1.92)	(1.89)	(2.11)	(1.79)	(0.89)	(0.68)	(1.64)
ReviseDowns		−0.061***	−0.065***	−0.095**	−0.079	−0.000	−0.000	−0.000
		(−3.03)	(−3.24)	(−2.16)	(−1.47)	(−1.32)	(−0.64)	(−1.07)
PosE		0.468	0.427	0.390		0.000	0.002*	0.002
		(1.44)	(1.32)	(0.69)		(0.77)	(1.80)	(1.22)
NegES		0.045	0.001	−0.662		−0.000	0.000	−0.002
		(0.13)	(0.00)	(−1.24)		(−0.03)	(0.24)	(−0.83)

Table 10 (continued)

Variable	(1) ALL 60 Days	(2) ALL 60 Days	(3) ALL 60 Days	(4) NO DOW-JONES 60 Days	(5) NO DOW-JONES OR EARNINGS SURPRISE 60 Days	(6) ALL Day 3–5	(7) ALL Day 3–10	(8) ALL Day 3–20
Guidance		−0.789	−0.774	1.438	−0.377	0.002	0.002	0.002
		(−0.96)	(−0.94)	(1.22)	(−0.20)	(1.20)	(0.72)	(0.52)
PosGuidnce		0.771	0.757	−1.081	1.244	−0.001	−0.002	−0.001
		(0.96)	(0.94)	(−0.97)	(0.67)	(−0.89)	(−0.78)	(−0.17)
NegGuidanc		0.045	0.016	−1.771*	−1.002	−0.001	−0.001	−0.005
		(0.06)	(0.02)	(−1.69)	(−0.61)	(−0.85)	(−0.73)	(−1.48)
Edgar8K		−0.068	−0.113	0.256	0.223	−0.000	0.000	0.000
		(−0.32)	(−0.53)	(0.87)	(0.81)	(−1.17)	(0.26)	(0.05)
Volatility		−13.394*	−14.165*	−21.883**	−20.111**	−0.038***	−0.061***	−0.092***
		(−1.86)	(−1.97)	(−2.47)	(−2.28)	(−3.79)	(−3.34)	(−2.69)
$AbRet_{i,[t-60,t-3]}$		−1.632	−1.618	−2.398*	−2.475**	−0.003**	−0.006**	−0.009
		(−1.38)	(−1.37)	(−1.95)	(−1.99)	(−1.98)	(−2.23)	(−1.43)
$AbReti,_{[t-2]}$		−4.899	−4.917	−5.308	−5.864	−0.014*	−0.027**	−0.034*
		(−1.22)	(−1.22)	(−1.08)	(−0.98)	(−1.75)	(−2.11)	(−1.76)
$AbReti,_{[t-1]}$		−7.127**	−7.049**	−10.192**	−11.344**	−0.010	−0.017	−0.051***
		(−2.32)	(−2.30)	(−2.58)	(−2.37)	(−1.54)	(−1.50)	(−3.38)
$AbRet_{i,[t,t+1]}$	−0.016	−0.022	−0.021	−0.036	−0.061*	−0.000	−0.000	−0.000*
	(−0.64)	(−0.90)	(−0.86)	(−1.06)	(−1.73)	(−0.52)	(−0.96)	(−1.81)
Size		0.144	0.086	0.093	0.110	−0.000	−0.000	0.000
		(1.66)	(0.93)	(0.98)	(1.14)	(−0.74)	(−0.44)	(0.12)

Table 10 (continued)

Variable	(1) ALL 60 Days	(2) ALL 60 Days	(3) ALL 60 Days	(4) NO DOW-JONES 60 Days	(5) NO DOW-JONES OR EARNINGS SURPRISE 60 Days	(6) ALL Day 3–5	(7) ALL Day 3–10	(8) ALL Day 3–20
BT		0.622***	0.599***	0.543***	0.501***	0.000*	0.001***	0.002***
		(8.53)	(8.17)	(4.93)	(4.61)	(1.79)	(3.98)	(5.61)
InstOwn		1.961***	1.976***	2.298***	2.373***	0.001**	0.003***	0.006***
		(4.55)	(4.59)	(5.54)	(5.60)	(2.54)	(3.31)	(2.91)
AnalystFollowers		0.229	0.239	−0.110	−0.127	0.000	0.001**	0.001
		(0.90)	(0.94)	(−0.43)	(−0.49)	(1.45)	(2.11)	(1.24)
SAFollowers		0.010	0.007	0.042	0.015	−0.000	−0.000	−0.000
		(0.26)	(0.19)	(0.79)	(0.26)	(−0.45)	(−1.07)	(−1.10)
Observations	86,641	86,641	86,641	37,221	33,575	86,731	86,714	86,697
Adjusted R^2	0.022	0.029	0.029	0.031	0.031	0.004	0.008	0.013

