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

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Abstract

We study the effects of social media on the informativeness of retail investor trading. Our identification strategy exploits the editorial delay between report submission and publication on Seeking Alpha, a popular crowdsourced investment research platform. We find the ability of retail order imbalances to predict stock returns and cash-flow news increases sharply in the intraday post-publication window relative to the pre-publication window. The findings are robust to controlling for report tone and stronger for reports authored by more capable contributors. The evidence suggests that recent technology-enabled innovations in how individuals share information help retail investors become better informed.

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1. Introduction

Investing has always been social, and a large literature highlights the influence of peers on investment decisions (e.g., Shiller and Pound, 1989; Duflo and Saez, 2002, 2003; Ivković and Weisbenner, 2007; Ouimet and Tate, 2020). In recent years, improvements in technology have greatly expanded the scope for sharing information. Retail investors have embraced finance social media sites as users as well as creators of content, discussing news events, sharing investment research, and debating investment strategies (Grennan and Michaely, 2020). While innovations in social media offer the potential for improved access to investment information, theory suggests that peer interactions may also exacerbate behavioral biases (Han, Hirshleifer, and Walden, 2018).

Empirical evidence on the effects of social media on retail investors is limited. Heimer (2016), Cookson, Engelberg, and Mullins (2020), and Chawla, Da, Xu, and Ye (2017) suggest that social media intensifies behavioral biases and spreads stale news. On the other hand, several recent studies find evidence that certain types of social media can provide investment value (Chen, De, Hu, and Hwang 2014; Jame, Johnston, Markov, and Wolfe, 2016; Bartov, Faurel, and Mohanram, 2018; Crawford, Gray, Johnson, and Price, 2018), yet it is unclear the extent to which social media informs retail traders. In this article, we study a popular investor social media site, Seeking Alpha, to identify when individual investors produce and share investment research, and we examine whether these activities increase the informativeness of their trading.

The Seeking Alpha platform, which curates crowdsourced investment research from non-professional analysts, offers several features that make it a natural setting to examine this question. First of all, Seeking Alpha (SA) provides broader access to in-depth investment analysis than most other social media platforms.[1] Consistent with this view, SA research reports and the comments they engender have been shown to predict future stock returns and earnings surprises (Chen et al., 2014).[2]

Seeking Alpha research reports provide investment analysis rather than break news, and their publication process includes an editorial review to ensure quality.[3] This review-induced publication delay permits us to separate the impact of SA research from earlier news events that may also influence trading. Specifically, we use the intraday window immediately after SA report publication to measure the level of social-network-induced trading, and we use the intraday window prior to publication (but after potential information events that may have influenced the report) to capture the counterfactual level of trading that would have occurred in the absence of the SA report. The review-induced delay injects an element of randomness into the intraday timing of publication, and consistent with our identifying assumption, we find no evidence that media articles, brokerage research, or earnings announcements systematically precede or follow SA research publications over intraday windows.

We begin our analysis by documenting that Seeking Alpha's investor-authored research caters to retail investor information demand. We analyze roughly 180,000 research reports discussing 4,900 stocks and find that after controlling for other firm characteristics, SA coverage is higher among firms with low institutional ownership and greater breadth of ownership, whereas

[1] For example, StockTwits limits the character length of posts, Estimize focuses primarily 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.

[2] In contemporaneous work, Gomez, Heflin, Moon, and Warren (2020) show that Seeking Alpha coverage leads to lower bid-ask spreads around earnings announcements.

[3] 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/

the opposite is true for brokerage research coverage. The research coverage evidence confirms Seeking Alpha's emphasis on providing an investment analysis platform for retail investors.

Our analysis points toward a causal relation between Seeking Alpha research and retail investor trading. We analyze retail trading using ten half-hour intraday event windows around Seeking Alpha report publication using trade and quote data from NYSE TAQ and the method of Boehmer, Jones, Zhang, and Zhang (2020) (BJZZ) to identify retail investor trades. Our regression approach includes individual report fixed effects, which benchmarks the post-publication intraday period to the pre-publication intraday period. The results indicate that retail trading is markedly higher after the publication of Seeking Alpha research. For example, aggregate retail trading in the first half-hour after Seeking Alpha report publication is 7.73% higher than in the half-hour before publication. Moreover, measures of report sentiment that predict future returns, such as report tone and contributors' investment positions (Campbell, DeAngelis, and Moon, 2019; Chen et al. 2014), explain retail investor trade order imbalances in the post-publication period. In contrast, we find no evidence of an increase in retail trading or report-sentiment-driven order flows prior to report publication, which is inconsistent with retail investors reacting to unobserved information events. The evidence suggests that Seeking Alpha has a distinct influence on the intensity and direction of retail trading.

To assess the effect of Seeking Alpha research on the informativeness of retail investor trading, we regress future five-day stock returns on half-hour order imbalances, each interacted with an SA post research publication indicator. The estimates indicate SA research publication leads to more informed retail trading. For example, the increase in future returns predicted by a one standard deviation increase in post-publication retail order imbalances is 0.26 percentage points larger than that predicted by pre-publication retail order imbalances. We do not find any increase in the informativeness of retail order imbalances over the five pre-publication half-hour windows, which suggests that the documented post-publication increase is not the continuation of pre-event trend. We also do not find evidence that the documented post-publication return predictability reverses over the subsequent quarter, alleviating concerns about price pressure. In further support of the view that retail trades reveal fundamental information, retail order imbalances' ability to predict analyst earnings forecast revisions and traditional media sentiment over the subsequent five days strengthens in the five half-hours after SA research is published.

