The Democratization of Investment Research and the Informativeness of Retail Investor Trading

Michael Farrell, T. Clifton Green, Russell Jame, and Stanimir Markov*

October 2019

Abstract

We explore whether crowdsourced investment research published on Seeking Alpha (SA) facilitates the process by which retail investors become informed. We find a sharp increase in retail trading within 30 minutes of publication that is directionally consistent with article sentiment. Moreover, the relation between retail order flow and future returns is three times as large on days when SA research articles are published. The incremental informativeness is stronger for articles that generate many comments or are authored by skilled contributors. Retail order flow on days with SA research also predicts future media article tone, consistent with retail trading being information-driven.

JEL: G14

Keywords: Investment Research, Seeking Alpha, Retail Investors, Informed Trading

---

*Farrell is from the Darden School of Business, University of Virginia, FarrellM@darden.virginia.edu. Jame is from the Gatton College of Business and Economics, University of Kentucky, russell.jame@uky.edu. Green is from the Goizueta Business School, Emory University, clifton.green@emory.edu. Markov is from the Naveen Jindal School of Management, University of Texas at Dallas, stan.markov@utdallas.edu. Jame acknowledges financial support from the Institute for Free Enterprise at the University of Kentucky. We thank Dan Bradley, Huaizi Chen (discussant), Alex Chinco (discussant), Frank Heflin (discussant), Byoung-Hyoung Hwang, Eric Kelley (discussant), Petra Vokata (discussant), Ming Shou (discussant), Musa Subasi (discussant), and seminar participants at the 2019 SFS Cavalcade, the 2019 Western Finance Association Meeting, the 2019 UConn Finance Conference, the 2019 Northern Finance Association, the 2019 Midwest Finance Association, the 2019 FARS Midyear Meeting, the 2019 Smokey Mountain Finance Conference, the 2019 Hawaii Accounting Research Conference, the Second Conference on Intelligent Information Retrieval in Accounting and Finance, Auburn University, Boston College, Middle Tennessee State University, and the University of Kentucky for helpful comments, and we thank Yanbin Wu for excellent research assistance. We thank Seeking Alpha for providing the data and George Moriarty (Executive Editor, VP Content) for details of the platform.

Conflict-of-Interest Disclosure Statement

Michael Farrell:

I signed a non-disclosure agreement with Seeking Alpha Ltd. who provided us with data.

Clifton Green:

I signed a non-disclosure agreement with Seeking Alpha Ltd. who provided us with data.

Russell Jame:

I signed a non-disclosure agreement with Seeking Alpha Ltd. who provided us with data. I received a $5,000 research grant from the Institute for Free Enterprise at University of Kentucky for this paper.

Stanimir Markov:

I signed a non-disclosure agreement with Seeking Alpha Ltd. who provided us with data.

1. Introduction

Information is a key ingredient for well-functioning financial markets. Without a broad base of investors with access to accurate information, pricing securities becomes difficult and markets can stagnate. At the same time, information with a high investment value tends to be costly to produce, which has left individual investors at a relative disadvantage. In recent decades, improvements in technology have significantly reduced the cost of gathering and sharing investment research, and these developments have been lauded for their potential to help improve access to information.[1] In this article, we study a popular investor social media site, Seeking Alpha, to identify when investors produce and share investment research, and we examine whether these activities improve individual investor decision making trading.

Seeking Alpha (SA) exemplifies the democratization of investment research by crowdsourcing research from thousands of non-professional research contributors, many of whom are active investors who trade in the stocks they analyze. Seeking Alpha's curated research is read by millions of investors each month and generates comments from hundreds of thousands of readers.[2] Chen, De, Hu, and Hwang (2014) document that SA research contains investment value, with research articles predicting future stock returns and earnings surprises. We explore the extent to which Seeking Alpha's crowdsourced investment research enhances the informativeness of retail investor trading.

Individual investors have traditionally been viewed as unsophisticated "noise" traders who use different information sources than their professional counterparts and underperform standard

---

[1] For example, early in the internet era SEC Commissioner Laura Unger anticipated technology's potential and concluded a speech with: "It looks as though investors stand to benefit greatly from the Information Revolution. The Internet has powered the revolution. It's also been a key element in the push for democratization of the flow of investment information." (June 2000) https://www.sec.gov/news/speech/spch387.htm
[2] https://seekingalpha.com/page/about_us.

benchmarks (e.g., Kumar and Lee, 2006; and Barber and Odean, 2013 review the literature). In recent years, however, studies have uncovered evidence of informed trading by individuals, with retail order flow predicting stock returns and future earnings surprises (Kaniel, Saar, and Titman, 2008; Kaniel, Liu, Saar, and Titman, 2012; Kelley and Tetlock, 2013, 2017; Boehmer, Jones, Zhang, and Zhang, 2019). Although the improved performance of individual investors over time could be associated with learning or changing demographics (e.g., Seru, Shumway, and Stoffman, 2010; and Linnainmaa, 2011), a key driver that remains unexplored is better access to investment information.

We begin by documenting that Seeking Alpha's crowdsourced investor-authored research is distinct from traditional Wall Street brokerage research. We analyze roughly 200,000 research articles discussing 5,000 stocks and find that after controlling for other firm characteristics, SA coverage (number of articles) is higher among firms with low institutional ownership and greater breadth of ownership, whereas the opposite is true for brokerage research coverage. The differences highlight Seeking Alpha's emphasis on retail investor-oriented research.

We find strong evidence that Seeking Alpha research influences retail investor trading. Using trade and quote data from NYSE TAQ and the method of Boehmer et al. (2019) to identify retail investor trades, we find a significant increase in the percentage of retail trading on days with SA articles, with the magnitude being considerably larger than the effects of brokerage research or media articles. We also find that retail investor trade order imbalances are directionally consistent with measures of article sentiment that have been shown to predict returns, such as article tone, the tone of comments that follow the article, and contributors' investment positions (Campbell, DeAngelis, and Moon, 2019; Chen et al. 2014). Importantly, the relation between order imbalances and article sentiment is significant in the half-hour after publication and insignificant beforehand, which, combined with SA's twenty-four-hour review process, helps alleviate concerns that unobserved public information may drive SA research sentiment and retail trading.

Analyzing the relation between daily retail order imbalances and future stock returns reveals robust evidence that Seeking Alpha leads to more informed trading. For example, a one standard deviation increase in retail order imbalance is associated with future ten-day returns that are 0.06% larger on average, yet this return differential rises to 0.18% on days with SA articles. In contrast, we find little evidence that retail trading is more informative in the one to five days prior to the publication of SA research, or that is it incrementally informative around traditional media articles. These findings are inconsistent with unobserved public information spuriously explaining the relation between SA research and informative retail trading. We also find that the incremental informativeness of retail order flow after SA research holds after controlling for article tone, comment tone, and contributor investment position, which suggests that retail investor's ability to benefit from SA research extends beyond cursory article assessments.

If retail investors are able to glean value relevant information from Seeking Alpha research, we would expect the benefits to be concentrated among higher quality and more novel articles. Supporting this view, we find that articles written by contributors with longer bios, and those whose past research has been more impactful, result in a stronger post-article connection between retail order flow and future returns. In addition, given the generally positive slant of the media and traditional brokerage research (e.g. Gurun and Butler, 2012; and McNichols and O'Brien, 1997), we conjecture that retail investors will be able to garner more information from Seeking Alpha research expressing negative views. Consistent with this view, we find that the relation between retail order flow and future returns is stronger for SA research articles with negative sentiment. Lastly, we find that retail order flow's ability to predict future returns is greater when the SA article elicits more comments, consistent with active investor engagement leading to better information signals.

In our final sets of tests, we present two complementary analyses to help address the concern that price pressure or liquidity provision, rather than informed trading, explains the relation between retail order imbalances and returns after Seeking Alpha research. First, we follow the approach in Boehmer et al. (2019) to isolate the informed component of retail order imbalances. Specifically, we regress retail order imbalances on past order imbalances and returns to decompose trading into a persistent component which captures price pressure, a contrarian component which captures liquidity provision, and a residual component which captures informed trading. We find that the incremental informativeness of retail order flow on Seeking Alpha research article days is driven entirely by the residual (informed) component.

Our second test builds on Kelley and Tetlock (2013), who argue that informed retail order flows should predict future cash flow news. Consistent with their work, we observe a significant relation between retail order imbalances and article tone over the following ten days. More importantly, we find that the relation is more than four times stronger when retail order imbalances are preceded by Seeking Alpha research. We also find evidence that retail order imbalances better predict analyst forecast revisions after informative SA articles, consistent with information-based trading. Collectively, the findings support the view that crowdsourced investment research facilitates the process by which retail investors become informed.

Our study contributes to a growing literature that examines the role of financial social media in revealing new information to capital markets. Seeking Alpha provides broader access to in-depth analysis than other social finance sites such as StockTwits (Bartov, Faurel, and Mohanram, 2018), Estimize (Jame, Johnston, Markov, and Wolfe, 2016), Motley Fool's CAP system (Avery, Chevalier, and Zeckhauser, 2016), or SumZero (Crawford, Gray, Johnson, and Price, 2018).[3] We analyze whether crowdsourced investment research improves retail investors' decision making. The evidence that Seeking Alpha research encourages retail investor participation and helps retail investors become more informed is consistent with social media platforms improving informational access for retail investors.[4]

Our analysis also adds to the literature that studies the performance of retail investors. Early studies find the trading performance of retail investors to be subpar due to behavioral biases or lack of sophistication (e.g., Barber and Odean, 2000, Kumar and Lee, 2006; Frazzini and Lamont, 2008; Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009). On the other hand, more recent work finds that retail investors as a group exhibit stock picking ability and speculates that retail investors have valuable information obtained from geographic proximity to firms, relations with employees, or insights into consumer preferences (e.g., Kaniel et al. 2012; Kelley and Tetlock, 2013, 2017; and Boehmer et al. 2019). Our findings shed light on how retail investors become informed. Specifically, the evidence that retail trading is more informed on Seeking Alpha research days suggests that technology-enabled improvements in how retail investors produce and share investment research are a likely channel by which individual investors have become better informed. Although retail order imbalances are directionally consistent with measures of SA tone and contributor investment position, the predictive ability of retail order imbalances extends beyond article sentiment, consistent with retail investors skillfully processing SA research.

[3] StockTwits is limited to 144 characters, Estimize focuses exclusively on short-term earnings forecasts, and the Motley Fool CAP system's stock picks lack detailed analysis. SumZero focuses on professional investors employed by mutual funds, hedge funds, and private equity funds.

[4] In contemporaneous work, Gomez, Heflin, Moon, and Warren (2018) show that Seeking Alpha coverage leads to lower bid-ask spreads around earnings announcements.

A third stream of literature examines the use of technology by regulators to level the informational playing field between institutional investors and retail investors.[5] We complement these studies by examining the extent to which a technology-enabled market innovation, Seeking Alpha, has democratized the flow of investment information. Our findings illustrate how technological change can enable new business models that improve retail investors' access to investment research and level the informational playing field among investors.

2. The Seeking Alpha Sample

Seeking Alpha is one of the largest investment-related social media websites in the United States and epitomizes the democratization of investment research.[6] The website hosts curated investment research from a network of thousands of individual contributors. SA had more than 39 million monthly visits in 2017, with the average visit lasting roughly 20 minutes (Seeking Alpha, 2018). Contributor testimonials indicate that some of the primary motivations for contributing research include direct compensation from SA, feedback on investment theses (via reader comments), and increased recognition and visibility which may lead to other professional opportunities.[7] Each SA research article is subject to a review process that can involve multiple revisions.[8] Chen, et al. (2014) find that Seeking Alpha's crowdsourced investment research

[5] Examples include the launch of the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) in 1993 (Asthana, Balsam, and Sankaraguruswamy, 2004; and Gao and Huang, 2019), and the mandated use of eXtensible Business Reporting Language (XBRL) in corporate filings in 2009 (Blankespoor, Miller, and White, 2014; and Bhattacharya, Cho, and Kim, 2018).

[6] Seeking Alpha editor Douglas House commented in 2016 that "Seeking Alpha's raison d'etre, of course, is to level the playing field for individual investors by leveraging the 'wisdom of crowds' via crowdsourcing." https://www.prnewswire.com/news-releases/slingshot-insights-partners-with-seeking-alpha-to-bring-transparency-to-expert-research-300308371.html

[7] See: https://seekingalpha.com/page/testimonials.

[8] One first-time SA contributor describes multiple rounds of revisions before acceptance, including requests to provide more sources, better flesh out investment theses, and offer additional financial statement analysis. The contributor concludes "There is so much that goes into an [SA] article that gives it substance and obviously a bit more difficult than I originally imagined." https://walletsquirrel.com/first-article-on-seeking-alpha/

contains valuable investment information, with articles and user commentaries predicting future stock returns and earnings surprises.

We obtain all research articles published between 2005 and 2017 on the Seeking Alpha website. For each article, we collect the following information: an article ID assigned by Seeking Alpha, article title, main text, date of publication, author name, and the ticker (or tickers) assigned to each article. Following Chen et al. (2014), we limit the sample to articles that are associated with one ticker. We further limit the sample to common stocks (CRSP share codes 10 and 11) with available data in the CRSP-Compustat merged database. Our final sample includes 192,398 single-ticker SA research articles covering 5,080 firms.

For each firm, we collect data on share price, shares outstanding, stock returns, volume, and closing bid and ask prices from CRSP. We obtain book value of equity, book value of debt, book value of assets, earnings before interest taxes depreciation and amortization (EBITDA), and total common shareholders from Compustat. We collect the number of shares held by institutions from the Thomson Reuters Institutional Holdings (S34) database. We obtain earnings announcement dates and sell-side analyst earnings forecast from the IBES unadjusted US detail history file, sell-side analyst recommendations from the IBES detail recommendation file, and earnings guidance from the IBES detail history guidance file. We obtain data on traditional media coverage, measured using Dow Jones News Service articles from RavenPack, for the period from 2005 to 2017. Following Reed, Samadi, and Sokobin (2018), we limit the RavenPack sample to articles with relevance and novelty scores of 100. For each article, we also collect the *Event Sentiment Score* (*ESS*), which ranges from 0 (very negative news) to 100 (very positive news) with a median value of 50 (neutral article).

Table 1 describes the dramatic increase in the breadth and depth of Seeking Alpha coverage over time. In 2005, there were 251 companies covered on SA, with 42 research contributors, 900 articles and 0 comments. In 2017, coverage rose to 2,369 companies, with 2,134 contributors, 22,276 articles, and roughly 31 comments per article. In an average year in the sample, 1,318 unique contributors publish 14,800 articles on 1,795 different companies, with each article receiving 21 comments, on average. Conditional on having Seeking Alpha coverage, the average firm has roughly 8.2 articles per year, written by 4.3 different contributors.

3. Determinants of Seeking Alpha Research Coverage

In this section, we examine the determinants of Seeking Alpha research coverage. Our main conjecture is that SA caters to retail investors more so than traditional brokerage research. Seeking Alpha's business model is built on reaching a wide audience of do-it-yourself investors, and Seeking Alpha contributors are often individual investors. In contrast, prior survey evidence and empirical work suggests that brokerage analysts cater to institutional investors. For example, Brown et al. (2015) report that more than 80% of surveyed analysts view hedge funds and mutual fund clients as very important, while only 13% view retail clients as important. Consistent with this survey evidence, several papers find that sell-side research is strongly increasing in total institutional ownership (see, e.g., Bhushan, 1989; Green, Jame, Markov, and Subasi, 2014).

We examine the determinants of Seeking Alpha coverage and sell-side coverage by estimating the following panel regression:

$$Coverage_{it} = \alpha + \beta_1 Inst.Ownership_{i,t-1} + \beta_2 Breadth\ of\ Ownership_{i,t-1} + \beta_3 Chars + Time_t + \varepsilon_{it.} \quad (1)$$

where *Coverage* is the natural log of 1 plus the total number of unique Seeking Alpha contributors writing at least one article for the stock during the calendar year (*SA Coverage*), or the natural log of 1 plus the total number of unique brokerage firms issuing at least one earnings forecast for the stock during the calendar year (*IBES Coverage*).

The two independent variables of primary interest are *Institutional Ownership*$_{i,t-1}$, defined as the percentage of the firm's shares held by institutional investors in year *t*-1, and *Breadth of Ownership*, defined as the number of common shareholders (both in logs). The vector of firm characteristics (*Chars*) includes: market capitalization (*Size*), book to market (*BM*), return volatility (*Volatility*), share turnover *(Turnover)*, past one-year return (*Return*$_{m-12,m-1}$), past one-year profitability (*Profitability*), and the number of unique media articles mentioning the firm the prior year (*Media Coverage*). See Appendix A for detailed definitions. We log all continuous variables other than *Profitability* and *Return*, and standardize all variables to have zero mean and unit variance. We include year fixed effects and cluster standard errors by firm.

Specification 1 of Table 2 examines the determinants of *SA Coverage* without controlling for *IBES Coverage.* In general, *SA Coverage* is higher for larger firms, firms with more frequent media coverage, and those with greater trading volume. In addition, *SA Coverage* is positively related to volatility, past one-year returns, and profitability. Consistent with our conjecture that Seeking Alpha research is a retail investor rather than an institutional investor phenomenon, we find a strong negative relation between *SA Coverage* and institutional ownership, and a strong positive relation between *SA Coverage* and total common shareholders. In particular, a one standard deviation increase in *Institutional Ownership* (*Breadth of Ownership*) is associated with a 22% decline (5% increase) in *SA Coverage*, and the findings are robust to controlling for *IBES Coverage*.