Table 10 presents results from estimating [1] using $AbRet_{i,[t+3,t+60]}$ (multiplied by 100) as the dependent variable. Columns 1 to 3 include all observations, and Column 4 (5) excludes observations with concurrently issued Dow Jones news content (Dow Jones news content or earnings surprises). Columns 5–8 repeat the analyses in Columns 1–3 for drift during the three to five days, three to 10 days, and three to 20 days following the article date. All variables are defined in Appendix 1. All estimations include year-month and industry fixed effects. *** (**, *) denotes significance at the $p < 0.01$ ($p < 0.05$, $p < 0.10$) level (one-tailed where a prediction is made and two-tailed otherwise) assessed using *t*-statistics (in parentheses) derived from White (1980) standard errors clustered by year-month to correct for cross-sectional correlation in error terms given firm, measured as of the date of the article.[31] We again bifurcate our sample, depending on how many times a given author has written about a given firm, and find that the market response to positive tone is stronger for the frequent contributors ($p = 0.02$). We also observe that the response to the short position disclosure is significantly *weaker* for frequent contributors ($p = 0.02$). This result implies that short-position disclosures are less surprising for certain authors writing about the same firm multiple times.

6 Conclusion

Motivated by concerns that financial positions present a conflict of interest that impairs an analyst's objectivity, we examine investor perceptions of the financial positions of nonprofessional analysts providing stock analysis on the social media outlet SeekingAlpha and offer two primary findings. First, NPA positions contribute directly to short-window returns surrounding an article's publication, holding constant the information in the article (i.e., tone, length, rigor, numerical content, etc.) as well as contemporaneously issued news (i.e., from managers, professional analysts, and the business press). These findings suggest that an NPA's stock positions convey credible information to investors. Second, we find that the price response attributed to article tone is significantly stronger for articles authored by NPAs with stock positions and that these effects appear driven mostly by tone contrary to an author's position. Overall, our results suggest that the disclosure of an NPA's financial positions enhances their credibility with investors.

As previously mentioned, our study is subject to two important caveats. First, SA has no way to ensure the truthful disclosure of stock positions (although, as we note, our evidence suggests that any deceptive disclosure practices are unlikely to be widespread). Second, like all research studies on social media, we cannot rule out the possibility that a significant corporate event occurs that also results in social media activity and that this alternative event explains at least a portion of our observed economic magnitudes. In sum, while we identify one mechanism useful for evaluating NPA credibility, future research may wish to more fully examine whether other NPA attributes affect investors' perceptions of their credibility.

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[31] Specifically, we regress $CountToDate_{i,k,t}$, which is the number of times author k has written about firm i as of date t on calendar month ("year-month") fixed effects and compute the residual. Positive (negative) residuals are considered high (low) levels of coverage. We orthogonalize this measure to time period since article counts are increasing over time, and to better emulate an author's record relative to other authors, at the time each article is published.

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Appendix 1: Variable Definitions