The incremental information revealed by retail trades after Seeking Alpha research is largely orthogonal to the information revealed by SA research report tone, and contributor investment position, consistent with retail investors actively gleaning valuable information rather than passively following opinions expressed by social media contributors. We hypothesize that higher quality research reports will lead to more informed trading, and we explore whether reports that are authored by more accomplished or capable contributors offer more opportunities for extracting valuable information. Consistent with our conjecture, we find that retail order imbalances predict future stock returns and cash flows news more convincingly after reports that receive more comments and those authored by contributors with strong academic backgrounds or a track record of impactful reports.[4]

Kogan, Moskowtiz, Niessner (2020), Mitts (2020), and Dyer and Kim (2020) find that a small percentage of Seeking Alpha research reports, identified ex ante as misleading or "fake", distort market prices. Drawing on these studies, we identify fake reports as those that are posted anonymously or have a low textual authenticity score and investigate whether they affect retail

[4] Our primary analysis emphasizes intraday windows around the publication of SA reports for clean identification. We also conduct a daily analysis that includes reports released outside of market hours and find evidence consistent with SA reports having a larger effect on retail trade informativeness than brokerage research or traditional media articles.

trading differently. We find that fake reports influence retail trading intensity and direction similarly or more than non-fake reports. In addition, retail order imbalances after fake report publication predict one week returns but not five week returns, whereas retail order imbalances after non-fake report publication predict five week returns even more strongly. These results are consistent with a small subset of SA research inducing uninformed retail trading that pushes prices from fundamentals over short horizons.

Our study contributes to the debate about the role of social media in capital markets. Since its arrival in the late 90s, regulators have repeatedly expressed concerns about social media impeding market efficiency and harming retail investors.[5] While a host of recent studies provide evidence that different types of social media contain investment value (Chen et al., 2014; Jame et al., 2016; and Bartov, Faurel, and Mohanram, 2018), there is little evidence to suggest that it leads to more informative retail trading. To the contrary, existing evidence emphasizes that social media can exacerbate behavioral biases harmful to performance (Heimer, 2016; Cookson, Engelberg, and Mullins, 2020; Amann and Schaub, 2020).[6] Our results establish the role of crowdsourced investment research in informing retail investor decision-making, while at the same time validating concerns about misleading research content (Kogan, Moskowtiz, Niessner, 2020; and Mitts, 2020).

Our analysis also advances the literature that studies the informativeness of retail trading. Early studies conclude that individual investors are unsophisticated "noise" trades who tend to suffer from behavioral biases and may push prices away from fundamentals (e.g., Barber and Odean, 2000; Kumar and Lee, 2006; Frazzini and Lamont, 2008; Hvidkjaer, 2008; Barber, Odean,

[5] See, for example, the SEC's 2015 Investor Alert: *Social Media and Investing – Stock Rumors*, from the Office of Investor Education and Advocacy: https://www.sec.gov/oiea/investor-alerts-bulletins/ia_rumors.html

[6] A related set of studies conduct a micro-level analysis of information flows across peers and within a retail trader network to better understand trading behavior (Rantala, 2019; Ozsoylev, Walden, Yavuz, and Bildik 2014; Kaustia and Knüpfer, 2012; and Ahern, 2017). Our focus is complementary in that we study the flow of information from a social finance media site, Seeking Alpha, to retail investors in aggregate.

and Zhu, 2009). In contrast, more recent work finds evidence of informed trading by individuals and speculates that retail investors gain insights from geographic proximity to firms, relations with employees, or insights into consumer preferences (e.g., Kaniel, Liu, Saar, and Titman, 2012; Kelley and Tetlock, 2013, 2017; and Boehmer et al. 2020). Our findings highlight a specific mechanism, technology-enabled improvements in how retail investors produce and share investment research, as a likely channel by which individual investors become better informed.[7]

Another stream of literature examines the use of technology by regulators to level the informational playing field between institutional investors and retail investors.[8] Seeking Alpha is a technology-enabled market innovation whose ostensible purpose is to democratize the flow of investment analysis. Our findings illustrate how technological change enables new business models that can improve retail investors' access to investment research and level the informational playing field among investors.

2. Data and Descriptive Statistics

We discuss the Seeking Alpha sample in Section 2.1 and key variables in Section 2.2. We explore the determinants of Seeking Alpha research coverage in Section 2.3.

2.1 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.[9] The website hosts curated

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[7] Whether this translates to better individual retail investor trading performance is an empirical question which can be addressed only with order-level data (e.g., Barrot, Kaniel and Sraer, 2016).

[8] 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).

[9] Seeking Alpha editor Douglas House commented in 2016 that "Seeking Alpha's raison d'être, 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

investment research from a network of thousands of individual contributors. SA has roughly 40 million monthly visits and 15 million unique visitors.[10] 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.[11] Seeking Alpha research reports aim to provide analysis rather than break news, and each report is subject to an editorial review process that may involve multiple revisions. Chen, et al. (2014) find that Seeking Alpha's crowdsourced investment research contains valuable investment information, with reports and user commentaries predicting future stock returns and earnings surprises.

We obtain all research reports published between 2006 and 2017 on the Seeking Alpha website.[12] For each report, we collect the following information: a report ID assigned by Seeking Alpha, report title, main text, date of publication, author name, and the ticker (or tickers) assigned to each report. Following Chen et al. (2014), we limit the sample to reports 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 and TAQ. Our final sample includes 183,969 single-ticker SA research reports covering 4,910 firms.

Table 1 describes the increase in the breadth and depth of Seeking Alpha coverage over time. In 2006, there were 724 companies covered on SA, with 228 research contributors, and 2,590 research reports. In 2017, coverage rose to 2,305 companies, with 2,091 contributors, and 21,402 reports.[13] In an average year in the sample, 1,508 unique contributors publish 16,489 reports on

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[10] https://seekingalpha.com/page/who_reads_sa

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

[12] Seeking Alpha began posting reports in 2004, however the sample of reports prior to 2006 is negligible. For example, in 2005 SA covered less than 5% of all common stocks in CRSP.

[13] The fraction of firms with Seeking alpha coverage in the CRSP-Compustat-TAQ merged sample is 15.2% in 2006, rises to 72.2% in 2015, and is 64.6% in 2017.

1,962 different companies. Conditional on having Seeking Alpha coverage, the average firm has roughly 8.0 reports per year, written by 4.6 different contributors. Our analysis emphasizes the roughly one-third of research reports that are published during trading hours. On average, 5,533 reports are published each year between 10:30 am and 3:30 pm, and of these, 4,067 have no confounding information events (media articles, sell-side research, or earnings announcements released within the ten half-hour intervals around SA report publication).