Specifications 3 and 4 present analogous results for brokerage analyst coverage (*IBES Coverage*). As expected, and in sharp contrast to the *SA Coverage* patterns, *IBES Coverage* is strongly positively related to institutional ownership and strongly negatively related to breadth of ownership. Collectively, these results suggest that traditional sell-side research emphasizes institutional investors, whereas the Seeking Alpha platform caters to retail investors and provides a unique window into retail investors' information acquisition activities.

4. Seeking Alpha Research and Retail Investor Trading

In this section, we analyze the effects of Seeking Alpha research on retail investor trading. Section 4.1 examines whether retail investors trade more actively on days when SA research is published, and Section 4.2 explores whether the direction of retail trading is consistent with SA research sentiment. Our analysis focuses on trading near the release of SA articles. Although retail investors could potentially benefit from Seeking Alpha over longer horizons, evidence that retail investors react quickly to SA research helps convincingly connect the two, and an association between retail order flow and article sentiment helps rule out that the trading is merely attention-based (Barber and Odean, 2008).

4.1 Retail Trading Intensity around Seeking Alpha Research

We identify retail trading using the approach of Boehmer, Jones, Zhang, and Zhang (2019) (hereafter: BJZZ), which exploits two key institutional features of retail trading. First, most equity trades by retail investors take place off-exchange, either filled from the broker's own inventory or sold by the broker to wholesalers (Battalio, Corwin, and Jennings, 2016). TAQ classifies these types of trades with exchange code "D." Accordingly, we identify retail trades by limiting our analysis to trades executed on exchange code "D."

Second, retail traders typical receive a small fraction of a cent price improvement over the National Best Bid or Offer (NBBO) for market orders (ranging from 0.01 to 0.2 cents), while institutional orders tend to be executed at whole or half-cent increments. Thus, we follow BJZZ and identify trades as retail purchases (sales) if the trade took place at a price just below (above) a round penny. The BJZZ approach is conservative in the sense that it has a low type 1 error (i.e., trades classified as retail are very likely to be retail). While this approach does omit some retail trading, including nonmarketable limit orders and retail traders that take place on registered exchanges, it "picks up a majority of overall retail trading activity" (BJZZ page 6).[9]

We consider two complementary measures of retail trading intensity. The first, *Retail Turnover*$_{it}$ is the total trading volume in stock *i* on day *t* classified as retail, scaled by stock *i*'s shares outstanding. We also calculate *Percentage Retail Turnover*, defined as the total trading volume in stock *i* on day *t* classified as retail, scaled by the aggregate trading volume for stock *i* on day *t*, which allows us to examine whether SA leads to trading differences between retail and institutional investors. We estimate the effects of Seeking Alpha research on retail investor trading using the following daily panel regression:

$$Retail\,Trade_{it} = \alpha + \beta_1 SA_{it-1,t} + \beta_2 IBES_{i,t-1,t} + \beta_3 Media_{it-1,t} + \beta_4 Char_{iy-1} + Time_t + Firm_i + \varepsilon_{it.} \qquad (2)$$

where *Retail Trade* is *Retail Turnover* or *Percentage Retail Turnover*, *SA* is equal to one if Seeking Alpha issued a research report for firm *i* on day *t* or *t*-1,[10] and *IBES* and *Media* are defined similarly. ***Char*** includes *Size*, *book-to-market* (*BM*), *Institutional Ownership*, *Volatility*, *Turnover*, *Return*, *Profitability*, *IBES Coverage*, and *Media Coverage*, all measured at the end of the previous year. Detailed variable descriptions are provided in Appendix A. All continuous independent variables

[9] BJZZ also note that, during a conference discussion of their work, Eric Kelley presented that the correlation between the BJZZ order imbalance measure and the imbalances calculated from Kelley and Tetlock (2013)'s proprietary retail data with observed trade directions is in the range of 0.345 to 0.507, with an average of 0.452.

[10] We define day *t* as the first possible day in which an investor could have traded on the article. Thus, for articles issued before the open or during trading hours, day *t* is equal to the publication date. For articles issued after hours (or weekends/holidays), day *t* is the subsequent trading day.

are standardized to have mean zero and unit variance. *Time* and *Firm* indicate time (calendar day) and firm fixed effects. Standard errors are clustered by firm.

Our TAQ sample begins in 2007, and we consider all firm-years with Seeking Alpha coverage (at least one SA research report).[11] We exclude days with earnings announcements in our primary analysis since these anticipated firm disclosures lead to increased coverage by all types of financial media, a situation which complicates efforts to isolate the effects of Seeking Alpha. The resulting sample is comprised of 4,372,388 firm-day observations.

Specifications 1 and 2 of Table 3 report the results for *Retail Turnover.* We find that *Retail Turnover* increases by roughly 13-16% on days with SA research. Specifications 3 and 4 confirm that the increase in trading for retail investors is greater than for institutional investors. For example, Specification 4 shows that *Percent Retail Trading* increases by 0.60 percentage points, which is a nearly 8% increase relative to the mean of 7.72%.

Table 3 also provides evidence that trading intensity is greater after the release of traditional brokerage research or media coverage, although the economic magnitudes are considerably smaller. For example, in Specification 4 the coefficient on *SA* is roughly 9 times larger than the coefficient on *IBES* and more than 15 times larger than the coefficient on *Media.* These findings are consistent with Seeking Alpha being an economically important source of investment research for retail investors.

4.2 Seeking Alpha Research Sentiment and Retail Order Imbalances

[11] To be conservative, BJZZ focus on the sample period from 2010-2015 due to the gradual upward trend in sub-penny trading prior to 2010 and the potentially complicating effects of the tick size pilot program after 2015. Our findings are similar if we limit the sample to the 2010-2015 period. For example, in Figure IA.1 we present results by month over our 2007-2017 sample period.

In this section, we more directly test whether information shared on SA influences retail investor trades by studying the relation between SA sentiment and retail order imbalances. Our first sentiment measures rely on textual analysis of SA articles and the comments that they generate. Specifically, we classify SA research as having positive (negative) sentiment when the average fraction of positive (negative) words across all single-ticker articles published on Seeking Alpha about company *i* on day *t* is above the sample median (using the word list in Loughran and McDonald's, 2011 as in Chen et al. 2014). Similarly, SA comments express positive (negative) sentiment when the average fraction of negative (positive) words across all single-ticker comments published on Seeking Alpha about company *i* on day *t* is above the sample median.

We also measure sentiment using the SA contributor's investment position. Seeking Alpha requires investors to disclose their investment positions, and we construct a long (short) indicator variable that takes the value of one if the contributor discloses a long (short) position (Campbell, DeAngelis, and Moon, 2019). When several contributors disclose investment positions, we take the average across contributors for company *i* on day *t*. We estimate the panel regression:

$$\begin{aligned} Retail\ OIB_{it} = {} & \alpha + \beta_1 SA_{it-1,t} + \beta_1 SASentiment_{it-1,t} + \beta_3 IBES_{i,t-1,t} \\ & + \beta_4 IBESSentiment_{i,t-1,t} + \beta_5 Media_{it-1,t} + \beta_5 MediaSentiment_{it-1,t} \\ & + \beta_7 InstOib_{it} + \beta_8 Char + Time_t + Firm_i + \varepsilon_{it}. \end{aligned} \tag{3}$$

Retail $OIB_{i,t}$ is the retail order imbalance for firm *i* on day *t*, defined as the difference between daily retail buy volume and retail sell volume, scaled by total daily retail trading volume (BJZZ). $SA_{it\text{-}1,t}$, $IBES_{it\text{-}1,t}$, and $\beta_5 Media_{it\text{-}1,t}$ indicate the publication of a SA article, IBES research report , or a media article for firm *i* on days *t* or *t*-1. $SASentiment_{it\text{-}1,t}$ is a six dimensional vector of SA sentiment as defined above. $IBESSentiment_{it\text{-}1,t}$ is a two dimensional vector of sell-side research sentiment: *IBES×Positive* is equal to one if IBES research is a recommendation upgrade or an upward forecast revision, and zero otherwise, and *IBES×Negative* is defined analogously. Similarly, $MediaSentiment_{it\text{-}1,t}$ is a two dimensional vector of media sentiment: *Media×Positive* is an indicator equal to one if the average *ESS* (RavenPack sentiment score) across all stock-focused articles published on days *t*-1 and *t* exceeds 50 (the ESS score assigned to neutral articles), and *Media×Negative* is an indicator equal to one if the average ESS is less than 50. The control variables include institutional order imbalance, *InstOib*, which is calculated as total order imbalance across all TAQ trades less retail order imbalance.[12] We also include the following vector of firm characteristics, *Char,* taken from BJZZ: past one-week returns ($Ret_{w\text{-}1}$), past one month returns ($Ret_{m\text{-}1}$), returns over the prior two to seven months ($Ret_{m\text{-}7,m\text{-}2}$), market capitalization (*Size*), monthly turnover (*Turnover*), volatility of daily returns (*Volatility*), book-to-market (*BM*), and retail order imbalances over the prior week ($Retail\ OIB_{w\text{-}1}$). With the exception of returns, all control variables are measured at the end of the previous year and are in natural logs.

The results are reported in Table 4. We find robust evidence that Seeking Alpha research sentiment predicts retail order imbalances. For example, in Specification 2, which includes both firm and day fixed effects, retail order imbalance increases (decreases) by 1.28% (1.86%) when a SA contributor discloses a long (short) investment position, 0.43% (0.80%) when the article's positive (negative) tone is above the median, and 0.24% (0.53%) when the comments' positive (negative) tone is above the sample median. In Specification 3, we sum the six measures of SA sentiment to construct a composite measure of sentiment, and we find that a unit increase in composite sentiment increases retail order imbalance by 0.67%. In comparison, the relation between retail order imbalance and brokerage sentiment is typically not statistically significant, although we do find that retail order flow is significantly related to the sentiment of media

[12] Our trade-based retail investor classification approach provides an imperfect measure of total retail trading in that it focuses on market orders and emphasizes low Type 1 error. As a result, classifying institutional trading as the difference between total order imbalance and retail order imbalance is also imperfect.

articles.[13] In Table IA.1 in the Internet Appendix, we repeat the analysis using institutional order flow as the dependent variable. We find that institutional order flow also reacts to Seeking Alpha article tone, although the effect is considerably smaller. For example, the coefficient on the composite sentiment measure is 0.67 for retail order flow vs. 0.12 for institutional order flow.

The order imbalance evidence in Table 4 is consistent with retail investors reacting to Seeking Alpha research. Although we control for media articles in our analysis, it is possible that unobserved company news drives both retail order imbalances and Seeking Alpha research sentiment. To address this issue, we examine the intraday relation between Seeking Alpha article sentiment and retail order flow. Discussions with Seeking Alpha representatives indicate that the review process requires at least 24 hours between initial submission and the posting of an article on the Seeking Alpha website. If SA contributors and retail traders are reacting to public news, we would expect the relation between retail order imbalances and SA research sentiment estimated shortly before publication (while the article is in review) to be as strong as when it is estimated in a short-window after publication.

We repeat the analysis in Table 4 with *Retail OIB* measured over eleven half-hour windows around the article release. To avoid confounding effects, we consider only SA articles that are not preceded or followed by other SA articles in any of the windows, resulting in a sample of 135,686 articles. We plot the resulting coefficients and confidence bounds in Figure 1 and tabulate full results in Table IA.2 in the Internet Appendix. We find no evidence of a relation between SA article sentiment and retail order flow in any of the pre-publication windows, which alleviates the

[13] The coefficients on the remaining control variables (tabulated in Table IA.1 of the Internet Appendix) are consistent with BJZZ. For example, we find a highly positive coefficient on $Retail\ OIB_{w-1}$, consistent with retail investor trading being highly persistent. We also document a strong negative relation between retail order imbalances and past one-week and one-month returns, indicating that retail investors tend to be short-term contrarians. In Section 6.2, we isolate the informed components of retail order flow by controlling for these relations.

concern that retail investors are reacting to public news. Moreover, we observe the strongest relation in the first half hour after publication, consistent with retail investors reacting very quickly to SA research.

5. Seeking Alpha Research and the Informativeness of Retail Investor Trading

Early work on retail investors finds evidence that retail trading is at best uninformed and at worst a negative predictor of future stock returns, with the literature concluding that retail investors are noise traders who are influenced by behavioral biases (e.g., Barber and Odean, 2000; Frazzini and Lamont, 2008; Hvidkjaer, 2008; Barber, Odean, and Zhu, 2009). More recently, several studies find evidence consistent with retail investor trading being informed (e.g. Kaniel, Saar, and Titman, 2008; Kaniel et al. 2012; Kelley and Tetlock, 2013, 2017; and BJZZ, 2019).

The improved performance of individual investors over time has been explained in terms of investor learning or changing investor demographics. For example, Barber and Odean (2002) find evidence of detrimental overconfidence among early adopters of online trading, and Seru, Shumway, and Stoffman (2010) find evidence consistent with learning about skill (or lack thereof) among individual investors.

We conjecture that the improved performance of retail investors is due in part to improved access to investment research. Seeking Alpha provides individual investors with opportunities to share information and learn from other investors, and the evidence that SA article comments are incrementally informative (Chen et al., 2014) supports the idea that retail investors benefit from SA investment research. In addition, the evidence in Tables 3 and 4 of elevated retail trading in response to SA research that is directionally consistent with measures of article and comment sentiment suggests that investors react to Seeking Alpha research. In this section, we explore whether SA research enhances the informativeness of retail trading.

5.1 Retail Order Imbalances and Stock Returns: Baseline Results

We examine the informativeness of retail order imbalances on days in which Seeking Alpha research is published by estimating the following panel regression:

$$\begin{aligned} Ret_{it+1,t+x} = \ & \alpha + \beta_1 RetailOIB_{it} + \beta_2 RetailOIB_{it} \times Event_{it-1,t} + \beta_3 RetailOIB_{it} \\ & \times Log(Size)_{it} + \beta_4 InstOIB_{it} + \beta_5 InstOIB_{it} \times Event_{it-1,t} + \beta_6 InstOIB_{it} \\ & \times Log(Size)_{it} + \beta_7 Event_{it-1,t} + \beta_8 Char_{i,y-1} + Time_t + \varepsilon_{it,} \end{aligned} \quad (4)$$

where $Ret_{it+1,t+x}$ is the return on stock *i* from the close of day *t*+1 to the close of day *t*+*x*, with *x* equal to 1, 5, or 10. *Retail OIB* is the total retail buy volume less total retail sell volume, scaled by total retail trading volume, and *Institutional OIB* is the total non-retail buy volume less total non-retail sell volume, scaled by total non-retail trading volume. $Event_{it-1,t}$ is a vector of event indicators: $SA_{it,t-1}$, $IBES_{it,t-1}$, and $Media_{it,t-1}$. As previously defined, *Char* is a vector of firm characteristics taken from BJZZ and includes past returns estimated over the prior week (Ret_{w-1}), prior month (Ret_{m-1}), and prior two to seven months ($Ret_{m-7,m-2}$), market capitalization (*Size*), monthly turnover (*Turnover*), volatility of daily returns (*Volatility*), and book-to-market (*BM*). We also include *Retail OIB* × *Log (Size*) and *Inst. OIB* × *Log Size* to control for the possibility that the profitability of retail and institutional trading may vary with firm size, as documented in BJZZ. With the exception of returns, all control variables are measured at the end of the previous year and are in natural logs, and all continuous variables are standardized to have mean zero and unit variance.

Table 5 presents the results. Consistent with BJZZ, we find that retail order imbalance is a strong positive predictor of future returns on non-event days. However, order flow is an even stronger predictor for future returns on days with Seeking Alpha research. For example, in Specification 3, a one standard deviation increase in retail order imbalance (roughly 0.40) is associated with a roughly 0.06% increase in 10-days returns on days without Seeking Alpha research, but a 0.18% (0.058% + 0.123%) increase on days with Seeking Alpha research. We find considerably weaker evidence that retail trades are more informed on days with traditional media articles, and no evidence that retail investors benefit from traditional sell-side research, which further highlights the unique role of Seeking Alpha in broadening access to investment research and helping retail investors make better trading decisions.[14]

There is evidence that institutional investors also trade more profitably after Seeking Alpha research, although at the 10-day horizon the effect is roughly 40% of the estimated magnitude for retail investors and the coefficient is statistically insignificant.[15] The evidence that institutional investors benefit less from SA research than retail investors is consistent with retail investors paying greater attention to Seeking Alpha. For example, institutions may emphasize more exclusive information sources such as private social networks (Crawford et al., 2018), meetings with managers (Solomon and Soltes, 2015; Bradley, Jame, and Williams, 2018), or alternative data sets (Katona, Painter, Patatoukas, and Zheng, 2019).

Chen et al. (2014) and Campbell, DeAngelis, and Moon (2019) show that Seeking Alpha article tone, comment tone, and position disclosures predict future returns. In Specifications 4-6 of Table 5, we include these variables as additional controls. The evidence of increased informativeness of retail order imbalance on SA days is virtually unchanged after controlling for these measures of article sentiment. For example, over the 10-day horizon, controlling for SA sentiment reduces the coefficient on Retail OIB × SA by only 2.5%.[16] This suggests that retail

[14] In contemporaneous work, Akbas and Subasi (2019) find evidence that retail investors trade profitably after corporate news events, but they do not benchmark their findings to other information sources such as Seeking Alpha or brokerage research, and they do not explore the relative informativeness of non-retail order imbalances.