Variable	Definition
$AbRet_{i,t}$	The firm's return measured on day t or over days [t to $t+k$] adjusted by a matching size, market-to-book, and momentum portfolio return over the same period. If the article was published after-hours, on a weekend, or holiday, day t equals the first trading day following the article's release (winsorized).
Position	Takes value −1 if *Short* exceeds *Long* on a given day, 1 if *Long* exceeds *Short* on a given day, and 0 if *Long* and *Short* both equal 0. On days where *Long* = *Short* and both *Long* and *Short* are nonzero, *Position* is undefined.
Short	The percentage of articles about firm i on day t in which the nonprofessional analyst (NPA) discloses a short position.
Long	The percentage of articles about firm i on day t in which the NPA discloses a long position.
NegPct	The percentage of words for all Seeking Alpha articles on day t that are classified as having negative sentiment using Loughran and McDonald's (2011) dictionary (winsorized).
PosPct	The percentage of nonnegated words for all Seeking Alpha articles on day t that are classified as having positive sentiment using Loughran and McDonald's (2011) dictionary (winsorized).
CogProc	Count of cognitive processing words, such as "believe," "cause," and "consider" from LIWC, a commonly used psycholinguistic software package.
Numbers	The number of numbers, either as strings of digits and valid punctuation or written out in letters, divided by the total number of words appearing in SA articles about a firm on a given day (winsorized).
lWordCount	The natural log of the total number of words appearing in Seeking Alpha articles about a firm on a given day (winsorized).
$ComNegPct_{i,t}$	The percentage of words appearing in comments posted between day t and $t+k$ about the Seeking Alpha article classified as having negative sentiment using Loughran and McDonald's (2011) dictionary.
$ComPosPct_{i,t}$	The percentage of nonnegated words appearing in comments posted between day t and $t+k$ about the Seeking Alpha article classified as having positive sentiment using Loughran and McDonald's (2011) dictionary.
DJNegPct	The percentage of words in all Dow Jones news content published on day t, or in the days between article publication and first trading day if different, classified as having negative sentiment using Loughran and McDonald's (2011) dictionary (winsorized).
DJPosPct	The percentage of nonnegated words in all Dow Jones news content published on day t, or in the days between article publication and first trading day if different, classified as having positive sentiment using Loughran and McDonald's (2011) dictionary (winsorized).
IDJ	An indicator equaling 1 if there is Dow Jones content about the firm published on day t, or in the days between article publication and first trading day if different.
Upgrades	The number of analysts revising recommendations upward between day t-3 and the later of the article's publication date or first trading day following the article's publication date (winsorized).

Variable	Definition
Downgrades	The number of analysts revising recommendations downward between day *t-3* and the later of the article's publication date or first trading day following the article's publication date (winsorized).
ReviseUps	The number of analysts issuing earnings forecasts exceeding the prevailing consensus between day *t-3* and the later of the article's publication date or first trading day following the article's publication date.
ReviseDowns	The number of analysts issuing earnings forecasts lower than the prevailing consensus between day *t-3* and the later of the article's publication date or first trading day following the article's publication date.
PosES	Indicator equaling 1 if the firm announces earnings exceeding the most recent consensus estimate according to IBES between day *t-3* and the later of the article's publication date or first trading day following the article's publication date.
NegES	Indicator equaling 1 if the firm announces earnings below the most recent consensus estimate, according to IBES, between day *t-3* and the later of the article's publication date or first trading day following the article's publication date
Guidance	An indicator variable equaling 1 if the firm issues at least one piece of earnings guidance between day *t-3* and the later of the article's publication date or first trading day following the article's publication date.
PosGuidance	An indicator variable equaling 1 if the firm issues at least one piece of earnings guidance between day *t-3* and the later of the article's publication date or first trading day following the article's publication date that exceeds the prevailing analyst consensus on the forecast date.
NegGuidance	An indicator variable equaling 1 if the firm issues at least one piece of earnings guidance between day *t-3* and the later of the article's publication date or first trading day following the article's publication date that falls below the prevailing analyst consensus on the forecast date.
Volatility	The sum of squared daily returns in the calendar month preceding day *t* (winsorized).
Edgar8K	An indicator variable equaling 1 if the firm issues at least one 8-K filing between day *t-3* and the later of the article's publication date or first trading day following the article's publication date.
Size	The natural log of the market value equity as of the end of the month prior to the article's publication date (winsorized).
BTM	The book value of equity as of the end of the most recent fiscal year divided by the market value of equity as of the end of the prior year (winsorized).
InstOwn	The proportion of shares owned by institution investors per the quarterly Thomson Reuters ownership report closest but prior to the article publication date (winsorized).
AnalystFollowers	The natural log of 1 plus the number of analysts issuing estimates in the IBES summary report in the month prior to the article's publication (winsorized).
SAFollowers	The natural log of 1 plus the number of followers reported on the author's bio page as of the date the biographies were collected (winsorized).
FirstDisc	Indicator taking value of 1 the first time an NPA discloses a given position about a firm.

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