2.2 Measuring Retail Investor Trading and Other Key Variables

Our approach for identifying retail trading relies on the methodology of Boehmer, Jones, Zhang, and Zhang (2020) (BJZZ).[14] Their approach 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

[14] 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 IA2 we present results by month over the sample period.

nonmarketable limit orders and retail traders that take place on registered exchanges, it "probably picks up a majority of overall retail trading activity" (BJZZ page 8).[15]

For each firm, we collect data on share price, shares outstanding, stock returns, and volume 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 and sell-side analyst recommendations from the IBES detail recommendation file. We obtain data on traditional media coverage, measured using Dow Jones News Service articles from RavenPack, for the period from 2006 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 IA1 in the Internet Appendix provides summary statistics on the characteristics of stocks covered in Seeking Alpha reports. We consider the following attributes: market capitalization (*Size*), book to market (*BM*), daily return volatility (*Volatility*), daily share turnover *(Turnover)*, past one-year return ($Return_{m\text{-}12,m\text{-}1}$), past one-year profitability (*Profitability*), the number of sell-side analysts covering the firm in the prior year (*IBES Coverage*), the number of unique media articles mentioning the firm the prior year (*Media Coverage*), the percentage of the firm's shares held by institutional investors in the prior year (*Institutional Ownership*), and the

[15] 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.

number of common shareholders in the prior year (*Breadth of Ownership*). See Appendix A for more detailed definitions. As a benchmark, we also report the average values for the value-weighted and equal-weighted market portfolios (*VW Market* and *EW Market*, respectively). We find that the average size of a firm covered by an SA report is roughly $61 billion, which is smaller than the corresponding size of the value-weighted average ($89 billion), but considerably larger than the equal-weighted market average ($4.6 billion). Relative to the *VW Market,* we also find that SA coverage tilts towards more volatile firms, more liquid firms, firms with stronger past returns, and firms with lower institutional ownership. However, the *VW Market* attribute almost always falls within the interquartile range of the SA attribute, suggesting that SA coverage is not dramatically different from the market portfolio. In the next section, we more carefully analyze the determinants of Seeking Alpha research coverage.

2.3 Determinants of Seeking Alpha Research Coverage

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, Call, Clement, and Sharp (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:

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

where *Coverage* is the natural log of 1 plus the total number of unique Seeking Alpha contributors writing at least one report for stock *i* during the calendar year *t* (*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*, 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 we 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 25% decline (6% 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.

3. Identification Strategy

The biggest obstacle to evaluating the impact of Seeking Alpha research on retail investor trading is estimating the counterfactual level of trading that would have occurred in the absence of a Seeking Alpha research report. SA research may be driven by an underlying information event, making it difficult to separate the effect of the event itself (news) from the subsequent analysis of the event (SA research). Our identification strategy exploits the time delay between potential unobserved information events and the publication of Seeking Alpha research reports.

The Seeking Alpha platform is designed to provide investment analysis rather than break news, and it naturally takes time for an SA contributor to read, process, and write reports based on any underlying news events. Moreover, the editorial review process also introduces a lag between the creation of a report and when it is later published on Seeking Alpha. Discussions with SA representatives indicate that the report review process typically requires 24 hours between the initial submission and posting of a report on the Seeking Alpha platform, with turnaround times of less than three hours being extremely rare.

The publication delay implies that the period immediately prior to the publication release, during the report review process and after potentially unobserved information events, provides an opportunity to measure the counterfactual level of retail trading that would have occurred in the absence of the Seeking Alpha research report. Put another way, if SA research contributors and retail investors are reacting to earlier information events, we would expect the relation between SA research and retail trading estimated shortly before publication to be as strong as when it is estimated shortly after publication. On the other hand, if retail investors react to SA contributors' analysis of earlier events, we should observe a sharp change in retail investor behavior in the post-publication period relative to the pre-publication period.[16]

We analyze ten half-hour intervals around the publication of Seeking Alpha research, separated into 2.5-hour pre- and post-event periods. The pre-event window consists of the five half-hour intervals [-5, -1], with the post-event covering half-hours [1, 5]. We also consider shorter [-1] and [1] pre- and post-event periods, which offers stronger identification by focusing immediately around the event but provides reduced statistical power and misses any effects that occur beyond the first half-hour after publication. Many Seeking Alpha users subscribe to alerts on the stocks they follow and therefore receive real-time notifications via text or email when reports are published. This feature of the platform makes it plausible to expect swift reactions to new research reports.

A simple comparison of post-event trading to pre-event trading is potentially confounded by intraday seasonality, and we address this by including time-of-day fixed effects. We measure

[16] Seeking Alpha's research compensation arrangements reward exclusivity, yet it is possible that some contributors publish reports on their own personal blogs first, which could reduce the power of our tests. We explore this possibility in greater detail in Section IA.4 of the Internet Appendix, and we find no evidence to suggest that this practice is prevalent or consequential.

the intraday windows in calendar time to facilitate the inclusion of half-hour fixed effects,[17] and the fixed effects are allowed to vary each month in the sample to control for intraday seasonality that may vary over time. Event window 0 trades are excluded from our main tests but examined it in Figures 1-3, where we plot each half-hour of the [-5, 5] window.

Trading outside regular market hours tends to be sparse, and trading during the first half-hour is often disproportionally driven by events occurring before the market opens. To ensure that we can reliably measure and compare pre- and post-event retail trading, we therefore analyze retail trades occurring between 10 am and 4 pm, and we require that reports be published between 10:30 am and 3:30 pm.[18] We note that for reports published before 12:30 pm (after 1:30 pm), the full pre- (post-) publication period will be less than 2.5 hours. This sample, which we refer to as *All Intraday* reports, contains 61,282 reports.