[15] The positive coefficients on *Retail OIB × SA* and *INST OIB × SA* raise the question of who takes the losing side of these trades. Since TAQ order imbalances capture liquidity-demanding trades by construction, liquidity-suppliers such as market makers and investors submitting limit orders therefore must be less profitable after SA research.

[16] This finding is perhaps surprising given the evidence that retail order imbalances trade in the direction of article sentiment (Table 4), and the evidence that article sentiment tends to predict returns. However, while SA sentiment is

investors' ability to process SA research articles extends beyond quick assessments of SA research sentiment.

In Table IA.3 of the Internet Appendix, we confirm that our finding of the incremental informativeness of retail order imbalances around Seeking Alpha research is robust to several alternative methodological choices including: (1) measuring retail order imbalances using number of trades instead of share volume; (2) measuring returns using closing midpoints instead of transaction prices; (3) measuring returns using volume-weighted average prices; (4) including firm-days with earnings news (earnings announcements or earning guidance); (5) using Fama-MacBeth regressions to estimate Equation (4); (6) adding firm fixed effects to the panel regression; and (7) excluding the top ten most actively researched stocks from the sample.

We also explore the stability of the results over time by estimating Equation (4) monthly (Specification 3 in Table 5). We plot the cumulative coefficients on *Retail OIB×SA* in Figure IA.1. We observe a jump in the second half of 2008, consistent with SA research being particularly valuable during the financial crisis, and a fairly stable and positive drift over the full sample period. To confirm that our results are not driven by the financial crisis period, we re-estimate the model after excluding the second half of 2008, and continue to find that the coefficient on Retail OIB × SA is statistically significant at the 1% level.

5.2 Retail Order Imbalances and Stock Returns: Cross-Sectional Analysis

The evidence from the prior section points to the possibility that retail investors are able to skillfully process Seeking Alpha articles. If retail investors are able to glean value-relevant

---

a significant predictor of returns, the economic relation over our sample period is relatively weak. For example, a panel regression of 10-day ahead returns on *SA Sentiment* yields a statistically significant estimate on *SA Sentiment* (t=2.09) but its overall explanatory power is small (R-squared = 0.01%).

information from Seeking Alpha research, we would expect the benefits to be concentrated among higher quality and more novel articles. In this section, we explore whether the incremental informativeness of retail investor order flow after Seeking Alpha research varies with contributor and article characteristics.

Our first measure of research quality is the length of the SA contributor's bio. We conjecture that longer bios signal both greater past accomplishments as well as a greater commitment to contributing to the SA community, both of which may contribute to higher quality research (see, e.g., Brown and Khavis, 2018). Our second measure is the average price impact of the contributor's past five articles. Consistent with contributor skill being persistent, the correlation between the average price impact over the previous five articles and the price impact of the current article is 0.27.

Traditional brokerage research and financial media tend to focus on positive news (e.g., McNichols and O'Brien, 1997; Gurun and Butler, 2012), and we hypothesize that negative sentiment research may provide more value-relevant information to investors. Moreover, Campbell, DeAngelis, and Moon (2019) show that articles in which the contributor discloses a long or a short position generate significantly larger market reactions, suggesting that investment disclosures may be associated with more credible and higher quality research.

Finally, Seeking Alpha is unique in providing investors with a platform where they can not only access research articles but also share their reactions to an article as well as their own views on the stock. Readers' comments incorporate valuable information distinct from the information incorporated in an article (Chen et al. 2014), and we anticipate that this additional information will result in more informed trading.

To test these predictions, we augment Equation (4) by interacting *Retail OIB*×SA with *Comments*, an indicator of whether the number of comments elicited by the article exceeds the yearly median; *Contributor Skill*, an indicator of whether the average absolute two-day market-adjusted reaction to a contributor's last five articles exceeds the yearly median; *Bio Length*, an indicator of whether the number of words in the contributor's bio exceeds the yearly median; *Net Negative Sentiment*, computed as (Short + Negative Tone + Comment Negative Tone) – (Long + Positive Tone + Comment Positive Tone), with all of its components defined as in Table 4; and *Position*, an indicator equal to one if the contributor discloses either a long or short position.[17] We also compute a composite informativeness measure (*Informative)* by adding the five conditioning variables, and we convert this measure to a zero-one indicator variable based on its median breakpoint.

We report the results in Table 6, tabulating only the coefficients on the variables of interest for brevity (full results are reported in Table IA.5 in the Internet Appendix). In Specifications 1-4, we find results that are largely consistent with our predictions. In particular, all five coefficients are in the expected direction, with four of them being economically large and statistically significant. For example, among articles with above median comments, a one-standard deviation increase in *Retail OIB* in Specification 1 is associated with a 0.36% increase in 10-day ahead returns (0.06% + 0.04% + 0.26%), which is roughly six times larger than the unconditional effect of 0.06% reported in Table 5. The incremental benefits associated with investor interaction through comments may help explain why Seeking Alpha benefits investors in ways not present with traditional media. In Specification 5, we document similar (albeit slightly reduced) point estimates

[17] We include the conditioning variables (e.g., *Comments*, *Net Negative Sentiment*) themselves in the regression, although there is no need to also include the double interactions (e.g., *Retail OIB* × *Comments* or *SA* × *Comments*) since the conditioning variables are always equal to zero on days without SA research.

when we include all five of the conditioning variables in one regression, which suggests that each of the conditioning variables is incrementally useful in facilitating greater information production among retail investors. Finally, Specification 6 confirms that our results hold for the composite measure, *Informative*.[18]

6. Additional Tests

The evidence that Seeking Alpha research leads to incrementally informative retail order flow and that the relation is stronger for heavily commented articles and those written by skilled contributors is consistent with Seeking Alpha serving a valuable informational role for individual investors. In this section, we consider alternative explanations related to public information, price pressure, and liquidity provisions. In addition, we offer more direct evidence that Seeking Alpha helps retail investors forecast cash flow news.

6.1 Does Seeking Alpha Research Proxy for Unobserved Public Information Releases?

The results from Tables 5 and 6 are consistent with Seeking Alpha research facilitating more informative retail trading. However, one concern is that an omitted variable, such as major news announcement, drives both the incremental informativeness of retail order imbalances and the occurrence of Seeking Alpha articles. We control for media articles in our analysis, and the evidence in Table 5 that retail investor trading is more informative after SA research than media articles is inconsistent with a public news interpretation.[19] However, it is possible that the arrival

[18] We also document that *Informative* articles are associated with significantly greater retail trading (as defined in Table 3) and a significantly stronger relation between *SA Sentiment* and retail order imbalance (as defined in Table 4). The results of these analyses are tabulated in Tables IA.6 and IA.7 in the Internet Appendix, respectively.

[19] In our main tests, we exclude earnings announcements and earnings guidance. However, when we include these variables, we find that retail trading is also more informative around *SA Articles* relative to days with earnings announcements or earnings guidance.

of public news is measured with error, and in this section we provide additional event-time analysis to more thoroughly investigate the potential role of unobserved public information.

As discussed in Section 4.2, it generally takes at least 24 hours between the submission of an article and the posting of the article on the Seeking Alpha website. Thus, if public information arrives that facilitates both more informative retail trading and Seeking Alpha research, we would expect that retail trading should also be more informative on the day (or days) prior to the posting of a Seeking Alpha article. To examine this possibility, we estimate Specification 3 of Table 5 after including event time indicator variables from $SA\_Event_{i,t\text{-}5}$ (an indicator designating that an SA article was published five days ago) to $SA\_Event_{i,t+5}$ (an indicator designating that an SA article will be published in five days). In order to stay consistent with the previous analysis, we continue to group days *t*-1 and *t* together ($SA\_Event_{\mathrm{i,t\text{-}1,t}}$) as the primary event period.[20] Since the unobserved news interpretation should also explain the cross-sectional patterns documented in Table 6 (e.g., influential articles should be more likely to piggyback off of news), we estimate the regression for both the full sample of SA articles and for the subset of *Informative* articles as defined in Table 6.

Table 7 reports the coefficients for each event-time indicator variable and also tests whether the estimate is significantly different from the estimate of $SA\_Event_{i,t\text{-}1,t}$. As in Tables 5 and 6, we find that retail trading on day *t* is significantly more informative if an *SA Article* is published on either day *t* or day *t*-1 (Panel A), and this effect is substantially larger for more informative articles (Panel B). We find no evidence that retail trading on day *t* is more informative if a Seeking Alpha article was published on days *t*-2 through *t*-5, which suggests that much of the benefits associated with analyzing Seeking Alpha articles accrue to the those who trade in the first couple of days after

[20] In untabulated analysis, we find very similar estimates for *t*-1 and *t*-0.

the article.[21] More importantly, we find little evidence that retail trading on day t is incrementally informative if a Seeking Alpha article will be published in the next one to five days (days t+1 through t+5), with none of the estimates being statistically significant at the 10% level. Furthermore, for the subset of more informative articles, the estimates are always significantly smaller than the estimate on $SA\_Event_{i,t-1,t}$. Collectively, the evidence mitigates the concern that unobserved public information spuriously explains the relation between SA research and informative retail trading.

6.2 Decomposing Retail Trading into Price Pressure, Liquidity Provision, and Informed Trading

In Table 4 we find that retail investor order imbalances are highly persistent (i.e., the coefficient on $Retail\ OIB_{w-1}$ is significantly positive). This finding raises the concern that buying or selling pressure could explain the predictability of returns, particularly if there is greater persistence in order imbalances after Seeking Alpha research. In other words, Seeking Alpha research may amplify noise trading among retail investors, generating price pressure and resulting in short-term return predictability.[22] Table 4 also documents that retail investor order imbalances are contrarian over short horizons (e.g., the coefficient on Ret_{w-1} is significantly negative). Short-term contrarian trading is a common proxy for liquidity provision (e.g., Nagel, 2012; Jame, 2018), raising the possibility that the positive association between retail order imbalances and future returns is attributable to liquidity provision rather than informed trading.

[21] This finding is also consistent with the evidence in Table 5, which shows that roughly 41% of the incremental 10-day returns is captured in the first day subsequent to the trade (0.050%/0.123%).

[22] This view is bolstered by the evidence that "fake" articles, i.e., those that are financially sponsored (but undisclosed) by the covered firm, are at least occasionally associated with significant price impact (Kogan, Moskowitz, Niessner, 2018, Clarke, Chen, Du, and Hu, 2019). We note that articles that have been identified as fake by the SEC have been removed from Seeking Alpha and are excluded from our sample. In separate analysis, we collect a list of fake articles from the *Financial Times* (https://ftalphaville-cdn.ft.com/wp-content/uploads/2017/04/10231526/Stock-promoters.pdf). Examining the incremental informativeness of retail order imbalance around these fake articles, we find negative but statistically insignificant estimates. The fake news evidence is inconsistent with retail investors benefiting from the price pressure associated with fake articles.

We explore the potential role of price pressure and liquidity provision following the approach in BJZZ. In particular, we decompose retail order imbalances into three components: *OIB Persistence* (a proxy for price pressure), *OIB Contrarian* (a proxy for liquidity provision), and *OIB Other* (a proxy for informed trading). The three components are estimated as the fitted value from the following panel regression: $Retail\ OIB_{it} = \alpha + \beta_1 Retail\ Oib_{iw\text{-}1} + \beta_2 Ret_{i,w\text{-}1} + \varepsilon_{it,}$ where $OIB\ Persistence = \hat{\beta}_1 OIB_{w-1}$; $OIB\ Contrarian = \hat{\beta}_2 Ret_{w-1}$; and $OIB\ Other = \hat{\varepsilon}_{it}$. We then estimate Equation (4) after replacing total retail order imbalance (*Retail OIB)* with *OIB Persistence, OIB Contrarian*, or *OIB Informed*.

Specifications 1 through 3 of Table 8 report the results for the full sample, and Specifications 4 through 6 report results for the subsample of *Informative* articles, as defined in Table 6. In both samples, the coefficients on *OIB Persistence*×*SA* and *OIB Contrarian*×*SA* are statistically insignificant, whereas the coefficient on *OIB Other*×*SA* is highly significant. The evidence is inconsistent with either the liquidity provision or price pressure explanations and points towards SA articles contributing to more informative retail trading.

A second approach to disentangle price pressure from informed trading is to explore the return patterns over longer horizons. In particular, the price pressure explanation predicts reversals over longer holding periods as prices revert to fundamentals. In contrast, the informed trading explanation predicts, at a minimum, that returns should not revert. To the extent that retail investors trade on information that is slowly impounded in prices, we may observe a drift over longer horizons.

We re-estimate Specification 3 of Table 5 using returns measured over the subsequent 10, 20, 40, or 60 trading days. For brevity, in Figure 2 we only plot the coefficients on *Retail OIB* (non-SA days) and the coefficients on *Retail OIB* + *Retail OIB* × *SA* (SA days) in the full sample and subsample of *Informative* SA articles, as defined in Table 6. The results provide no evidence that the extra returns predicted by retail order imbalance on SA days reverse. For example, in the subsample of *Informative* articles, a one-standard deviation increase in retail order imbalances is associated with a 0.32% increase over a 10-day holding period and a 0.33% increase over a 60-day holding period. We find no evidence of a drift either, suggesting that the information that retail investors trade on SA days is impounded into prices within ten trading days.

6.3 The Ability of Retail Order Flow to Predict Future Cash Flow News

If retail trading on Seeking Alpha research days better predicts future returns because it reflects more information about firm fundamentals, then retail order imbalances should also better predict future cash flows news. To test this prediction, we estimate the following panel regression:

$$Y_{it+1,t+10} = \alpha + \beta_1 RetailOIB_{it} + \beta_2 RetailOIB_{it} \times Event_{it-1,t} + \beta_3 RetailOIB_{it} \times Log(Size)_{it} + \beta_4 InstOIB_{it} + \beta_5 InstOIB_{it} \times Event_{it-1,t} + \beta_6 InstOIB_{it} \times Log(Size)_{it} + \beta_7 Event_{it-1,t} + \beta_8 Char_{i,y-1} + \beta_9 LagMediaSentiment + \beta_{10} LagRevision + Time_t + \varepsilon_{it}. \quad (5)$$

The dependent variable, $Y_{it+1,t+10}$, is a proxy for innovations in expected firms' cash flows that is constructed using media article sentiment or analysts' earnings forecast revisions.

We contend that two media articles with the same negative sentiment convey more information about cash flows than a single article with the same negative sentiment. We therefore construct a measure of aggregate *Media Sentiment* by summing the *Event Sentiment Score*s of all articles published in the window [t+1, t+10], after subtracting 50 from each of them to ensure that summing articles with negative sentiment is meaningful. We define forecast *Revisions* as the total number of upward forecast revisions less the total number of downward forecast revisions over the [*t*+1, *t*+10] window.[23] We exclude observations where there are no media articles (or forecast

[23] A related proxy for cash flow news is the analyst forecast error (earnings surprise). Earnings announcements are available during the 10-day window for only 16% of firm-days, which significantly reduces statistical power. In

revisions) over days t+1 through t+10, and we winsorize *Media Sentiment* and *Revisions* at the 1st and 99th percentiles. In addition to the independent variables from Equation (4), we also include lags of *Media Sentiment* (or *Revisions*) to control for potential persistence in public news. Following Kelley and Tetlock (2013), we construct *Lag Media Sentiment* and *Lag Revision* over day 0, days [-5,-1], and days [-26,-6].

Specification 1 of Table 9 reports the results for *Media Sentiment.* Consistent with Kelley and Tetlock (2013), retail order imbalances predict future media tone. More importantly, the effect is substantially stronger on days after Seeking Alpha research. Specifically, a one-standard deviation increase in retail order imbalances on a typical day is associated with 0.29 higher future article tone, whereas after Seeking Alpha research is published, future article tone is 1.37 higher (0.29 + 1.08). The ability of retail order imbalances to predict media tone is even stronger in the subsample of *Informative* SA articles (Specification 2).

Specifications 3 and 4 present the results for forecast *Revisions.* We find a positive and marginally significant coefficient on *Retail OIB* × *SA* in the full sample of articles (p-value of 0.06). When we limit the sample to *Informative* SA Articles, the coefficient on Retail OIB × SA increases considerably and becomes statistically significant at a 1% level. Collectively, the evidence is consistent with Seeking Alpha articles, particularly *Informative* articles, helping retail investors become more informed about firm cash flows.

7. Conclusion

Individual investors are typically at an information disadvantage relative to professional investors. In recent years, innovations in technology have helped spur the democratization of

untabulated analysis, we find a positive but insignificant incremental effect of SA research on the ability of retail order flow to predict earnings surprises.

investment research, with the popular provider of informative crowdsourced research Seeking Alpha playing a central role (Chen et al. 2014). In this article, we explore whether this phenomenon enhances the informativeness of retail investor trading.

Our initial findings confirm anecdotal evidence that Seeking Alpha research is geared towards retail investors, with SA coverage being significantly negatively related to institutional ownership and positively related to number of shareholders. We also find strong evidence that retail investors react to Seeking Alpha research, with significant increases in retail investor trading activity on days with Seeking Alpha articles. Moreover, retail order imbalances are significantly related to the sentiment of research articles and comments, and the relation begins within a half-hour of publication.

More importantly, we document that Seeking Alpha research enhances the informativeness of retail investor trades. In particular, the relation between retail order flow and future stock returns is roughly three times as strong on days with Seeking Alpha research articles, and the SA findings are stronger than the analogous evidence for media articles or traditional brokerage research. We find that the informativeness of retail trading after SA research continues to hold after controlling for SA tone, suggesting that retail investors extract value-relevant information from SA articles that extends beyond article tone.

Consistent with this view, we find that retail investor trading is particularly informed after more informative SA research. For example, articles written by contributors with longer bios, and by those whose past research has been more impactful, result in a stronger post-article connection between retail order flow and future returns. The predictive ability of retail order flow after SA research is also stronger for negative sentiment research, consistent with these articles being more novel, and when the SA article elicits more comments, consistent with active investor engagement leading to better information signals. Finally, we find that retail order flow incrementally predicts future news article tone and changes in earnings forecast after informative Seeking Alpha research, suggesting that Seeking Alpha allows retail investors to garner information about future cash flow news.

We conclude that a recent technology-induced innovation, the crowdsourcing of investment research, helps facilitate the process by which retail investors become informed. We acknowledge, however, that not all technological innovations enhance retail investor trading performance. For example, information sharing on a closed, professionals-only platform, SumZero, is only likely to improve the trading performance of professional investors (Crawford et al. 2018). Moreover, many new sources of information target professional investors, and active portfolio managers expend tremendous resources to acquire investment information from FinTech companies (e.g. Grennan and Michaely, 2018). Although Zhu (2018) suggests that these new sources of information yield broad benefits in the form of improved firm monitoring, Katona, Painter, Patatoukas, and Zeng (2019) argue that unequal access to new alternative datasets benefits institutional investors at the expense of retail investors.

Appendix A: Variable Definitions:

A.1 Seeking Alpha Variables

- *SA Coverage* – the number of Seeking Alpha contributors writing an article for a firm during the calendar year. (Source: Seeking Alpha).
- *SA Articles* – the number of Seeking Alpha articles written for a firm during the calendar year. (Source: Seeking Alpha).
- *SA* – An indicator equal to one if a Seeking Alpha research article about firm *i* is published on day *t* or day *t*-1. (Source: Seeking Alpha).
- *Negative (Positive) Tone* – An indicator equal to one when the average fraction of negative (positive) words across all single-ticker SA articles published about firm *i* on day *t* or *t*-1 exceeds the sample median. (Source: Seeking Alpha). We identify negative and positive words using Loughran and McDonald's (2011) list.
- *Comment Negative (Positive) Tone* – An indicator equal to one when the average fraction of negative (positive) words across all comments on single-ticker SA articles published on days *t* or *t*-1 exceeds the sample median. We exclude comments made after the beginning of the next trading day. For articles without comments the value of this variable is zero. (Source: Seeking Alpha).
- *Short (Long) Position* – An indicator equal to one if the contributor discloses a short (long) investment position in the researched company. This measure is averaged across all single-ticker articles published about firm *i* on day *t* or *t*-1. (Source: Seeking Alpha).
- *Composite Sentiment* – Calculated as (*Long* + *Pos. Tone* + Comment *Pos. Tone*) - (*Short* + *Neg. Tone* + Comment *Neg. Tone*). (Source: Seeking Alpha).
- *Net Negative Tone –Composite Sentiment* × -1, and then converted to an indicator variable based on the median breakpoint. (Source: Seeking Alpha).
- *Position* – An indicator equal to one if a contributor discloses either a long or short investment position in the researched company. This measure is averaged across all single-ticker articles published about firm *i* on day *t* or *t-1*. (Source: Seeking Alpha).
- *Comment* – An indicator equal to one when the number of comments on a SA article exceeds the sample median. We do not count comments made after the beginning of the next trading day. (Source: Seeking Alpha).
- *Contributor Skill* – An indicator equal to one when the average market reaction to a contributor's last five articles exceeds the sample median. Market reaction is measured as two-day absolute market-adjusted return. (Source: Seeking Alpha/CRSP).
- *Bio Length* – the total number of words in the contributors' bio. This measure is averaged across all single-ticker articles published about firm *i* on day *t* or *t*-1.This variable is converted to an indicator variable based on the median breakpoint. (Source: Seeking Alpha).
- *Informative Article* – a measure of aggregate informativeness defined as: *Comment* + *Contributor Skill* + *Bio Length* + *Net Negative Tone* + *Position*. This variable is converted to an indicator variable based on the median breakpoint. (Source: Seeking Alpha).

A.2 Other Variables:

- *Size* – the market capitalization computed as share prices times total shares outstanding at the end of the year (Source: CRSP).

- *Book-to-Market (BM)* – the book-to-market ratio computed as the book value of equity during the calendar year scaled by the market capitalization at the end of the calendar year. Negative values are deleted and positive values are Winsorized at the 1st and 99th percentile. (Source: CRSP/Compustat).
- *Volatility* – the standard deviation of daily returns during the calendar year (Source: CRSP).
- *Profitability* – EBITDA scaled by book value of assets. Winsorized at the 1st and 99th percentiles. (Source: Compustat).
- $Return_{m\text{-}1,\ m\text{-}12}$ – the buy-and-hold gross return over the prior 12 months. Alternative holding periods are computed analogously. (Source: CRSP).
- *Institutional Ownership* – the percentage of the firm's shares held by institutions at year end. (Source: Thomson Reuters Institutional Holdings S34).
- *Breadth of Ownership* – the total number of common shareholders (Source: Compustat).
- *IBES Coverage* – the number of unique brokerage houses issuing earnings forecasts for a firm during the calendar year. (Source: IBES).
- *Media Coverage* – the total number of media articles about a firm during the calendar year. The sample is limited to articles with a RavenPack relevance and novelty scores of 100. (Source: RavenPack).
- *IBES* – an indicator variable equal to one if an IBES investment recommendation or earnings forecast was issued for a firm on day t or day $t\text{-}1$. (Source: IBES).
- *IBES × Positive* – an indicator variable equal to one if an positive earnings forecast revision or recommendation upgrade was issued for a firm on day t or day $t\text{-}1$. We include both one-quarter ahead earnings forecasts (FPI = "6") and one-year ahead forecasts (FPI = "1"). (Source: IBES).
- *IBES × Negative* – an indicator variable equal to one if a negative earnings forecast revision or recommendation downgrade was issued for a firm on day t or day $t\text{-}1$. (Source: IBES).
- $Forecast\ Revision_{t,t+x}$ – the number of positive (i.e. upward) forecast revisions from days $t+1$ to $t+x$ less the number of negative forecast revisions. Revisions include both one-quarter ahead earnings forecasts (FPI = "6") and one-year ahead forecasts (FPI = "1"). (Source: IBES).
- *Media* – an indicator variable equal to one if a Media article was issued for a firm on day t or day $t\text{-}1$. (Source: RavenPack).
- *ESS* – the *Event Sentiment Score* reported by RavenPack. Scores range from 0 (very negative article) to 100 (very positive article) and have a median value of 50 (neutral article)
- *Media × Positive* – an indicator variable equal to one if the average the *Event Sentiment Score* of each article is greater than 50. (Source: RavenPack).
- $Media\ Sentiment_{\ t+1,t+x}$ – *the* sum of the *centered ESS* score across articles written about the firm from days t+1 through t+x. We center the *ESS* score by subtracting 50 from the *ESS* score reported by RavenPack. (Source: RavenPack).
- *Earnings Event* – an indicator variable equal to one if earnings or earnings guidance is announced for the firm for day t or day $t\text{-}1$. (Source: IBES).
- *Retail OIB* – retail buy volume less retail sell volume, scaled by total retail trading volume. Retail trading and order imbalances are classified using the approach outlined in Boehmer, et al. (2019). (Source: TAQ).
- *Institutional OIB* – the non-retail share volume bought less the non-retail share volume sold, scaled by the non-retail volume traded. Non-retail trading is signed used the Lee and Ready (1991) algorithm. When Daily Trade and Quote (DTAQ) data is available (2015-2017), the

Lee and Ready (1991) algorithm as classified by WRDS. For the Monthly Trade and Quote *(MTAQ)* data sample (2007-2014), the *Interpolated Lee and Ready Algorithm* of Holden and Jacobsen (2014) is used. (Source: TAQ).

References:

Akbas, F., and Subasi, M., 2019, Corporate news releases and the profitability of retail trades, Working Paper.

Asthana, S., Balsam, S., and Sankaraguruswamy, S., 2004. Differential response of small versus large investors to 10-K filings on EDGAR. *The Accounting Review* 79, 571-589.

Avery, C., Chevalier, J., and Zeckhauser, R., 2016. The "CAPS" prediction system and stock market returns. *Review of Finance* 20, 1363-1381.

Barber, B. and Odean, T., 2000. Trading is hazardous to your wealth: The common stock investment performance of individual investors. *Journal of Finance* 55, 773-806.

Barber, B. and Odean, T., 2002. Online investors: Do the slow die first? *Review of Financial Studies* 15, 455-488.

Barber, B. and Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies* 15, 455-488.

Barber, B. and Odean, T., 2013. The Behavior of individual investors, *in* 'Handbook of the Economics of Finance', Vol 2. Elsevier, 1533-1570.

Barber, B., Odean, T., and Zhu, N., 2009. Do retail trades move markets? *Review of Financial Studies* 22, 151-186.

Bartov, E., Faurel, L., and Mohanram, P., 2018. Can Twitter help predict firm-level earnings and stock returns? *The Accounting Review* 93, 25-57.

Battalio, R., Corwin, S., and Jennings, R., 2016. Can brokers have it all? On the relation between make-take fees and limit order execution quality. *Journal of Finance* 71, 2913-2238.

Bhattacharya, N., Cho, Y., and Kim, J., 2018. Levelling the playing field between large and small institutions: evidence from the SEC's XBRL mandate. *The Accounting Review*, forthcoming.

Bhushan, R., 1989. Firm characteristics and analyst following. *Journal of Accounting and Economics* 11, 255-274.

Blankespoor, E., Miller, B., and White, H., 2014, Initial evidence on the market impact of the XBRL mandate. *Review of Accounting Studies* 19, 1468-1503.

Boehmer, E., Jones, C., Zhang, X., and Zhang, X., 2019. Tracking retail investor activity. Working paper.

Bradley, D., Jame, R., and Williams. J, 2018. Non-Deal roadshows, informed trading, and analyst bias.

Brown, L., Call, A., Clement, M., and Sharp, N., 2015. Inside the "black box" of sell-side financial analysts. *Journal of Accounting Research* 53, 1-47.

Brown, L., and Khavis, J., 2018. The Reliability of crowdsourced earnings forecasts. Working paper.

Campbell, J., DeAngelis, M., and Moon, J., 2019. Skin in the game: Personal stock holdings and investors' response to stock analysis on social media. *Review of Accounting Studies*, forthcoming.

Chen, H., De, P., Hu, J., and Hwang, B.H., 2014. Wisdom of the crowds: The value of stock opinions transmitted through social media. *Review of Financial Studies* 27, 1367-1403.

Clarke, J., Chen, H., Du, D., and Hu, Y.J., 2019. Fake news, investor attention, and market reaction. *Information Systems Research*, forthcoming.

Crawford, S., Gray, W., Johnson, B., and Price, R., 2018. What motivates buy-side analysts to share recommendation online? *Management Science* 64, 2473-2972.

Frazzini, A., and Lamont, O., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics* 88, 299-322.

Gao, M., and Huang, J., 2019. Informing the market: The effect of modern information technologies on information production. *Review of Financial Studies*, forthcoming.

Gomez, E., Heflin, F., Moon, J., and Warren, J., 2018, Crowdsourced financial analysis and information asymmetry at earnings announcements, Working Paper.

Green, T.C., Jame, R., Markov, S., and Subasi, M., 2014. Broker-hosted investor conferences. *Journal of Accounting and Economics* 58, 142-166.

Gurun, U., and Butler, A., 2012. Don't believe the hype: Local media slant, local advertising, and firm value. *Journal of Finance* 67, 561-597.

Grennan, J., and Michaely, R., 2018. FinTechs and the Market for Financial Analysis. Working paper.

Holden, C.W., and Jacobsen, S., 2014. Liquidity measurement problems in fast, competitive markets: Expensive and cheap solutions. *Journal of Finance* 69, 1747-1785.

Hvidkjaer, S., 2008. Small trades and the cross-section of stock returns. *Review of Financial Studies* 21, 1123-1151.

Jame, R., Johnston, R., Markov, S., and Wolfe, M., 2016. The value of crowdsourced earnings forecasts. *Journal of Accounting Research* 54, 1077-1110.

Jame, R., 2018. Liquidity provision and the cross-section of hedge fund returns. *Management Science* 64, 3288-3312.

Kaniel, R., Saar, G., and Titman, S., 2008. Individual investor sentiment and stock returns. *Journal of Finance* 63, 273-310.

Kaniel, R., Liu, S., Saar, G., and Titman, S., 2012. Individual investor trading and return patterns around earnings announcements. *Journal of Finance* 67, 639-680.

Katona, Z., Painter, M., Patatoukas, P., and Zeng, J., 2019, Alternative data and price discovery: Evidence from outer space. Working paper.

Kelley, E., and Tetlock, P., 2013. How wise are crowds? Insights from retail orders and stocks returns. *Journal of Finance* 68, 1229-1265.

Kelley, E., and Tetlock, P., 2017. Retail short-selling and stock prices. *Review of Financial Studies* 30, 801-834.

Kogan, S., Niessner, M., and Moskowitz, T., 2018. Fake news: Evidence from financial markets. Working paper.

Kumar, A., and Lee, C., 2006. Retail investor sentiment and return comovements. *Journal of Finance* 61, 2451-2486.

Linnainmaa, J., 2011, Why Do (Some) Households Trade So Much? *The Review of Financial Studies*, 24, 1630–1666.

Loughran, T., and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance* 66, 35-65.

McNichols, M., and O'Brien, P., 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35, 167-199.

Nagel, S., 2012. Evaporating liquidity. *Review of Financial Studies* 25, 2005-2039.

Reed, A., Samadi, M., and Sokobin, J., 2018. Shorting in broad daylight: Short sales and venue choice. Working paper.

Seru, A., Shumway, T., and Stoffman, N., 2010. Learning by trading. *Review of Financial Studies* 23, 705-739.

Solomon, D., and Soltes, E., 2015. What are we meeting for? The consequences of private meetings with investors 58, 325-355.

Tetlock, P., 2007. Giving content to investment sentiment: The role of media in the stock market. *Journal of Finance* 62, 1139-1168.

Zhu, C., 2018. Big data as a governance mechanism. *Review of Financial Studies*, forthcoming.

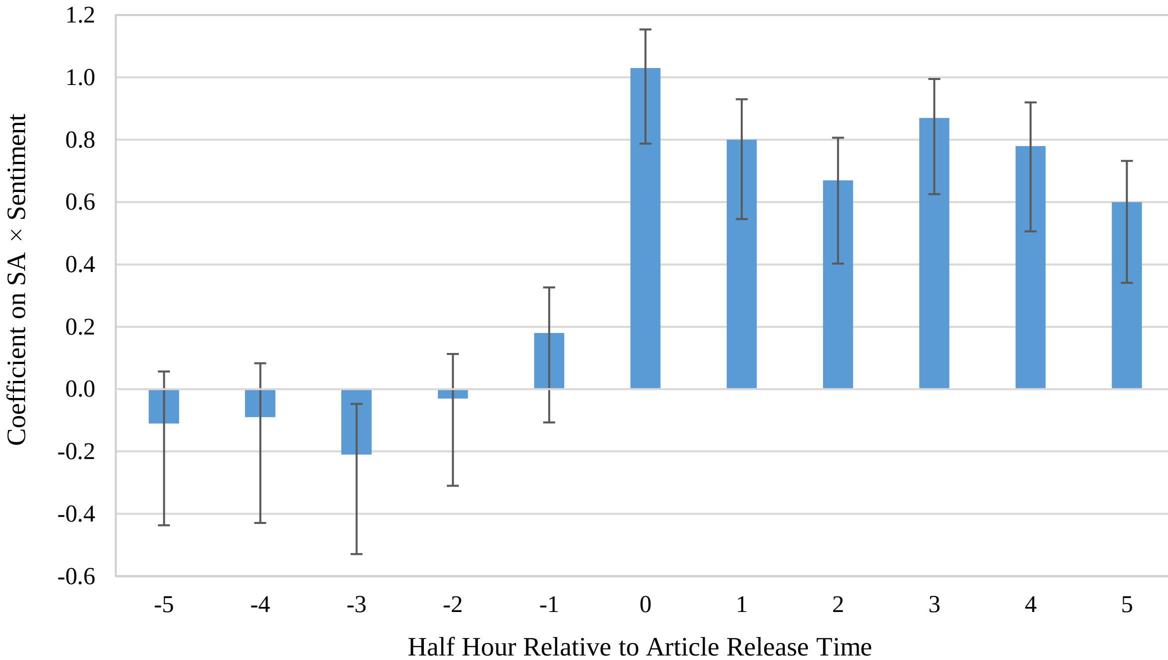

Figure 1. Seeking Alpha Research Sentiment and Retail Investor Order Imbalances: Intraday Analysis
The figure plots coefficients and confidence bounds obtained by regressing half-hour retail order imbalances on SA article sentiment measures. We regress retail order imbalances on the composite sentiment score of SA articles over 30-minute event-time windows, where event-time 0 is the 30-minute period in which the article was first published on Seeking Alpha. The control variables are identical to Specification 3 of Table 4. The figure reports the coefficient estimate on SA × *Composite Sentiment* and the 95% confidence intervals for each thirty-minute window. The sample spans from 2007-2017 and includes 135,686 Seeking Alpha articles.