An important identifying assumption is that other confounding events that influence retail trading are just as likely to occur during the pre-publication window as in the post-publication window. This assumption could in principle be violated if Seeking Alpha's editorial team systematically seeks to release reports immediately before or after the arrival of important information events. While this seems unlikely, we empirically address this possibility by examining the distribution of earnings announcements, analyst reports, and media articles in the Seeking Alpha pre- and post-publication windows using a linear probability model (more details available in Section IA.2 of the Internet Appendix and tabulated in Table IA2). We find no evidence of a significant relation between the intraday timing of SA research reports relative to earnings announcements, sell-side research reports, and media articles, which helps build

[17] For example, a report published at 2:15 pm has periods -1, 0, and 1 which cover [1:30-2:00), [2:00-2:30), and [2:30-3:00 pm).
[18] In robustness tests, we repeat the analysis after including reports published outside of market hours. The results are qualitatively similar (Section IA.6 and Table IA6 of the Internet Appendix).

confidence that any changes in retail trading immediately after SA research can be attributed to Seeking Alpha rather than the arrival of other information.

Even if the timing of Seeking Alpha reports is random, in some cases the [-5, 5] intraday publication window may nevertheless coincide with other major information events, which can add considerable noise to our analysis. Thus, in some specifications we also exclude SA research reports that have a confounding information event, defined as a media article, sell-side research report, or earnings announcement over the [-5, 5] window. The resulting *No Event* sample includes 45,038 SA research reports.[19] Figure IA1 in the Internet Appendix confirms that the distribution of *All Intraday* reports and the subset of *No Event* reports is relatively uniform between 10:30 am and 3:30 pm. For example, in the full sample, the median number of reports in a 30-minute window is 5,986, with a maximum of 7,016 (11:30-11:59) and a minimum of 5,451 (12:30-12:59).

4. The Impact of Seeking Alpha Research on the Intensity and Direction of Retail 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 after the publication of SA research, Section 4.2 explores whether the direction of retail trading is consistent with SA research sentiment, and Section 4.3 explores the potential effects of stale reports.

4.1 Seeking Alpha Research and Retail Trading

We explore the effects of SA research on retail investor trading intensity using the following regression:

$$\begin{aligned} Retail\,Trd_{i,t} &= \alpha + \beta_1 Post\_SA_{i,t} + Controls_{i,t} + Report_i \\ &+ HalfHour_t \times Month + \varepsilon_{i,t.} \end{aligned} \tag{2}$$

[19] Another potentially important confounding event is that some SA contributors may choose to post their research reports on their personal blogs prior to release on Seeking Alpha. We explore this possibility in greater detail in Section 4.3.

Retail_Trd is either *Retail Volume*, defined as log (1 + Retail Volume) in half-hour window *t* around the publication of report for firm *i* or *Percent Retail Trading*, defined as total retail trading volume in half-hour window *t* for firm *i* scaled by total trading volume for firm *i* in the same window. Our primary variable of interest is *Post_SA*, which is an indicator equal to one if the trading is measured after the release of the report and zero if trading is measured prior to the release of the report. The sample is limited to the [-5, 5] event window around the report release, excluding event period 0. Thus, *Post_SA* equals one over the [1, 5] window and zero over the [-1, -5] window. *Controls* includes the return and the absolute return over the previous half-hour ($Ret_{i,t-1}$, $AbsRet_{i,t-1}$) and the previous two to five half-hours ($Ret_{i,[t-5,t-2]}$, $AbsRet_{i,[t-5,t-2]}$). We include absolute returns as a proxy for any incrementally important new information that may capture retail investor attention, and we include signed returns to control for the possibility that retail investors may react differentially to good versus bad news. *Report* denotes fixed effects for each SA report. We also include half-hour fixed effects, and the loadings on the fixed effects are allowed to vary each month in the sample (i.e., *Half Hour* × *Month* fixed effects), which controls for intraday seasonality that may vary over time.[20] Standard errors are clustered by date.[21]

Specification (1) of Table 3 reports results for the full sample when the event window is [-5,5] and the dependent variable is the natural logarithm of retail volume. The coefficient on the post-publication dummy is statistically significant at 6.00%, implying a 6.18% ($e^{0.06}$-1) increase in retail volume in the post-publication five half hours relative to the pre-publication five half hours. Specification (2) limits the sample to the 45,038 reports that do not coincide with earnings

[20] For example, *Percent Retail* is much smaller in the last 30 minutes of the trading day, particularly in more recent periods, which is likely attributable to the growth in passive investment vehicles that typically rebalance at the end of the trading day.

[21] The serial correlation in firm residuals is close to zero ($\rho = 0.007$), which obviates the need for clustering by firm. In untabulated analysis, we confirm that clustering by both firm and date leads to similar standard errors.

announcements, media coverage, or sell-side reports over the [-5, 5] window. We find that the coefficient on *Post_SA* increases to 8.88%. In Specification (3), we further limit the sample to observations in the [-1, 1] window and continue to find a large increase in retail volume.

The results from Section 2.3 suggest that the Seeking Alpha platform caters more towards retail investors than institutional investors. We examine retail investors' relative intensity of trading after SA research by setting *Retail_Trd* to *Percent Retail*. The *Post_SA* research coefficients are significant in each specification. For example, Specification (4) indicates that the percentage of retail trading increases by 0.17 percentage points (relative to a mean value of 7.75%) following SA reports, consistent with retail investors reacting to SA research more than institutional investors.

We next examine individual half-hour windows before and after the publication time by re-estimating Specification (2) after including retail trades in the half-hour of publication and replacing *Post_SA* with ten separate indicator variables for each half-hour period ranging from -4 to 5, with period -5 being the omitted group. Figure 1 reports the results. We observe that the estimated coefficients in the pre period [-4, -1] are economically small (less than 2.65% in absolute value) and statistically insignificant. This is inconsistent with pre-trends explaining the increase in retail trading following the release of the report. In contrast, each of the post-event windows estimates are large (ranging from 8.56% to 10.14%) and all are highly statistically significant. We also observe a large increase in retail trading in period 0, the half-hour period that contains the publication, consistent with retail investors responding very quickly to SA research.