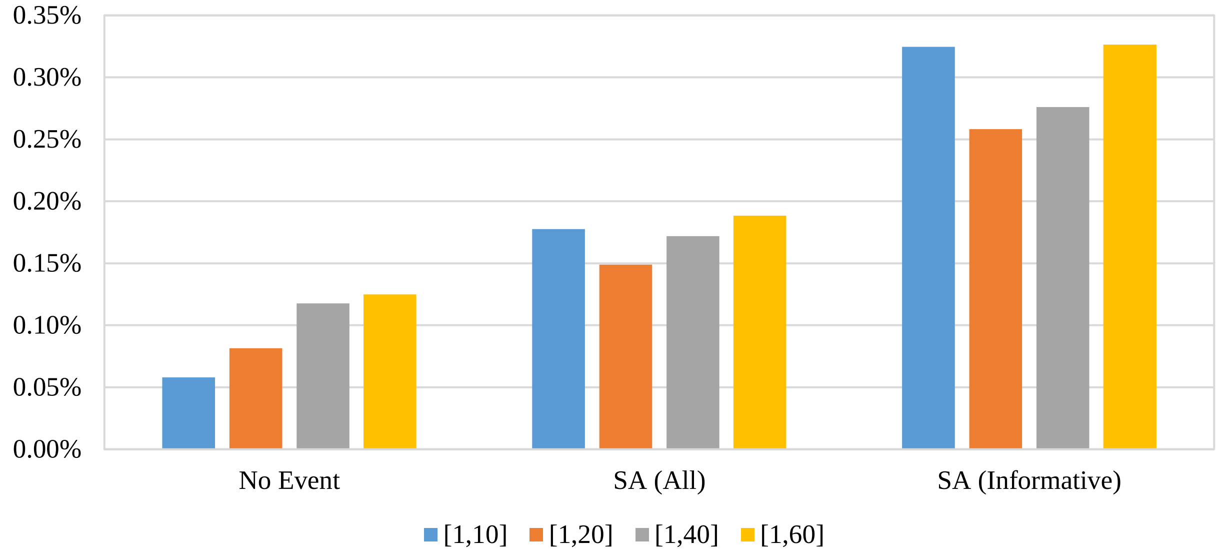

Figure 2. SA Research and the Informativeness of Retail Order Imbalances: Longer Horizon Analysis
The figure plots coefficients obtained by regressing stock returns on retail order imbalances. We estimate Specification 3 of Table 5, with the holding period extended to 10, 20, 40, and 60 days. *No Event* plots the coefficient estimates on *Retail* OIB_{it}, *SA* plots the sum of the coefficients on *Retail* OIB_{it} and *Retail* $OIB{\times}SA_{it}$, and *Informative SA* plots the sum of the coefficients on *Retail* OIB_{it} and *Retail* $OIB{\times}SA_{it}$ when the sample is limited to *Informative* SA articles (as defined in Specification 6 of Table 6).

Table 1. Summary Statistics for the Seeking Alpha (SA) Investment Research Article Sample

The table reports information on Seeking Alpha research articles by year. The sample is comprised of 192,398 single-ticker research articles (*SA Articles*), for 5,080 unique firms, written by 9,130 unique contributors (*SA Contributors)*, for which the referenced stock is available in the CRSP-Compustat merged database. *Firms Covered by SA* is the number of firms in CRSP/Compustat with at least one single-ticker article on Seeking Alpha. *CRSP/Compustat Coverage* is the fraction of the CRSP/Compustat universe with coverage on Seeking Alpha. *Ave SA Coverage* is the average number of unique contributors writing an article about the firm conditional on the firm having non-zero coverage. *Average Comments per Article* is the average number of comments written within one trading day of the release of the article.

Year	*Firms Covered by SA*	*CRSP/Compustat Coverage*	*SA Articles*	*SA Contributors*	*Contributor-Firm Pairs*	*Average SA Coverage*	*Average Comments Per Article*
2005	251	5.27%	900	42	343	1.37	0.00
2006	986	21.13%	3,571	262	2,427	2.46	0.00
2007	1,576	34.17%	8,921	619	5,160	3.27	0.15
2008	1,424	31.55%	8,077	863	4,705	3.30	3.89
2009	1,344	31.50%	8,818	794	4,749	3.53	4.06
2010	1,434	35.57%	7,989	792	4,655	3.25	4.12
2011	1,579	40.75%	11,757	1,162	7,053	4.47	7.38
2012	1,865	49.89%	21,247	1,638	12,256	6.57	11.51
2013	2,563	71.00%	21,285	2,101	13,757	5.37	50.46
2014	2,586	71.69%	26,595	2,244	15,545	6.01	16.34
2015	2,796	74.82%	27,893	2,272	16,197	5.79	17.08
2016	2,559	69.39%	23,069	2,212	12,917	5.05	25.25
2017	2,369	66.49%	22,276	2,134	12,751	5.38	30.57
Average	1,795	46.40%	14,800	1,318	8,655	4.29	20.58

Table 2. Determinants of Seeking Alpha and IBES Coverage

The table presents the results from the following panel regression:

$$Coverage_{it} = \alpha + \beta_1 Institutional\ Ownership_{i,t-1} + \beta_2 Breadth\ of\ Ownership_{i,t-1} + \beta_3 Char_{\,i,t-1} + Time_t + \varepsilon_{it.}$$

In Specifications 1 and 2, *Coverage* is the natural log of one plus the total number of unique Seeking Alpha contributors writing at least one article for the stock during the calendar year (*SA Coverage*). In Specifications 3 and 4, *Coverage* is the natural log of one plus the total number of unique brokerage firms issuing at least one earnings forecast for the stock during the calendar year (*IBES Coverage*). *Institutional Ownership*$_{i,t-1}$ is the percentage of the firm's shares held by institutional investors at the end of the previous year, and *Breadth of Ownership* is the number of common shareholders. *Char*$_{i,t-1}$ is a vector of firm characteristic controls. Detailed variable descriptions appear in Appendix A. All variables are standardized to have mean zero and unit variance. All specifications include year fixed effects, and standard errors are clustered by firm with *t*-statistics reported in parentheses. The sample spans 2005-2017 and consists of 42,280 firm-year observations.

	Log (SA Coverage)		*Log (IBES Coverage)*	
	[1]	[2]	[3]	[3]
Inst. Ownership	-0.22	-0.23	0.14	0.15
	(-16.10)	(-17.01)	(14.69)	(15.30)
Log (Breadth of Ownership)	0.05	0.05	-0.06	-0.07
	(4.99)	(5.51)	(-9.54)	(-9.87)
Log (Size)	0.55	0.50	0.69	0.67
	(23.00)	(18.96)	(49.91)	(46.78)
Log (BM)	0.01	0.01	0.00	0.00
	(1.30)	(0.83)	(0.42)	(0.36)
Log (Vol)	0.19	0.18	0.05	0.05
	(13.86)	(13.68)	(6.17)	(5.39)
Log (Turn)	0.12	0.08	0.31	0.31
	(9.75)	(7.16)	(25.13)	(24.78)
Return	0.02	0.02	0.04	0.04
	(3.69)	(3.62)	(4.34)	(4.31)
Profitability	0.03	0.03	-0.04	-0.04
	(3.57)	(4.15)	(-6.94)	(-7.24)
Log (Media Coverage)	0.06	0.06	0.01	0.01
	(6.14)	(5.93)	(1.99)	(1.59)
Log (IBES Coverage)		0.10		
		(7.02)		
Log (SA Coverage)				0.04
				(6.85)
Fixed Effects	Year	Year	Year	Year
R-squared	41.81%	42.05%	76.78%	76.82%

Table 3. Seeking Alpha Research Coverage and Retail Investor Trading

The table presents the results from the following panel regression:

$$Retail\ Trading_{it} = \alpha + \beta_1 SA_{it-1,t} + \beta_2 IBES_{it-1,t} + \beta_3 Media_{it-1,t+} \beta_4 Char + Time_t + Firm_i + \varepsilon_{it.}$$

In Specifications 1 and 2, *Retail Trading*$_{it}$ denotes *Retail Turnover*$_{it}$, which is one plus the total retail trading volume in stock *i* on day *t*, scaled by stock *i*'s shares outstanding, measured in natural logs. In Specifications 3 and 4, *Retail Trading* denotes *Percentage Retail Turnover*, which is the total retail trading volume in stock *i* on day *t* scaled by aggregate trading volume for stock *i* on day *t*. Trades are classified as retail using the approach of Boehmer, Jones, Zhang, and Zhang (2019). $SA_{it-1,t}$ is an indicator variable equal to one if Seeking Alpha issued a research report for firm *i* on day *t* or *t*-1. $IBES_{it-1,t}$ is an indicator variable equal to one if IBES issued a research report for firm *i* on day *t* or *t*-1, and $Media_{it-1,t}$ is an indicator variable equal to one if firm *i* was covered by the traditional media on day *t* or *t*-1. *Char* is a vector of firm characteristics measured at the end of the previous year. More details are available in Appendix A. All continuous independent variables are standardized to have mean zero and unit variance. *Time* and *Firm* indicate time (calendar day) and firm fixed effects. Standard errors are clustered by firm. The sample spans 2007-2017 and includes 4,372,388 firm-day observations.

	Log (Retail Turnover)		Percent Retail Turnover	
	[1]	[2]	[3]	[4]
SA	0.16	0.13	1.30	0.62
	(16.78)	(25.40)	(16.82)	(20.26)
IBES	0.09	0.08	0.36	0.07
	(24.15)	(45.30)	(9.83)	(6.57)
Media	0.05	0.05	0.07	0.04
	(22.30)	(35.55)	(2.67)	(3.87)
Log (Size)	-0.08	-0.12	-2.64	-3.94
	(-7.08)	(-7.41)	(-20.73)	(-20.85)
Log (BM)	0.01	-0.03	-0.09	-0.13
	(1.73)	(-4.42)	(-1.23)	(-1.84)
Inst Ownership	-0.09	-0.01	-2.75	-1.00
	(-17.89)	(-1.84)	(-34.97)	(-10.91)
Log (Breadth of Ownership)	0.00	0.02	0.46	0.29
	(0.70)	(1.57)	(7.79)	(2.19)
Log (Vol)	0.10	0.07	0.82	0.47
	(14.13)	(11.66)	(8.36)	(6.56)
Log (Turn)	0.17	0.11	0.52	0.23
	(9.47)	(12.70)	(4.10)	(2.41)
Return	0.01	0.01	-0.28	-0.29
	(2.40)	(2.93)	(-3.11)	(-5.67)
Profitability	-0.03	0.01	-0.68	0.04
	(-6.55)	(1.14)	(-12.06)	(0.53)
Log (IBES Coverage)	0.02	0.02	0.01	0.08
	(1.35)	(1.75)	(0.09)	(0.73)
Log (SA Coverage)	0.07	0.02	0.96	0.11
	(12.59)	(6.68)	(18.67)	(2.94)
Log (Media Coverage)	-0.03	0.01	-0.07	0.04
	(-3.79)	(1.69)	(-1.03)	(0.88)
Fixed Effects	Time	Time & Firm	Time	Time & Firm
R-squared	27.43%	45.90%	34.29%	46.45%

Table 4. Seeking Alpha Research Sentiment and Retail Investor Order Imbalances

The table presents the results from the following panel regression:

$$Retail\ OIB_{it} = \alpha + \beta_1 SA_{it-1,t} + \beta_2 SASentiment_{it-1,t} + \beta_3 IBES_{it-1,t} + \beta_4 IBESSentiment_{it-1,t} + \beta_5 Media_{it-1,t} + \beta_6 MediaSentiment_{it-1,t} + \beta_7 InstOib_{it} + \beta_8 Char + Time_t + Firm_i + \varepsilon_{it.}$$

Retail OIB$_{it}$ is defined as retail buy volume less retail sell volume, scaled by total retail trading volume for firm *i* on day *t*. Retail buys and sells are classified as in Boehmer, et al. (2019). $SA_{it-1,t}$ is an indicator variable equal to one if there is a SA research article for firm *i* on day *t* or *t*-1, and $IBES_{it-1}$ and $Media_{it-1}$ are defined analogously. In Specifications 1 and 2, *SASentiment* is a vector of six variables: *Long (Short) Position*, an indicator variable equal to one if the author discloses a long (short) position; *Negative Tone (Positive Tone)*, an indicator variable equal to one if the fraction of negative (positive) words in the article exceeds the median, and *Comment Negative Tone (Comment Positive Tone)*, an indicator variable equal to one if the fraction of negative (positive) words in the comments exceeds the median. In Specification 3, *Composite Sentiment is* defined as: *Long + Positive Tone + Comment Positive Tone – Short –Negative Tone – Comment Negative Tone*. *IBES×Positive* (*IBES×Negative)* is an indicator variable equal to one if the IBES report includes a recommendation upgrade or upward forecast revision (downgrade or downward revision). *Media×Positive* (*Media×Negative)* is an indicator variable equal to one if the average *ESS* (RavenPack sentiment score) across all stock-focused articles published on days *t*-1 and *t* is greater than (less than) 50. *InstOib* is institutional buy volume less institutional sell volume, scaled by total institutional trading volume. Institutional trading is signed using the Lee and Ready (1991) algorithm. *Char* is a vector of firm characteristics that includes *Size, BM, Volatility, Turnover, Ret (w*-1*), Ret (m*-1), and *Ret (m*-7*, m*-2*)* and *Retail OIB (w*-1*)*. *Time* and *Firm* indicate time (calendar day) and firm fixed effects. Standard errors are clustered by firm. The sample spans from 2007-2017 and includes 4,030,795 firm-day observations.

	[1]	[2]	[3]
SA	1.31%	1.35%	1.16%
	(9.56)	(10.35)	(13.35)
SA × Long Position	1.12%	1.28%	
	(5.64)	(7.99)	
SA × Short Position	-1.54%	-1.86%	
	(-3.94)	(-4.97)	
SA × Negative Tone	-0.82%	-0.81%	
	(-6.15)	(-6.29)	
SA × Positive Tone	0.32%	0.43%	
	(2.63)	(3.53)	
SA × Comment Negative Tone	-0.45%	-0.53%	
	(-3.09)	(-3.72)	
SA × Comment Positive Tone	0.22%	0.24%	
	(1.69)	(1.75)	
SA × Composite Sentiment			0.67%
			(11.33)
IBES	0.92%	0.79%	0.79%
	(9.99)	(8.77)	(8.77)
IBES × Positive	0.51%	0.29%	0.30%
	(2.64)	(1.58)	(1.58)
IBES × Negative	-0.12%	-0.42%	-0.42%
	(-0.61)	(-2.24)	(-2.24)
Media	0.25%	0.30%	0.30%
	(3.54)	(4.41)	(4.40)
Media × Positive	0.35%	0.52%	0.52%
	(4.44)	(6.74)	(6.75)
Media × Negative			
Institutional OIB	-4.69%	-5.00%	-5.00%
	(-16.35)	(-17.37)	(-17.37)
Controls	Yes	Yes	Yes
Fixed Effects	Time	Time & Firm	Time & Firm
R-squared	1.60%	2.09%	2.08%

Table 5. Seeking Alpha Research and the Informativeness of Retail Investor Order Imbalances

The table presents the results from the panel regression:

$$Ret_{it+1,t+x} = \alpha + \beta_1 Retail\ OIB_{it} + \beta_2 Retail\ OIB_{it} \times Event_{\text{it-1,t}} + \beta_3 Retail\ OIB_{it} \times \text{Log}(Size)_{\text{it}} + \beta_4 Inst\ OIB_{\text{it}} + \beta_5 Inst\ OIB_{it} \times Event_{\text{it-1,t}} + \beta_6\ Inst\ OIB \times \text{Log}(Size)_{\text{it}} + \beta_{11} Event_{it-1,t} + \beta_{14} Char_{iy-1} + \beta_{15} SASentiment_{\ it-1,t} + Time_{\text{t}} + \varepsilon_{it.}$$

$Ret_{it,,t+x}$ is the stock return from the close of day t to the close of day t+x. $Retail\ OIB_{it}$ is the total retail buy volume less total retail sell volume, scaled by total retail trading volume for stock i on day t (Boehmer et al., 2019). $\text{Event}_{it-1,t}$ is a vector of event indicators: $SA_{it\text{-}1,t}$, $IBES_{it\text{-}1,t}$, and $Media_{it\text{-}1,t}$ as defined in Table 3. $RetailOIB_{it} \times Event_{it\text{-}1,t}$ interacts *Retail OIB* with the event indicator variable. $RetailOIB_{it} \times Size_{it}$ interacts *Retail OIB* with the natural log of firm size. *Char* is a vector of firm characteristics that includes *Size*, *BM*, *Volatility*, *Turnover*, *Ret* (*w*-1), *Ret* (*m*-1), and *Ret* (*m*-7, *m*-2). *SASentiment* is the vector of six sentiment variables described in Table 4, and $Time_{\text{t}}$ is a calendar day fixed effect. Detailed variable definitions appear in Appendix A. The coefficients on *Char*, *SA*, *IBES*, and *Media* are suppressed here for brevity and reported in Table IA.4 in the Internet Appendix. All continuous variables are standardized. Standard errors are clustered by month, and *t*-statistics are reported in parentheses. The sample spans 2007-2017 and comprises 4,011,555 firm-day observations.

	1-Day Return [1]	*5-Day Return* [2]	*10-Day Return* [3]	*1-Day Return* [4]	*5-Day Return* [5]	*10-Day Return* [6]
Retail OIB	0.010%	0.039%	0.058%	0.010%	0.039%	0.058%
	(4.97)	(7.34)	(6.22)	(4.98)	(7.34)	(6.22)
Retail OIB × SA	0.050%	0.066%	0.123%	0.050%	0.062%	0.120%
	(4.52)	(2.50)	(3.58)	(4.34)	(2.35)	(3.45)
Retail OIB × IBES	0.010%	0.011%	-0.003%	0.010%	0.011%	-0.003%
	(1.13)	(0.55)	(-0.12)	(1.12)	(0.55)	(-0.12)
Retail OIB × Media	0.010%	0.016%	0.021%	0.010%	0.016%	0.021%
	(2.79)	(1.98)	(1.75)	(2.79)	(1.98)	(1.75)
Retail OIB × Log (Size)	-0.010%	-0.027%	-0.037%	-0.010%	-0.027%	-0.037%
	(-4.91)	(-5.03)	(-4.47)	(-4.90)	(-5.03)	(-4.47)
Institutional OIB	-0.040%	-0.050%	-0.046%	-0.040%	-0.050%	-0.046%
	(-10.88)	(-6.96)	(-4.01)	(-10.86)	(-6.95)	(-4.00)
Inst OIB × SA	0.040%	0.055%	0.055%	0.040%	0.052%	0.052%
	(3.26)	(2.25)	(1.31)	(3.19)	(2.13)	(1.24)
Inst OIB × IBES	-0.010%	-0.005%	0.003%	-0.010%	-0.005%	0.003%
	(-0.95)	(-0.19)	(0.10)	(-0.94)	(-0.18)	(0.10)
Inst OIB × Media	0.000%	0.016%	0.010%	0.000%	0.016%	0.010%
	(0.61)	(1.37)	(0.66)	(0.61)	(1.37)	(0.66)
Inst OIB × Log (Size)	0.000%	0.001%	0.008%	0.000%	0.001%	0.008%
	(0.25)	(0.09)	(0.92)	(0.26)	(0.10)	(0.93)
SA × Long Position				0.060%	0.095%	0.045%
				(4.05)	(1.95)	(0.54)
SA × Short Position				-0.210%	-0.383%	-0.168%
				(-3.91)	(-2.46)	(-0.70)
SA × Negative Tone				-0.030%	-0.075%	-0.074%
				(-1.86)	(-1.76)	(-1.09)
SA × Positive Tone				0.040%	0.130%	0.216%
				(2.76)	(3.31)	(3.68)
SA × Com. Neg Tone				-0.050%	-0.054%	-0.083%
				(-3.14)	(-1.27)	(-1.04)
SA × Com. Pos Tone				0.040%	0.026%	0.042%
				(2.62)	(0.69)	(0.73)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Time	Time	Time	Time	Time	Time

Table 6. SA Research and the Informativeness of Retail Order Imbalances: Cross-Sectional Analysis

The table presents the results of a panel regression of stock returns on retail order imbalances interacted with SA research article characteristics. In particular, Specification 3 of Table 5 is augmented by interacting *Retail OIB* × *SA* with several measures of SA article content. *Comments* is an indicator variable equal to one if the SA article has greater than the median number of comments; *Contributor Skill* is an indicator variable equal to one if the two-day absolute market-adjusted returns across the last five articles written by the contributor is greater than the median; *Bio Length* is an indicator variable equal to one if the number of words in the contributor's bio is greater than the median; *Net Negative Tone*, computed as (*Short* + *Negative Tone* + *Comment Negative Tone*) – (*Long* + *Positive Tone* + *Comment Positive Tone*), where all the components are as defined in Table 4; *Position*, an indicator variable equal to one if the author discloses either a *Long* or *Short* position, and *Informative*, computed as *Comment* + *Contributor Skill* + *Bio Length* + *Net Negative Tone* + *Position*, and then converted to an indicator variable equal to one when its value exceeds the sample median. These conditioning variables are equal to zero on days without Seeking Alpha research, and therefore they are included only as interactions with *Retail OIB* × *SA* and *SA*. The table reports only the coefficients on *Retail OIB* × *SA* and *Retail OIB* × *SA* × *CV* for brevity (full table resented as Table IA.5 in the Internet Appendix). Standard errors are clustered by firm, and *t*-statistics are reported in parentheses. The sample spans 2007-2017 and comprises 4,011,555 firm-day observations.

	[1]	[2]	[3]	[4]	[5]	[6]
Retail OIB × *SA*	0.04%	0.04%	0.07%	0.03%	-0.15%	0.03%
	(1.21)	(1.18)	(1.95)	(0.62)	(-2.15)	(0.81)
Retail OIB × *SA* × *Comments*	0.26%				0.24%	
	(3.17)				(3.01)	
Retail OIB × *SA* × *Contrib. Skill*		0.18%			0.16%	
		(2.49)			(2.30)	
Retail OIB × *SA* × *Bio Length*			0.14%		0.13%	
			(2.15)		(2.00)	
Retail OIB × *SA* × *Net Neg. Tone*				0.10%	0.09%	
				(2.52)	(2.31)	
Retail OIB × *SA* × *Position*				0.06%	-0.01%	
				(0.79)	(-0.11)	
Retail OIB × *SA* × *Informative*						0.25%
						(3.42)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Time	Time	Time	Time	Time	Time

Table 7. Seeking Alpha Research and the Informativeness of Retail Order Imbalances: Event Time Analysis

The table presents the coefficients from the estimation of Specification 3 of Table 5, augmented to include additional leads and lags of the SA indicator variable, $SA_{i,t-x}$, and its interactions with $Retail\ OIB_{it}$, $RetailOIB_{it} \times SA_{i,t-x}$, where x indicates the date of the article relative to the day of trading. The first row reports the coefficients on $RetailOIB_{it} \times SA_{i,t-x}$ and the respective t-statistics in parentheses. The second row reports coefficient differences and the respective t-statistics in parentheses. Standard errors are clustered by month. The sample analyzed in Panel A includes all SA articles, whereas the sample in Panel B includes only *Informative* articles, as defined in Specification 6 of Table 6. The sample period spans 2007-2017.

Panel A: All Seeking Alpha Articles

	Article Date Relative to Trade Day									
	-5	-4	-3	-2	[-1,0]	1	2	3	4	5
$Retail\ OIB_{it} \times SA_{t-x}$	0.00%	0.06%	0.02%	-0.02%	0.11%	0.04%	0.10%	0.06%	0.02%	-0.07%
	(0.06)	(1.62)	(0.42)	(0.47)	(3.47)	(0.84)	(1.69)	(1.06)	(0.39)	(-1.18)
Days [-1,0] - Day [t]	0.11%	0.05%	0.09%	0.13%		0.07%	0.01%	0.05%	0.09%	0.18%
	(2.18)	(0.93)	(1.90)	(2.85)		(1.44)	(0.24)	(0.69)	(1.43)	(2.58)

Panel B: Informative Seeking Alpha Articles

	Article Date Relative to Trade Day									
	-5	-4	-3	-2	[-1,0]	1	2	3	4	5
$Retail\ OIB_{it} \times SA_{t-x}$	0.02%	0.07%	0.01%	-0.03%	0.26%	0.04%	0.09%	0.06%	0.03%	-0.07%
	(0.49)	(1.74)	(0.23)	(-0.68)	(4.19)	(0.90)	(1.56)	(0.94)	(0.55)	(-1.19)
Days [-1,0] - Day [t]	0.24%	0.19%	0.25%	0.29%		0.21%	0.16%	0.20%	0.23%	0.33%
	(3.64)	(2.58)	(3.51)	(3.98)		(3.04)	(2.13)	(2.39)	(2.78)	(3.51)

Table 8. SA Research and the Informativeness of Retail Order Imbalances: Decomposition Analysis

The table presents select coefficients from the estimation of Specification 3 of Table 5 when retail trading is replaced with one of its three components: persistence, contrarian, or other (a proxy for informed retail trading). These components are estimated as the fitted values from the panel regression:

$$Retail\ OIB_{it} = \alpha + \beta_1 Retail\ OIB_{it-1,t-5} + \beta_2 Ret_{t-1,t-5} + \varepsilon_{it},$$

where $\widehat{OIB}_{it}^{Persistence} = \hat{\beta}_1 OIB_{i,t-1,t-5}$, $\widehat{OIB}_{it}^{Contrarian} = \hat{\beta}_2 Ret_{i,t-1,t-5}$, and $\widehat{OIB}_{it}^{Other} = \hat{\varepsilon}_{it}$, respectively (Boehmer et al., 2019 provide details). The sample in Specifications 1-3 includes all Seeking Alpha articles, whereas the sample in Specifications 4-6 includes only *Informative* SA articles, as defined in Specification 6 of Table 6. The coefficients on the control variables are suppressed for brevity (full table is presented as Table IA.8 in the Internet Appendix). The number of firm-day observations is 4,011,555 and 3,897,473, respectively. The sample period is 2007-2017.

	All SA Articles			Informative SA Articles		
	Persistence	*Contrarian*	*Other (Informed)*	*Persistence*	*Contrarian*	*Other (Informed)*
	[1]	[2]	[3]	[4]	[5]	[6]
Retail OIB	0.09%	0.06%	0.05%	0.09%	0.06%	0.05%
	(6.16)	(1.95)	(5.97)	(6.15)	(1.91)	(5.84)
Retail OIB × SA	-0.02%	-0.06%	0.12%	-0.04%	-0.02%	0.27%
	(-0.54)	(-1.48)	(3.69)	(-0.63)	(-0.44)	(4.56)
Retail OIB × IBES	-0.05%	-0.05%	0.00%	-0.05%	-0.05%	0.00%
	(-1.74)	(-1.44)	(0.15)	(-1.75)	(-1.19)	(0.12)
Retail OIB × Media	0.02%	-0.02%	0.02%	0.02%	-0.02%	0.02%
	(0.93)	(-0.72)	(1.61)	(0.91)	(-0.76)	(1.65)
Retail OIB × Size	-0.03%	0.01%	-0.03%	-0.03%	0.01%	-0.03%
	(-2.31)	(0.54)	(-4.40)	(-2.40)	(0.59)	(-4.38)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Time	Time	Time	Time	Time	Time

Table 9. Seeking Alpha and the Informativeness of Retail Trading: Media Tone and Forecast Revisions

The table presents the results from the panel regression:

$$Y_{it+1,t+10} = \alpha + \beta_1 Retail\ OIB_{it} + \beta_2 Retail\ OIB_{it} \times Event_{it-1,t} + \beta_3 Retail\ OIB_{it} \times \mathrm{Log}(Size)_{it} + \beta_4 Inst\ OIB_{it} + \beta_5 Inst\ OIB_{it} \times Event_{it-1,t} + \beta_6\ Inst\ OIB \times \mathrm{Log}(Size)_{it} + \beta_{11} Event_{it-1,t} + \beta_{14} Char_{iy-1} + \beta_{15} LagMediaSentiment + \beta_{16} LagRevisions + Time_t + \varepsilon_{it.}$$

In Specifications 1 and 2, $Y_{it,,t+10}$ is *Media Sentiment*, defined as the sum of the Adjusted Event Sentiment Score (*ESS)* across all articles written from days *t+1* through *t*+10. In Specifications 3 and 4, $Y_{it,,t+10}$ is *Forecast Revisions,* defined as the number of upward forecasts revisions less the number of downward forecast revisions over days *t+1* through *t*+10. We limit the sample to observations where there is at least one media article or one forecast revision over the 10-day window. The table considers all SA articles and also the subset of *Informative* articles, as defined in Specification 6 of Table 6. *LagMediaSentiment* (*LagRevisions*) includes lags of *MediaSentiment (Forecast Revisions)* measured on days: [0], [-5,-1], and [-26,-6]. All other control variables are defined as in Table 5, with detailed variable definitions in Appendix A. The coefficient on *MediaSentiment* , *Char*, *SA*, *IBES, Media,* are not tabulated for brevity (full table is presented as Table IA.9 in the Internet Appendix). All continuous variables are standardized. Standard errors are clustered by month, and *t*-statistics are reported below each estimate. The sample period spans 2007-2017.

	Media Tone		Analyst Forecast Revisions	
	All SA Articles	Informative Articles	All SA Articles	Informative Articles
	[1]	[2]	[3]	[4]
Retail OIB	0.29	0.28	0.00	0.00
	(6.90)	(6.90)	(0.53)	(0.37)
Retail OIB × SA	1.08	1.42	0.07	0.20
	(5.86)	(4.27)	(1.92)	(3.16)
Retail OIB × IBES	0.04	0.04	-0.01	-0.01
	(0.82)	(0.81)	(-0.83)	(-0.70)
Retail OIB × Media	0.19	0.16	-0.01	-0.01
	(1.50)	(1.27)	(-0.59)	(-0.55)
Retail OIB × Log (Size)	0.23	0.22	-0.01	-0.01
	(5.70)	(5.40)	(-1.50)	(-1.34)
Institutional OIB	0.04	0.02	0.00	0.00
	(0.83)	(0.42)	(0.19)	(0.08)
Inst OIB × SA	0.37	0.56	0.07	0.08
	(1.98)	(1.80)	(2.09)	(1.53)
Inst OIB × IBES	-0.20	-0.18	-0.01	-0.01
	(-3.88)	(-3.50)	(-0.94)	(-0.81)
Inst OIB × Media	0.09	0.05	-0.04	-0.04
	(0.57)	(0.36)	(-2.39)	(-2.24)
Inst OIB × Log (Size)	0.15	0.12	0.00	0.00
	(3.66)	(3.01)	(0.66)	(0.27)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	Time	Time	Time	Time
Observations	3,238,659	3,139,04	1,710,882	1,644,240

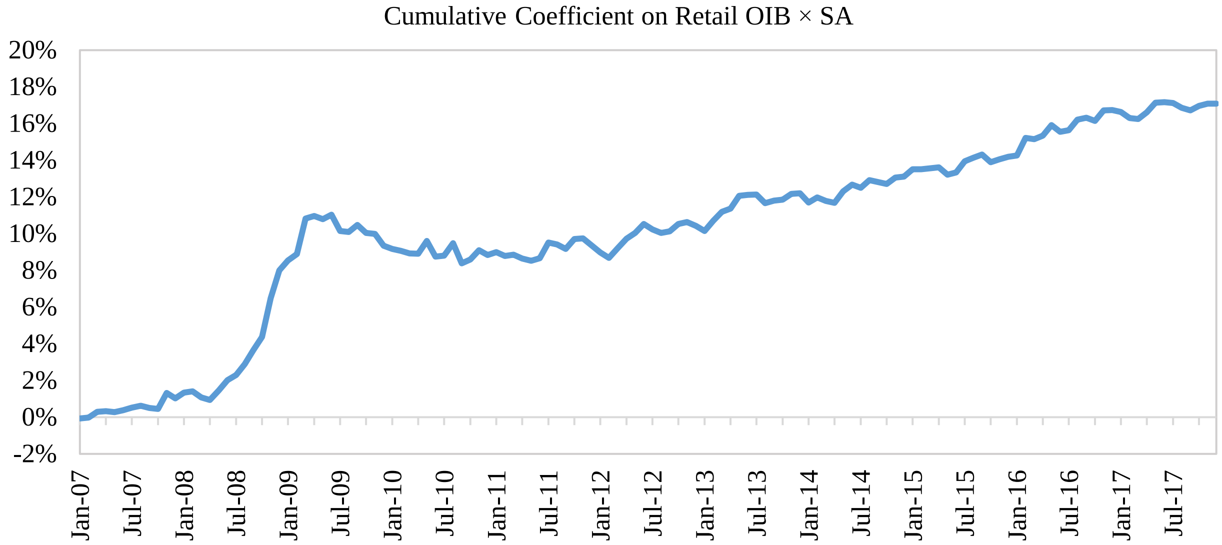

Figure IA.1. SA Research and the Informativeness of Retail Order Imbalances over Time

Each month, we estimate the following panel regression:

$$Ret_{it+1,t+x} = \alpha + \beta_1 Retail\ OIB_{it} + \beta_2 Retail\ OIB{\times}SA_{it} + \beta_3 Retail\ OIB{\times}IBES_{it} + \beta_4 Retail\ OIB{\times}Media_{it} + \beta_5 Retail\ OIB{\times}Size_{it} + \beta_6 Inst\ OIB_{it} + \beta_7 Inst\ OIB{\times}SA_{it} + \beta_8 Inst\ OIB{\times}IBES_{it} + \beta_9 Inst\ OIB{\times}Media_{it} + \beta_{10}\ Inst\ OIB{\times}Size_{it} + \beta_{11} SA_{it} + \beta_{12} IBES_{it} + \beta_{13} Media_{it} + \boldsymbol{\beta_{14} Char_{iy-1}} + \beta_{15} SASentiment_{it-1,t} + Time_t + \varepsilon_{it.}$$

The regression is identical to Specification 3 of Table 5 except that the regression is estimated separately each month. The figure plots the cumulative coefficient on *Retail OIB × SA* for each month over the full-sample period.