4.2 Seeking Alpha Research Sentiment and Retail Order Imbalances

In this section, we examine whether investment research published on the Seeking Alpha platform influences the direction of retail trading by studying the relation between SA report sentiment and retail order imbalances. We classify SA research as having positive (negative) tone when the fraction of positive (negative) words in the SA report is above the sample median, using the word list of Loughran and McDonald (2011) as in Chen et al., (2014). We also measure sentiment using the SA contributor's disclosed investment position. 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). We also consider a composite sentiment measure, constructed by aggregating the four indicator variables, (*Long* + *Pos. Tone*) – (*Short* + *Neg. Tone*).

We then estimate the following panel regression:

$$\begin{aligned} Retail\_OIB_{i,t} = {} & \alpha + \beta_1 Post\_SA \times SA\_Sentiment_{i,t} + \beta_2 Post\_SA_{i,t} \\ & + Controls_{i,t} + Report_i + HalfHour_t \times Month + \varepsilon_{i,t.} \end{aligned} \tag{3}$$

$Retail\_OIB_{i,t}$ is the retail order imbalance for firm *i* during half-hour *t*, defined as the difference between retail buy volume and retail sell volume, scaled by total retail trading volume (BJZZ). *Post_SA* is defined as in Equation (2) and *Post_SA* × *SA_Sentiment* interacts the event-time indicators with the sentiment measures. The remaining controls and fixed effects are as in Equation (2).

Specification (1) of Table 4 indicates that retail order imbalances are significantly related to three of the four tone measures in the predicted direction. For example, retail order imbalances decrease by -1.04 percentage points (pp) when a contributor discloses a short position (the coefficient on *Long* is positive but insignificant). Similarly, order imbalances change by 0.66pp (-1.32pp) when the fraction of positive (negative) words in the report exceeds the sample median. Specification (2) shows that a one-unit increase in *Composite Sentiment* is associated with a 0.79pp increase in *Retail_OIB.* Specifications (3) and (4) report very similar estimates for *Composite Sentiment* after excluding reports with confounding events and when shrinking the event window to [-1, 1].

Figure 2 reports the estimates from Specification (2) after replacing $Post\_SA \times SA\_Sentiment$ with $SA\_Sentiment$ interacted with ten separate indicator variables for each half-hour period ranging from -4 to 5, with period -5 being the omitted group. All of the pre-event estimates are statistically insignificant. Similar to Figure 1, we see a sharp significant increase in period 0, the calendar half-hour that contains the publication time. The increase remains stable through period 3 and significantly declines in periods 4 and 5. The evidence suggests that retail investors react quickly to the investment analysis provided by SA contributors.

4.3 Stale Seeking Alpha Research Reports

The results in Tables 3 and 4 suggest that SA research reports induce significant amounts of retail trading that is directionally consistent with the sentiment of the report. One potentially important attenuating factor is that some contributors may post their research reports on other websites before posting on Seeking Alpha. In this case, attentive investors may be able to trade on these SA reports before they are posted to Seeking Alpha, and our approach would therefore underestimate the effects of SA research on retail trading.

To explore the potential impact of "stale" reports, for all contributors who have authored at least ten reports, we visit the contributor's author page to identify whether they provide a link to a website (more details are available in Section IA.4 in the Internet Appendix). We find that roughly 41% of contributors provide a link to a website. For the sample of contributors with webpages, we manually search the webpage to examine whether any of their SA research is available on their website. We find that only 8% of authors with websites post *any* of their research on their site.[22] Since we generally cannot determine the timing of the publication on personal

[22] The reluctance of SA contributors to post research on their personal website may stem from SA's condition that authors will be compensated for articles that are exclusive to Seeking Alpha: https://seekingalpha.com/page/premium-partnership-faq.

websites, we classify an author's SA reports as stale if we are able to find any SA reports on their linked webpage. Using these criteria, only 5.2% of *No Event* reports are classified as stale (1,847 reports by 63 contributors).

In Table IA3 in the Internet Appendix, we repeat Specification (2) of Table 3 and Specification (3) of Table 4 for stale and non-stale reports. The evidence is consistent with pre-posting attenuating our results, with the increase in *Retail* Volume following SA reports being roughly 30% larger for non-stale reports (6.58% versus 5.12%). Similarly, retail order imbalances are roughly 40% more correlated with report sentiment for non-stale reports (0.97pp versus 0.68pp). The evidence is consistent with stale Seeking Alpha reports inducing weaker retail trading responses. However, stale reports are rare, and therefore their inclusion does not meaningfully impact the overall findings.

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

There are at least two reasons to believe that SA may help retail investors trade in a more informed way. First, retail investors tend to trade in the direction of report and comment tone, and these variables have been shown to forecast stock returns (Chen et al., 2014). Second, retail investors may be skilled in gleaning additional valuable information from SA reports. This finding would be broadly consistent with growing evidence suggestive of retail investor skill (e.g. Kaniel, Saar, and Titman, 2008; Kaniel et al. 2012; Kelley and Tetlock, 2013, 2017; and BJZZ, 2020). On the other hand, SA reports could reinforce well-known biases of retail investors and potentially exacerbate mispricing (e.g., Heimer, 2016; Cookson, Engelberg, and Mullins, 2020; and Chawla et al., 2017).

5.1 Seeking Alpha Research, Retail Investor Trading, and Future Stock Returns

Our primary measure of retail trade informativeness is based on the association between retail order imbalances and future stock returns. We focus on one-week ahead returns, as in BJZZ, but also consider longer-horizon returns. As in previous sections, we compare retail informativeness in the post-event window to the informativeness in the pre-event window. Specifically, we estimate the following intraday panel regression.