Table IA.1: Seeking Alpha Article Tone and Retail Investor Order Imbalance

Panel A repeats Table 4 without suppressing reporting of the control variables. In Panel B, we replicate Table 4 using Institutional order imbalances as the dependent variable.

Panel A: Retail OIB

	[1]	[2]	[3]
SA	1.31%	1.35%	1.16%
	(9.56)	(10.35)	(13.35)
SA × Long Position	1.12%	1.28%	
	(5.64)	(7.99)	
SA × Short Position	-1.54%	-1.86%	
	(-3.94)	(-4.97)	
SA × Negative Tone	-0.82%	-0.81%	
	(-6.15)	(-6.29)	
SA × Positive Tone	0.32%	0.43%	
	(2.63)	(3.53)	
SA × Comment Negative Tone	-0.45%	-0.53%	
	(-3.09)	(-3.72)	
SA × Comment Positive Tone	0.22%	0.24%	
	(1.69)	(1.75)	
SA × Composite Sentiment			0.67%
			(11.33)
IBES	0.92%	0.79%	0.79%
	(9.99)	(8.77)	(8.77)
IBES × Positive	0.51%	0.29%	0.30%
	(2.64)	(1.58)	(1.58)
IBES × Negative	-0.12%	-0.42%	-0.42%
	(-0.61)	(-2.24)	(-2.24)
Media	0.25%	0.30%	0.30%
	(3.54)	(4.41)	(4.40)
Media × Positive	0.35%	0.52%	0.52%
	(4.44)	(6.74)	(6.75)
Media × Negative	-0.50%	-0.38%	-0.38%
	(-6.36)	(-5.04)	(-5.03)
Ret (w-1)	-0.68%	-0.68%	-0.68%
	(-20.10)	(-19.96)	(-20.00)
Ret (m-1)	-0.41%	-0.46%	-0.46%
	(-14.11)	(-14.64)	(-14.65)
Ret (m-7, m-2)	0.04%	-0.06%	(-0.00)
	(1.98)	(-2.21)	(-2.21)
Log (Turn)	0.08%	-0.81%	-0.81%
	(1.22)	(-8.69)	(-8.70)
Log (Vol)	0.17%	0.27%	0.27%
	(2.62)	(2.65)	(2.64)
Log (Size)	0.32%	0.55%	0.55%
	(4.18)	(3.13)	(3.12)
Log (BM)	-0.34%	-0.63%	(-0.01)
	(-7.12)	(-7.72)	(-7.73)
Inst Oib	-4.69%	-5.00%	-5.00%
	(-16.35)	(-17.37)	(-17.37)
Retail Oib (w-1)	3.38%	2.93%	2.93%
	(67.00)	(61.91)	(61.92)
Fixed Effects	Time	Time & Firm	Time & Firm
R-squared	1.60%	2.09%	2.08%

Panel B:Institutional OIB			
	[1]	[2]	[3]
SA	0.00%	0.30%	0.21%
	(0.10)	(3.92)	(4.48)
SA × Long Position	0.20%	0.40%	
	(1.80)	(3.81)	
SA ×Short Position	0.00%	-0.17%	
	(0.04)	(-0.81)	
SA × Negative Tone	-0.30%	-0.23%	
	(-3.62)	(-2.92)	
SA × Positive Tone	-0.10%	-0.02%	
	(-1.42)	(-0.28)	
SA × Comment Negative Tone	-0.30%	-0.08%	
	(-3.74)	(-0.88)	
SA × Comment Positive Tone	-0.30%	-0.01%	
	(-3.08)	(-0.10)	
SA × Composite Sentiment			0.12%
			(3.62)
IBES	0.20%	0.24%	0.24%
	(4.60)	(5.01)	(5.00)
IBES × Positive	-0.60%	-0.33%	-0.33%
	(-6.26)	(-3.38)	(-3.38)
IBES × Negative	-0.60%	-0.36%	-0.36%
	(-6.08)	(-3.86)	(-3.86)
Media	0.20%	0.09%	0.09%
	(5.36)	(2.22)	(2.23)
Media × Positive	0.00%	0.26%	0.26%
	(0.65)	(6.28)	(6.27)
Media × Negative	-0.30%	-0.23%	-0.23%
	(-7.43)	(-5.28)	(-5.29)
Ret (w-1)	0.30%	0.33%	0.33%
	(16.00)	(16.84)	(16.84)
Ret (m-1)	0.30%	0.28%	0.28%
	(16.25)	(14.47)	(14.48)
Ret (m-7, m-2)	0.30%	0.25%	0.25%
	(3.66)	(5.28)	(5.28)
Log (Turn)	0.50%	-0.09%	-0.09%
	(10.22)	(-1.43)	(-1.43)
Log (Vol)	-0.50%	-0.02%	-0.02%
	(-12.51)	(-0.31)	(-0.31)
Log (Size)	0.70%	0.93%	0.93%
	(12.65)	(8.91)	(8.91)
Log (BM)	-0.10%	-0.05%	-0.05%
	(-1.92)	(-1.20)	(-1.20)
Retail Oib	-1.50%	-1.64%	-1.64%
	(-16.64)	(-17.82)	(-17.82)
Inst Oib (W-1)	3.10%	2.71%	2.71%
	(100.03)	(91.04)	(91.04)
Fixed Effects	Time	Time & Firm	Time & Firm
R-squared	4.98%	5.68%	6.38%

Table IA.2. Seeking Alpha Research Sentiment and Retail Investor Order Imbalances: Intraday Analysis
This table tabulates the coefficients and t-statistics obtained from regressing half-hour retail order imbalances on SA article sentiment measures (i.e., Figure 1 of the paper). In addition, it reports analogous results for institutional order imbalances. The sample spans from 2007-2017 and includes 135,686 Seeking Alpha articles.

	Retail Order Imbalances		Institutional Order Imbalances	
Half-Hour	[1]	[2]	[3]	[4]
Window	Coefficient	*t*-statistic	Coefficient	*t*-statistic
-5	-0.07%	(-0.44)	0.03%	(0.25)
-4	-0.07%	(-0.44)	-0.03%	(-0.35)
-3	-0.18%	(-1.14)	0.15%	(1.54)
-2	-0.03%	(-0.21)	-0.04%	(-0.47)
-1	0.16%	(1.18)	0.06%	(0.70)
0	1.04%	(8.69)	0.41%	(5.64)
1	0.79%	(6.30)	0.15%	(2.16)
2	0.67%	(5.07)	0.14%	(1.99)
3	0.83%	(6.89)	0.12%	(1.78)
4	0.75%	(5.66)	0.21%	(3.12)
5	0.64%	(4.97)	0.12%	(1.67)

Table IA.3. Seeking Alpha Research and Informativeness of Retail Order Imbalances: Robustness

The table repeats the analysis in Table 5 in alternative ways for robustness. The regressions include the full set of controls from Table 5, but for brevity, only the coefficient on *RetailOIB×SA* is tabulated. *Baseline Specification* reports the results from the main model reported in Specifications 1 through 3 of Table 5. *OIB Trades* measures retail order imbalances using the number of trades instead of trading volume. *CRSP Midpoint* calculates returns under the assumption that the trade took place at the mid-point of closing bid and ask price on day *t*, instead of the closing price on day *t*. *VWAP Returns* calculates returns under the assumption that the trade took place at the volume weighted average price (VWAP) on day *t*. *Add Confounding Events* includes firm-days with earnings news or guidance on day *t* or *t*-1. *Fama-MacBeth* reports the average estimates from daily cross-sectional regression. For this test, standard errors are calculated using a Newey-West adjustment, where the lag length is equal to the return horizon. *Add Firm Fixed Effects* adds firm dummies to the baseline specification. *Exclude Top 10 of SA Firms* estimates the baseline specification after removing the 10 firms most heavily covered by Seeking Alpha.

	Coefficient on *Retail OIB × SA (Spec 1-3)*		
	1-day Return	5-day Return	10-day Return
	[1]	[2]	[3]
Baseline Specification	0.050%	0.066%	0.123%
	(4.52)	(2.50)	(3.58)
OIB Trades	0.056%	0.043%	0.091%
	(4.68)	(1.44)	(2.27)
CRSP Midpoint Returns	0.056%	0.071%	0.127%
	(5.75)	(3.19)	(4.12)
VWAP Returns	0.064%	7.800%	0.135%
	(5.10)	(2.89)	(3.90)
Add Confounding Events	0.520%	0.068%	0.127%
	(4.95)	(2.70)	(3.87)
Fama-Macbeth	0.059%	0.054%	0.106%
	(4.42)	(1.65)	(2.40)
Add Firm Fixed Effects	0.051%	0.066%	0.124%
	(4.49)	(2.48)	(3.55)
Exclude Top 10 SA Firms	0.049%	0.068%	0.127%
	(4.42)	(2.71)	(3.80)

Table IA.4. The Informativeness of Retail Trading after Seeking Alpha Research
This table repeats Table 5 without suppressing reporting of the control variables.

	[1]	[2]	[3]	[4]	[5]	[6]
Retail OIB	0.010%	0.039%	0.058%	0.010%	0.039%	0.058%
	(4.97)	(7.34)	(6.22)	(4.98)	(7.34)	(6.22)
Retail OIB × SA	0.050%	0.066%	0.123%	0.050%	0.062%	0.120%
	(4.52)	(2.50)	(3.58)	(4.34)	(2.35)	(3.45)
Retail OIB × IBES	0.010%	0.011%	-0.003%	0.010%	0.011%	-0.003%
	(1.13)	(0.55)	(-0.12)	(1.12)	(0.55)	(-0.12)
Retail OIB × Media	0.010%	0.016%	0.021%	0.010%	0.016%	0.021%
	(2.79)	(1.98)	(1.75)	(2.79)	(1.98)	(1.75)
Retail OIB × Log (Size)	-0.010%	-0.027%	-0.037%	-0.010%	-0.027%	-0.037%
	(-4.91)	(-5.03)	(-4.47)	(-4.90)	(-5.03)	(-4.47)
Institutional OIB	-0.040%	-0.050%	-0.046%	-0.040%	-0.050%	-0.046%
	(-10.88)	(-6.96)	(-4.01)	(-10.86)	(-6.95)	(-4.00)
Inst OIB × SA	0.040%	0.055%	0.055%	0.040%	0.052%	0.052%
	(3.26)	(2.25)	(1.31)	(3.19)	(2.13)	(1.24)
Inst OIB × IBES	-0.010%	-0.005%	0.003%	-0.010%	-0.005%	0.003%
	(-0.95)	(-0.19)	(0.10)	(-0.94)	(-0.18)	(0.10)
Inst OIB × Media	0.000%	0.016%	0.010%	0.000%	0.016%	0.010%
	(0.61)	(1.37)	(0.66)	(0.61)	(1.37)	(0.66)
Inst OIB × Log (Size)	0.000%	0.001%	0.008%	0.000%	0.001%	0.008%
	(0.25)	(0.09)	(0.92)	(0.26)	(0.10)	(0.93)
Ret (w-1)	-0.020%	-0.091%	-0.121%	-0.020%	-0.091%	-0.122%
	(-4.10)	(-3.68)	(-3.30)	(-4.14)	(-3.70)	(-3.33)
Ret (m-1)	-0.010%	-0.037%	-0.038%	-0.010%	-0.037%	-0.039%
	(-1.70)	(-1.16)	(-0.70)	(-1.71)	(-1.17)	(-0.71)
Ret (m-7, m-2)	0.000%	-0.001%	0.005%	0.000%	-0.001%	0.005%
	(-0.16)	(-0.03)	(0.08)	(-0.18)	(-0.04)	(0.07)
Turnover (m-1)	-0.020%	-0.066%	-0.142%	-0.020%	-0.065%	-0.141%
	(-3.24)	(-2.72)	(-2.97)	(-3.15)	(-2.69)	(-2.96)
Volatility (m-1)	0.010%	0.057%	0.084%	0.010%	0.057%	0.084%
	(1.42)	(1.39)	(1.12)	(1.44)	(1.40)	(1.12)
Log (Size)	0.000%	-0.011%	-0.021%	0.000%	-0.012%	-0.021%
	(-0.71)	(-0.41)	(-0.39)	(-0.75)	(-0.43)	(-0.40)
Log (BM)	0.000%	0.012%	0.025%	0.000%	0.012%	0.026%
	(0.32)	(0.42)	(0.45)	(0.33)	(0.43)	(0.45)
SA	0.020%	0.032%	0.026%	0.010%	0.003%	-0.035%
	(1.86)	(0.98)	(0.47)	(0.49)	(0.10)	(-0.67)
IBES	0.010%	0.033%	0.067%	0.010%	0.034%	0.067%
	(2.10)	(2.86)	(2.86)	(2.12)	(2.87)	(2.88)
Media	-0.020%	-0.037%	-0.019%	-0.020%	-0.036%	-0.018%
	(-2.11)	(-1.09)	(-0.33)	(-2.09)	(-1.08)	(-0.32)
SA × Long Disclosure				0.060%	0.095%	0.045%
				(4.05)	(1.95)	(0.54)
SA × Short Disclosure				-0.210%	-0.383%	-0.168%
				(-3.91)	(-2.46)	(-0.70)
SA × Neg. Tone				-0.030%	-0.075%	-0.074%
				(-1.86)	(-1.76)	(-1.09)
SA × Pos. Tone				0.040%	0.130%	0.216%
				(2.76)	(3.31)	(3.68)
SA × Comment Negative Tone				-0.050%	-0.054%	-0.083%
				(-3.14)	(-1.27)	(-1.04)
SA × Comment Positive Tone				0.040%	0.026%	0.042%
				(2.62)	(0.69)	(0.73)
Fixed Effects	Time	Time	Time	Time	Time	Time

Table IA.5. SA Research and the Informativeness of Retail Order Imbalances: Cross-Sectional Analysis
This table repeats Table 6 without suppressing reporting of the control variables.

	[1]	[2]	[3]	[4]	[5]	[6]
Retail OIB	0.06%	0.06%	0.06%	0.06%	0.06%	0.06%
	(6.21)	(6.22)	(6.22)	(6.22)	(6.21)	(6.22)
Retail OIB × SA	0.04%	0.04%	0.07%	0.03%	-0.15%	0.03%
	(1.21)	(1.18)	(1.95)	(0.62)	(-2.15)	(0.81)
Retail OIB × SA × Comment	0.26%				0.24%	
	(3.17)				(3.01)	
Retail OIB× SA × Contributor Skill		0.18%			0.16%	
		(2.49)			(2.30)	
Retail OIB × SA × Bio Length			0.14%		0.13%	
			(2.14)		(2.00)	
Retail OIB × SA × Net Negative				0.10%	0.09%	
				(2.52)	(2.31)	
Retail OIB× SA × Position				0.06%	-0.01%	
				(0.79)	(-0.11)	
Retail OIB × SA × Informative						0.25%
						(3.42)
Retail OIB × IBES	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	(-0.14)	(-0.13)	(-0.13)	(-0.13)	(-0.18)	(-0.14)
Retail OIB × Media	0.02%	0.02%	0.02%	0.02%	0.02%	0.02%
	(1.76)	(1.74)	(1.75)	(1.75)	(1.75)	(1.75)
Retail OIB × Log (Size)	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%
	(-4.55)	(-4.39)	(-4.48)	(-4.45)	(-4.48)	(-4.45)
Inst OIB	-0.05%	-0.05%	-0.05%	-0.05%	-0.05%	-0.05%
	(-4.01)	(-4.01)	(-4.01)	(-4.00)	(-4.00)	(-4.01)
Inst OIB × SA	0.05%	0.05%	0.05%	0.05%	0.05%	0.05%
	(1.29)	(1.28)	(1.29)	(1.24)	(1.20)	(1.26)
Inst OIB × IBES	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Inst OIB × Media	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(0.66)	(0.67)	(0.66)	(0.67)	(0.67)	(0.67)
Inst OIB × Log (Size)	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(0.93)	(0.92)	(0.92)	(0.93)	(0.94)	(0.93)
Ret (w-1)	-0.12%	-0.12%	-0.12%	-0.12%	-0.12%	-0.12%
	(-3.31)	(-3.30)	(-3.30)	(-3.33)	(-3.33)	(-3.32)
Ret (m-1)	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%
	(-0.70)	(-0.70)	(-0.70)	(-0.71)	(-0.71)	(-0.71)
Ret (m-7, m-2)	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)
Turnover (m-1)	-0.14%	-0.14%	-0.14%	-0.14%	-0.14%	-0.14%
	(-2.97)	(-2.97)	(-2.97)	(-2.96)	(-2.96)	(-2.97)
Volatility (m-1)	0.08%	0.08%	0.08%	0.08%	0.09%	0.08%
	(1.13)	(1.12)	(1.11)	(1.12)	(1.13)	(1.13)
Log (Size)	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
	(-0.36)	(-0.40)	(-0.40)	(-0.40)	(-0.39)	(-0.38)
Log (BM)	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%
	(0.45)	(0.45)	(0.45)	(0.45)	(0.45)	(0.45)
SA	0.10%	0.07%	0.07%	0.02%	0.06%	0.12%
	(1.99)	(1.52)	(2.86)	(0.35)	(0.99)	(2.50)
IBES	0.07%	0.07%	-0.02%	0.07%	0.07%	0.07%
	(2.86)	(2.87)	(-0.34)	(2.88)	(2.88)	(2.87)
Media	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
	(-0.32)	(-0.32)	(-0.32)	(-0.32)	(-0.32)	(-0.31)
SA × Comments	-0.16%				-0.14%	

	(-1.72)				(-1.62)	
SA × Contributor Skill		-0.11%			-0.10%	
		(-1.48)			(-1.45)	
SA × Bio Length			0.14%		0.15%	
			(2.15)		(2.50)	
SA × Net Negative Tone				-0.11%	-0.10%	
				(-2.92)	(-2.83)	
SA × Position				-0.06%	-0.02%	
				(-0.85)	(-0.31)	
SA × Informative						-0.21%
						(-2.41)
Fixed Effects	Time	Time	Time	Time	Time	Time

Table IA.6. Seeking Alpha Research Coverage and Retail Investor Trading - Cross Sectional Analysis

This table presents results from panel regressions where the dependent variable is *Percent Retail Turnover*. The regression includes all the control variables and fixed effects from Specification 4 of Table 3 and adds a conditioning variable that is interacted with the Seeking Alpha indicator variable (*SA* × *CV*). All conditioning variables are equal to zero on days without Seeking Alpha research, so *CV* is omitted from the regression. The conditioning variables include: *Comments*, *Contributor Skill*, *Bio Length*, *Net Negative Tone*, *Position*, and *Informative*. All the conditioning variables are defined as in Table 6. Standard errors are clustered by firm. The sample spans 2007-2017 and consists of 4,372,388 firm-day observations.

	[1]	[2]	[3]	[4]	[5]	[6]
SA	0.29	0.47	0.57	0.42	0.07	0.42
	(13.48)	(18.28)	(17.48)	(12.90)	(1.39)	(18.70)
SA × Comments	0.73				0.66	
	(10.49)				(10.28)	
SA × Contributor Skill		0.33			0.26	
		(8.01)			(6.92)	
SA × Bio Length			0.11		0.05	
			(1.94)		(0.88)	
SA × Net Negative Tone				0.11	0.07	
				(4.05)	(2.76)	
SA × Disclosed Position				0.50	0.30	
				(6.49)	(4.25)	
SA × Informative						0.46
						(8.55)
IBES	0.07	0.07	0.07	0.07	0.07	0.07
	(6.50)	(6.46)	(6.54)	(6.54)	(6.39)	(6.41)
Media	0.05	0.04	0.04	0.04	0.04	0.04
	(3.92)	(3.83)	(3.87)	(3.88)	(3.90)	(3.86)
Log (Size)	-3.94	-3.94	-3.94	-3.94	-3.94	-3.94
	(-20.93)	(-20.87)	(-20.85)	(-20.86)	(-20.94)	(-20.86)
Log (BM)	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13
	(-1.85)	(-1.84)	(-1.84)	(-1.85)	(-1.85)	(-1.85)
Inst Ownership	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
	(-10.90)	(-10.91)	(-10.91)	(-10.91)	(-10.90)	(-10.91)
Log (Breadth of Ownership)	0.29	0.29	0.29	0.29	0.29	0.29
	(2.19)	(2.19)	(2.19)	(2.19)	(2.19)	(2.19)
Log (Vol)	0.46	0.46	0.47	0.46	0.46	0.46
	(6.54)	(6.55)	(6.56)	(6.55)	(6.53)	(6.55)
Log (Turn)	0.23	0.23	0.23	0.23	0.23	0.23
	(2.41)	(2.40)	(2.41)	(2.41)	(2.41)	(2.40)
Return	-0.29	-0.29	-0.29	-0.29	-0.29	-0.29
	(-5.66)	(-5.67)	(-5.67)	(-5.66)	(-5.65)	(-5.65)
Profitability	0.04	0.04	0.04	0.04	0.04	0.04
	(0.53)	(0.53)	(0.53)	(0.53)	(0.53)	(0.54)
Log (IBES Coverage)	0.08	0.08	0.08	0.08	0.08	0.08
	(0.73)	(0.73)	(0.73)	(0.73)	(0.73)	(0.73)
Log (SA Coverage)	0.10	0.11	0.11	0.11	0.10	0.11
	(2.76)	(2.93)	(2.93)	(2.89)	(2.75)	(2.88)
Log (Media Coverage)	0.04	0.04	0.04	0.04	0.04	0.04
	(0.90)	(0.88)	(0.89)	(0.88)	(0.90)	(0.88)

Table IA.7. Seeking Alpha Article Tone and Retail Investor Order Imbalance - Cross Sectional Patterns

This table presents results from panel regressions where the dependent variable is *Retail OIB*. The regression includes all the control variables and fixed effects from Specification 3 of Table 4 and adds conditioning variables (CV) that are interacted with *Aggregate Tone* (*Aggregate Tone* × *CV*) and the Seeking Alpha indicator variable (*SA* × *CV*). Note, all the conditioning variables are equal to zero on days without Seeking Alpha research, and we therefore omit *CV* from the regression. In the interest of brevity, we only report the coefficients on *Aggregate Tone* and Aggregate *Tone* × *CV*. The conditioning variables include: *Comments*, *Contributor Skill*, *Bio Length*, *Position*, and *Informative*. All the conditioning variables are defined as in Table 6. Standard errors are clustered by firm. The sample spans 2007-2017 and consists of 4,372,388 firm-day observations.

	[1]	[2]	[3]	[4]	[5]	[6]
SA	1.05%	0.85%	1.21%	1.08%	0.81%	1.11%
	(9.51)	(8.37)	(12.28)	(12.04)	(6.35)	(11.77)
SA × *Comp Sentiment*	0.56%	0.68%	0.72%	0.51%	0.52%	0.59%
	(5.84)	(9.02)	(10.37)	(7.48)	(4.76)	(7.91)
SA × *Comp Sentiment* × *Comment*	0.20%				0.17%	
	(1.73)				(1.48)	
SA × *Comp Sentiment* × *Contr Skill*		0.01%			-0.01%	
		(0.11)			(-0.12)	
SA × *Comp Sentiment* × *Bio Length*			-0.12%		-0.15%	
			(-1.22)		(-1.47)	
SA × *Comp Sentiment* × *Position*				0.32%	0.30%	
				(3.10)	(2.92)	
SA × *Comp Sentiment* × *Informative*						0.22%
						(2.16)
SA × Comment	0.26%				0.17%	
	(1.69)				(1.12)	
SA × *Contributor Skill*		0.69%			0.68%	
		(5.48)			(5.30)	
SA × *Bio Length*			-0.13%		-0.20%	
			(-0.98)		(-1.55)	
SA × *Position*				0.24%	0.13%	
				(1.52)	(0.85)	
SA × *Informative*						0.29%
						(2.04)
IBES	0.79%	0.79%	0.79%	0.79%	0.79%	0.79%
	(8.77)	(8.77)	(8.77)	(8.77)	(8.78)	(8.77)
IBES × *Positive*	0.30%	0.29%	0.30%	0.30%	0.29%	0.29%
	(1.58)	(1.56)	(1.59)	(1.58)	(1.56)	(1.57)
IBES × *Negative*	-0.43%	-0.43%	-0.42%	-0.43%	-0.43%	-0.43%
	(-2.26)	(-2.28)	(-2.24)	(-2.26)	(-2.30)	(-2.26)
Media	0.30%	0.30%	0.30%	0.30%	0.30%	0.30%
	(4.41)	(4.41)	(4.40)	(4.41)	(4.41)	(4.41)
Media × *Positive*	0.52%	0.51%	0.52%	0.52%	0.51%	0.52%
	(6.74)	(6.73)	(6.75)	(6.75)	(6.73)	(6.74)
Media × *Negative*	-0.38%	-0.38%	-0.38%	-0.38%	-0.38%	-0.38%
	(-5.03)	(-5.04)	(-5.03)	(-5.03)	(-5.04)	(-5.03)
Ret (*w*-1)	-0.68%	-0.68%	-0.68%	-0.68%	-0.68%	-0.68%
	(-20.00)	(-20.02)	(-20.00)	(-19.99)	(-20.00)	(-20.00)
Ret (*m*-1)	-0.46%	-0.46%	-0.46%	-0.46%	-0.46%	-0.46%
	(-14.65)	(-14.66)	(-14.65)	(-14.65)	(-14.65)	(-14.65)

Ret (m-7, m-2)	-0.07%	-0.07%	-0.07%	-0.06%	-0.06%	-0.07%
	(-2.21)	(-2.21)	(-2.22)	(-2.21)	(-2.21)	(-2.21)
Log (Turn)	-0.81%	-0.81%	-0.81%	-0.81%	-0.81%	-0.81%
	(-8.70)	(-8.71)	(-8.70)	(-8.70)	(-8.71)	(-8.70)
Log (Vol)	0.27%	0.27%	0.27%	0.27%	0.27%	0.27%
	(2.64)	(2.63)	(2.64)	(2.64)	(2.62)	(2.64)
Log (Size)	0.55%	0.55%	0.55%	0.55%	0.55%	0.55%
	(3.11)	(3.13)	(3.12)	(3.12)	(3.12)	(3.11)
Log (BM)	-0.63%	-0.63%	-0.63%	-0.63%	-0.63%	-0.63%
	(-7.73)	(-7.73)	(-7.73)	(-7.73)	(-7.74)	(-7.73)
Institutional Oib	-5.00%	-5.00%	-5.00%	-5.00%	-5.00%	-5.00%
	(-17.37)	(-17.37)	(-17.37)	(-17.37)	(-17.37)	(-17.37)
Retail Oib (W-1)	2.93%	2.93%	2.93%	2.93%	2.93%	2.93%
	(61.92)	(61.92)	(61.92)	(61.92)	(61.92)	(61.92)

Table IA.8. SA Research and the Informativeness of Retail Order Imbalances: Decomposition Analysis
This table repeats Table 8 without suppressing reporting of the control variables.

	All SA Articles			Informative SA Articles		
	Persistence	*Contrarian*	*Other*	*Persistence*	*Contrarian*	*Other*
	[1]	[2]	[3]	[4]	[5]	[6]
Retail OIB	0.09%	0.06%	0.05%	0.09%	0.06%	0.05%
	(6.16)	(1.95)	(5.97)	(6.15)	(1.91)	(5.84)
Retail OIB × SA	-0.020%	-0.058%	0.122%	-0.04%	-0.02%	0.27%
	(-0.54)	(-1.48)	(3.69)	(-0.63)	(-0.44)	(4.56)
Retail OIB × IBES	-0.05%	-0.05%	0.00%	-0.05%	-0.05%	0.00%
	(-1.74)	(-1.44)	(0.15)	(-1.75)	(-1.19)	(0.12)
Retail OIB × Media	0.02%	-0.02%	0.02%	0.02%	-0.02%	0.02%
	(0.93)	(-0.72)	(1.61)	(0.91)	(-0.76)	(1.65)
Retail OIB × Log (Size)	-0.03%	0.01%	-0.03%	-0.03%	0.01%	-0.03%
	(-2.31)	(0.54)	(-4.40)	(-2.40)	(0.59)	(-4.38)
Institutional OIB	-0.05%	-0.05%	-0.05%	-0.05%	-0.05%	-0.05%
	(-4.28)	(-4.26)	(-4.01)	(-4.44)	(-4.43)	(-4.19)
Inst OIB × SA	0.04%	0.04%	0.06%	0.13%	0.13%	0.16%
	(0.95)	(0.96)	(1.31)	(1.79)	(1.78)	(2.13)
Inst OIB × IBES	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%
	(0.15)	(0.14)	(0.13)	(0.25)	(0.24)	(0.23)
Inst OIB × Media	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(0.59)	(0.73)	(0.53)	(0.67)	(0.80)	(0.62)
Inst OIB × Log (Size)	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(1.42)	(1.34)	(0.86)	(1.29)	(1.22)	(0.72)
Ret (w-1)	0.03%	0.03%	0.03%	-0.08%	-0.08%	-0.09%
	(0.57)	(0.58)	(0.49)	(-0.94)	(-0.93)	(-1.04)
Ret (m-1)	0.07%	0.07%	0.07%	0.07%	0.07%	0.07%
	(2.94)	(2.96)	(2.86)	(2.98)	(3.00)	(2.91)
Ret (m-7, m-2)	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%	-0.02%
	(-0.34)	(-0.33)	(-0.32)	(-0.30)	(-0.29)	(-0.28)
Turnover (m-1)	-0.13%	-0.11%	-0.12%	-0.13%	-0.11%	-0.13%
	(-3.47)	(-3.18)	(-3.32)	(-3.52)	(-3.19)	(-3.38)
Volatility (m-1)	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%	-0.04%
	(-0.63)	(-0.70)	(-0.70)	(-0.64)	(-0.71)	(-0.71)
Log (Size)	0.01%	0.01%	0.01%	0.01%	0.01%	0.01%
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)
Log (BM)	-0.14%	-0.13%	-0.14%	-0.13%	-0.13%	-0.14%
	(-2.81)	(-2.73)	(-2.97)	(-2.75)	(-2.67)	(-2.91)
SA	0.09%	0.09%	0.08%	0.09%	0.09%	0.09%
	(1.14)	(1.16)	(1.11)	(1.21)	(1.23)	(1.18)
IBES	-0.02%	-0.02%	-0.02%	-0.02%	-0.01%	-0.02%
	(-0.34)	(-0.31)	(-0.38)	(-0.29)	(-0.26)	(-0.33)
Media	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%
	(0.49)	(0.46)	(0.45)	(0.49)	(0.46)	(0.45)
Fixed Effects	Time	Time	Time	Time	Time	Time

Table IA.9. Seeking Alpha and the Informativeness of Retail Trading: Predicting Media Sentiment and Forecast Revisions

The table repeats Table 9 without suppressing reporting of the control variables.

	Media Sentiment		Forecast Revisions	
	All SA Articles	*Informative SA Articles*	*All SA Articles*	*Informative SA Articles*
	[1]	*[2]*	*[3]*	*[4]*
Retail OIB	0.29	0.28	0.00	0.00
	(6.90)	(6.90)	(0.53)	(0.37)
Retail OIB × SA	1.08	1.42	0.07	0.20
	(5.86)	(4.27)	(1.92)	(3.16)
Retail OIB × IBES	0.04	0.04	-0.01	-0.01
	(0.82)	(0.81)	(-0.83)	(-0.70)
Retail OIB × Media	0.19	0.16	-0.01	-0.01
	(1.50)	(1.27)	(-0.59)	(-0.55)
Retail OIB × Log (Size)	0.23	0.22	-0.01	-0.01
	(5.70)	(5.40)	(-1.50)	(-1.34)
Inst OIB	0.04	0.02	0.00	0.00
	(0.83)	(0.42)	(0.19)	(0.08)
Inst OIB × SA	0.37	0.56	0.07	0.08
	(1.98)	(1.80)	(2.09)	(1.53)
Inst OIB × IBES	-0.20	-0.18	-0.01	-0.01
	(-3.88)	(-3.50)	(-0.94)	(-0.81)
Inst OIB × Media	0.09	0.05	-0.04	-0.04
	(0.57)	(0.36)	(-2.39)	(-2.24)
Inst OIB × Log (Size)	0.15	0.12	0.00	0.00
	(3.66)	(3.01)	(0.66)	(0.27)
SA	4.77	7.16	0.02	-0.13
	(13.73)	(15.15)	(0.54)	(-1.97)
IBES	-1.83	-1.85	-0.01	-0.01
	(-13.85)	(-13.89)	(-0.59)	(-0.73)
Media	3.64	3.49	0.04	0.04
	(12.05)	(11.80)	(0.98)	(0.92)
Ret (w-1)	-1.15	-1.12	0.23	0.22
	(-11.44)	(-11.17)	(18.41)	(18.37)
Ret (m-1)	-1.00	-0.98	0.35	0.34
	(-8.50)	(-8.47)	(21.00)	(20.91)
Ret (m-7, m-2)	0.86	0.85	0.44	0.43
	(5.81)	(5.83)	(19.70)	(19.83)
Turnover (m-1)	-2.75	-2.64	-0.09	-0.09
	(-16.96)	(-16.50)	(-3.83)	(-4.03)
Volatility (m-1)	-0.03	-0.13	-0.06	-0.05
	(-0.18)	(-0.86)	(-2.51)	(-2.33)
Log (Size)	6.20	6.00	0.14	0.15
	(15.50)	(14.99)	(2.98)	(3.09)
Log (BM)	0.88	0.87	-0.15	-0.15
	(6.59)	(6.59)	(-8.82)	(-8.95)
Media Sentiment [0]	0.32	0.32	0.00	0.00
	(34.72)	(34.98)	(1.74)	(1.50)
Media Sentiment [-1,-5]	0.11	0.12	0.00	0.00
	(22.61)	(23.88)	(-7.41)	(-6.98)
Media Sentiment [-6,-26]	0.08	0.07	0.00	0.00
	(26.18)	(25.34)	(-6.97)	(-7.01)
Forecast Revision [0]	1.88	1.78	1.06	1.04
	(12.43)	(12.10)	(47.09)	(45.58)
Forecast Revision [-1,-5]	-0.29	-0.26	0.20	0.21

	(-8.99)	(-7.78)	(28.67)	(28.63)
Forecast Revision [-6,-26*]*	-0.09	-0.08	0.10	0.10
	(-5.35)	(-5.10)	(17.73)	(17.61)
Fixed Effects	Time	Time	Time	Time
Observations	3,238,659	3,139,042	1,710,882	1,644,240