$$Ret_{i,[t,t+5d]} = \beta_1 Retail\_OIB_{i,t} + \beta_2 Post\_SA_{i,t} \times Retail\_OIB_{i,t} + \beta_3 Inst\_OIB_{i,t} + \beta_4 Post\_SA_{i,t} \times Inst\_OIB_{i,t} + Controls_{i,t} + HalfHour_t \times Month + \varepsilon_{i,t.} \quad (4)$$

where $Ret_{i,[t,t+5d]}$ is the market-adjusted return, based on the bid-ask average price at the end of half-hour *t* until the close of trading after five full trading days.[23] *Retail_OIB* is defined as in Equation (3); to facilitate interpretation, we standardize it to have mean zero and unit variance. *Post_SA* × *Retail_OIB* interacts *Retail_OIB* with the *Post_SA* indicator. Institutional order imbalance (i.e., non-retail order imbalance) variables are defined analogously. *Controls* include all the controls from Equation (2), as well as indicators of extreme volume over the previous period ($High\ Vol_{i,t-1}$, $Low\ Vol_{i,t-1}$) and the previous two to five periods ($High\ Vol_{i,[t-5,t-2]}$, $Low\ Vol_{i,[t-5,t-2]}$), to control for the ability of abnormal volume to predict future returns (Gervais, Kaniel, and Mingelgrin, 2001; Mingelgrin, 2000). *Half Hour* × *Month* are defined as in Equation (2). Standard errors are clustered by month. We no longer include *Report* fixed effects since the dependent variable (5-day ahead returns) exhibits very little variation for a given report.

Table 5 reports the results. In Specification 1, we find that *Retail_OIB* is negative and insignificant, suggesting that retail trading in the pre-event window is uninformed.[24] In contrast,

[23] Thus, the returns reflect five-day returns plus the initial intraday return. Excluding the latter, i.e., assuming all trades occur at the closing price at the end of the publication day yields similar results.

[24] This finding raises the questions of whether retail trading is (i) only informative following SA reports and (ii) significantly less informative in the period immediately prior to the SA report. When we expand the sample to include retail trading on all firm-days (4.2 million firm-days) rather than just on days with SA research (61,282 firm-days),

we find the coefficient on *Retail_OIB* × *Post_SA* is positive and statistically significant. These point estimates suggest that a one-standard deviation increase in retail order imbalance is associated with a 0.054 percentage point decline in 5-day ahead returns prior to report release, but a 0.159pp increase (-0.054 + 0.213) after the report release (we confirm that the 0.159pp estimate is significantly greater than zero with t = 3.41). The coefficient on *Inst_OIB* × *Post_SA*, while positive, is smaller and statistically insignificant in each specification.[25] We find similar patterns in Specifications (2) and (3), where we exclude reports that coincide with confounding information events and limit the event window to [-1, 1].

Figure 3 plots the estimates from Specification (2) of Equation (4) after dropping *Retail_OIB* and *Post_SA* × $Retail\_OIB_{it}$ and adding *Retail_OIB* interacted with 11 separate SA indicator variables for each half-hour period ranging from -5 to +5.[26] We observe that four of the five the pre-event estimates are negative. In contrast, all the estimates over the [1, 5] window are positive, with the estimates for period 0 (the half-hour period of publication) and period 1 reliably greater than zero. The stark difference in trading between pre- and post-publication periods suggests that the informed trading in the half hour of publication is likely a reflection of retail investors quickly responding to SA research.

We also consider the relation between *Retail_OIB* and stock returns over longer horizons. Specifically, we estimate Equation (4) for weekly returns ranging from one-week ahead (the baseline analysis) through five-weeks ahead. We also report the cumulative returns for a five-week

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we find that (i) retail trading is informative in general (Table 10) and (ii) it is not significantly less informative in the days prior to the SA report (Table IA11).

[25] In the Internet Appendix, we find a weaker relationship between SA research and institutional trading intensity (Table IA4) and direction of trading (Table IA5). The difference in strength of findings is consistent with retail investors paying greater attention to Seeking Alpha, perhaps because institutional investors emphasize more exclusive information sources including private social networks (Crawford et al., 2018), private meetings with executives (Solomon and Soltes, 2015; Bradley, Jame, and Williams, 2020) or alternative data sets (Katona, Painter, Patatoukas, and Zheng, 2019).

[26] In order to estimate a period 0 effect, we also drop *Institutional_OIB* × *Post_SA* which is undefined for period 0.

holding period and a 12-week holding period. The results, based on Specification (2) of Table 5, are presented in Table 6. The individual estimates for weeks 2 through 5 are all statistically insignificant. Similarly, the cumulative estimates for week 5 (0.291pp) and week 12 (0.224pp) are very similar to the week 1 estimate (0.256pp). The absence of a notable drift suggests that retail investors are trading primarily based on information that is impounded into prices within one week of the report publication, and the lack of a significant reversal is inconsistent with retail trading reflecting uninformed price pressure (additional price pressure tests in Section 5.3 and Section IA.10.4 in the Internet Appendix reinforce this finding).

5.2 Seeking Alpha Research, Retail Investor Trading, and Future Stock Returns – Sensitivity Tests

In this section, we examine the sensitivity of our baseline estimate of the effect of SA research (Specification 2 in Table 5) to alternative implementation choices. The results are discussed in greater detail in Section IA.6 and Table IA6 of the Internet Appendix. We first explore the implication of stale reports. In Section 4.3, we report that stale research reports induce lower trading responses, which raises concerns about the measurement of counterfactual informed retail trading in the pre-SA publication period. We find that excluding stale reports increases our baseline estimate slightly from 0.256pp to 0.259pp.[27]

We also more carefully address earnings dates. Although our analysis excludes days with earnings announcements during the event windows, it is possible that the confounding effect of earnings news on the informativeness of retail trading may extend beyond day 0. We therefore

[27] Conducting the informativeness test solely on stale reports yields an estimate of -0.049pp (*t*=-0.17), consistent with information leakage diminishing the effect of SA research publication on retail trade informativeness (untabulated for brevity).

further exclude reports published on days +1 and -1. The resulting estimates are 0.265pp and 0.235pp, respectively, and both are highly significant.[28]

We next expand the sample of intraday research reports (those published between 10:30 am and 3:30 pm) to include all reports. For all reports issued after hours, the pre-period is the five half-hour periods at the end of the previous trading day (i.e., from 1:30 to 4:00 pm) and the post-period is the five-half hour at the beginning of the next trading day (i.e., from 9:30 am to 12:00 pm). The estimate of the effect of SA research on retail trade informativeness is lower (0.175pp), but still statistically significant (*t*-stat of 2.71).

Finally, we estimate and plot informativeness estimates by month in Figure IA2. We observe a sharp increase in the effect of SA research on retail trade informativeness from July 2008 to December 2008, followed by a subsequent steady increase. Our results are robust to excluding the financial crisis period from July to December 2008 (the coefficient is 0.230pp). We also split the sample into three equal calendar periods and find the estimates are statistically significant at the 10% level or higher for each period.

5.3 Seeking Alpha Research, Retail Investor Trading, and Future Cash Flows News

The evidence that retail order imbalances are more strongly correlated with future returns in the period immediately after Seeking Alpha research reports is consistent with retail trading becoming more informed. However, the findings are also consistent with alternative explanations. For example, SA reports could amplify noise trading among retail investors, generating price pressure that results in short-term return predictability. Liquidity provision could also play a role. Table 4 documents that retail investor order imbalances are contrarian over short horizons (e.g.,

[28]We also separately examine trade informativeness for reports issued immediately following or prior to an earnings announcement. We find that our results are similar for reports issued after earnings, and stronger for reports issued prior to the earnings (see Section IA.7 of the Internet Appendix for additional details).

the coefficients on $Ret_{i,[t-1]}$ and $Ret_{i,[t-5,t-2]}$ are significantly negative), and short-term contrarian trading is a common proxy for liquidity provision (Nagel, 2012; Jame, 2018), which raises the possibility that the positive association between retail order imbalances and future returns is attributable to liquidity provision rather than informed trading.

To distinguish between information-based trading and other explanations, we explore whether retail order imbalances become more strongly correlated with subsequent cash flow news, a prediction that is unique to the informed trading hypothesis. To test this prediction, we estimate the following panel regression:

$$\begin{aligned} CFNews_{i,[t,t+5d]} = \; & \alpha + \beta_1 Retail\_OIB_{i,t} + \beta_2 Post\_SA_{i,t} \times \; Retail\_OIB_{i,t} \\ & + \beta_3 Inst\_OIB_{i,t} + \beta_4 Post\_SA_{i,t} \times \; Inst\_OIB_{i,t} + Controls_{i,t} \\ & + HalfHour_t \times \; Month + \varepsilon_{i,t.} \end{aligned} \tag{5}$$

The dependent variable $CFNews_{i,[t,t+5d]}$ is a proxy for innovations in expected firms' cash flows over days t+1 through t+5, as measured by either the sentiment of media articles or the direction of 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+5], after subtracting 50 from each of them to ensure that summing articles with negative sentiment is meaningful. We define analyst forecast revisions (*Revisions*) as the total number of upward forecast revisions less the total number of downward forecast revisions over the [t+1, t+5] window. We exclude observations where there are no media articles (or forecast revisions) over days t+1 through t+5. 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 lagged *Media Sentiment* and *Revisions* over day [0], days [-5, -1], and days [-26, -6].

Specifications (1)-(3) of Table 7 report the results for *Media Sentiment.* The estimate in Specification (1) indicates that a one-standard deviation increase in retail order imbalances over the pre-event window [-5, -1] is associated with a 1.42 increase in five-day ahead media tone, but this estimate increases to 2.63 (1.42 + 1.21) over the [1, 5] post-event window (roughly 1/10 of the cross-sectional standard deviation of 28). We find similar results after excluding confounding events (Specification (2)); shrinking the event window to [-1, 1] in Specification (3), however, reduces the magnitude by roughly 50% and the estimate is no longer statistically significant.

Specifications (4)-(6) of Table 7 document analogous results for forecast revisions. Using the [-5, 5] event window, we find a positive and significant coefficient (0.20) on *Retail_OIB* × *Post_SA* for the sample of reports without confounding events. The point estimate is similar (0.31) and significant when we shrink the event window to [-1, 1]. Collectively, the evidence is consistent with retail trading being a stronger predictor of cash flows following the release of SA research.[29]

5.4 Exploring the Mechanism underlying SA's Effect on Retail Investor Informativeness

The evidence from the prior sections suggests that Seeking Alpha reports contribute to retail investor trading being more informed. It is possible that the increased informativeness could simply be a consequence of retail investors trading in the direction of report sentiment which has been shown to forecast stock returns (Chen et al., 2014). Alternatively, retail investors may be skilled in gleaning additional valuable information from SA reports. In particular, SA users often subscribe to real-time alerts for stocks that they already follow, which likely provides important

[29] In Figure IA3 in the Internet Appendix, we calculate the cash flow effects for each half-hour interval analogous to Figure 3. Between the two measures of cash flow news, only one of the pre-event half-hour coefficient estimates is statistically significant, whereas 8 of the 10 post-event coefficients are significant.

context for interpreting the analysis in SA research reports. This section offers evidence on the relative importance of these two channels.

5.4.1 Controlling for Report Tone

We begin by exploring whether retail investors' tendency to trade in the direction of report tone and position disclosures (as evidenced in Table 4) significantly contributes to their increased informativeness following SA research. Specifications (1) of Table 8 repeat Specifications (2) of Table 5 after including *Composite Sentiment* (as defined in Table 4) as a control. We find that *Composite Sentiment* predicts future returns (Chen et al., 2014) but leaves the estimates on *Retail_OIB* × *Post_SA* virtually unchanged.[30] Specifications (2) and (3) present analogous results after replacing 5-day ahead returns with 5-day ahead media sentiment and forecast revisions, respectively. Controlling for tone does not meaningfully attenuate the relation between retail order imbalances and future cash flow news. The findings suggest that retail investors' incremental informativeness extends beyond a cursory assessment of report tone.

5.4.2 The Role of Seeking Alpha Research Report Quality

We conjecture that if retail investors are able to glean value relevant information, then higher quality research reports will lead to more informed trading. Our first measure of report quality is based on contributor's academic accomplishments, as (self) reported in her bio. Chaudhuri, Ivković, Pollet, and Trzcinka (2020) find that funds managed by PhDs outperform otherwise similar funds, and Chevalier and Ellison (1999) find that managers with MBAs or degrees from universities with higher average SAT scores outperform other fund managers.

[30] This finding is perhaps surprising given the evidence that retail order imbalances are in the direction of report sentiment (Table 4), and the evidence that report sentiment tends to predict returns. However, while SA sentiment is a significant predictor of returns, the economic relation over our sample period is relatively weak. For example, the inclusion of *Composite Sentiment* only increases the R-squared by 0.07% (from 1.16% to 1.23%).

Accordingly, we define the indicator variable *Academic Quality* equal to one if the contributor bio mentions that the contributor has a PhD, an MBA, or graduated from a school in the top 50 of SAT scores based on the 75th percentile, as reported in the 2015 vintage of stateuniversity.com.

Recent work finds that SA contributor skill is highly persistent (Farrell, Jame, and Qiu, 2020), with contributors that have issued more impactful research, as measured by the price impact of prior reports, being more likely to publish impactful reports in the future. We consider two measures of contributor skill. Our first measure is based on *Signed Returns*, computed as the two-day market-adjusted reaction multiplied by the *sign* of the report, where *sign* =1 for positive reports and *sign* = -1 for negative reports. Our approach to signing reports follows Farrell, Jame, and Qiu (2020), and is based on position disclosure and report tone (more details are available in the Appendix). Signing reports is noisy and excludes roughly 25% reports that are classified as neutral. Therefore, we also consider *Unsigned Returns*, which equals one if the average absolute two-day market-adjusted reaction to a contributor's last five reports exceeds the yearly median and zero otherwise. The correlation between *Signed Returns* and *Unsigned Returns* is low (ρ =0.05), suggesting that both may contain independently useful information.

We expect that higher quality reports will garner more attention and discussion. Our fourth measure our Contributor skill is *Comments*, which is an indicator variable equal to one if the number of comments elicited by the report within 24 hours of the report release exceeds the yearly median. We also compute a composite quality measure (*Composite Quality),* defined as the sum of the four report quality measures.

We augment Equations (4) and (5) by interacting *Retail_OIB* and *Post_SA* × *Retail_OIB* with the different quality measures *(Academic Quality*, *Signed Return*, *Unsigned Return*, *Comments,* or *Composite Quality*). We report results for the composite quality measure in Table 9 and for the individual components in Table IA8. The findings are consistent with retail investors becoming more informed following higher quality reports. In particular, we find that *Post_SA* × *Retail_OIB* × *Composite Quality* is statistically significant and economically large. The negative (insignificant) coefficients on *Post_SA* × *Retail_OIB* are consistent with uninformed trading after reports with a composite quality score of 0 (roughly 23% of reports). However, for each one unit increase in composite quality, retail trade informativeness increases in the post-event window by an additional 0.347pp. Specifications (2) and (3) indicate that retail investors ability to forecast media tone and forecast revisions are also significantly stronger following higher quality reports.[31]

5.5. Seeking Alpha and the Informativeness of Retail Trading – Daily Approach

For identification purposes, our approach thus far has focused exclusively on Seeking Alpha reports that are published within the trading day, which eliminates 2/3 of the sample (61,282 SA reports are published between 10:30 and 3:30 out of 183,969 total SA reports). In this section, we consider an alternative daily empirical approach, which compares the informativeness of retail trading on *days* with SA research to the informativeness of their trading on all other days (hereafter *daily* approach).[32]

Measuring retail order flows over a longer horizon increases the possibility of confounding information events and makes it difficult to cleanly isolate the effects of SA research. Yet the daily approach has several benefits. It allows us to extend the sample to include all SA reports, including overnight reports, and benchmark the influence of SA research relative to media articles, brokerage

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[31] The coefficient on *Post_SA* × *Retail_OIB* × *Quality* using the four individual quality measures are all positive and at least marginally significant (p <0.10) predictors of one-week ahead returns. The individual quality measures are less robust predictors of media (none of the four estimates are significant in isolation) and forecast revisions (two of the four predictors are significant at the 10% level).

[32] In the Internet Appendix, we conduct tests of retail trading intensity and direction that parallel the intra-day tests in Tables 3 and 4, and we find similar results (see Tables IA9 and IA10).

research, and earnings announcements. It also facilitates comparison with Boehmer et al. (2020), who introduce the measure of retail trading and study retail trade informativeness at the daily level.

We examine the informativeness of retail order imbalances at the daily level by estimating the following panel regression:

$$\begin{aligned} Y_{i,[t+1,t+5]} = \ & \alpha + \beta_1 Retail\_OIB_{i,t} + \beta_2 Retail\_OIB_{i,t} \times Event_{i,t} \\ & + \beta_3 Retail\_OIB_{it} \times Log(Size)_{i,y-1} + \beta_4 Inst\_OIB_{i,t} \\ & + \beta_5 Inst\_OIB_{i,t} \times Event_{i,t} + \beta_6 Inst\_OIB_{i,t} \times Log(Size)_{i,t} \\ & + \beta_7 Event_{i,t} + \beta_8 Char_{i,t} + Day_t + \varepsilon_{i,t,} \end{aligned} \tag{6}$$

where $Y_{i,[t+1,t+5]}$ is stock *i*'s return from the close of day *t* to the close of day *t+5 (Stock Returns)*, the sum of the Adjusted Event Sentiment Score (ESS) across all media article over the same period (*Media Article Tone*), or the number of upward forecast revisions less the number of downward forecast revisions over the same period (*Forecast Revisions*). *Retail_OIB* is the daily retail buy volume less daily retail sell volume, scaled by daily 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.

$Event_{i,t}$ is a vector of event indicators: $SA_{i,t}$, $IBES_{i,t}$, $Media_{i,t}$, and $Earnings_{i,t}$. We define $SA_{i,t}$ as one if an SA research report is published between 1:30 pm on day *t*-1 and 4 pm on day t, and zero otherwise, in effect assuming that reports published between 1:30 and 4 pm influence retail trading on the day of publication and the day after. This assumption is motivated by the intraday evidence that retail trading remains elevated for at least five periods after report release (Figure 1).[33] We define all other events (i.e., *IBES*, *Media*, and *Earnings*) analogously.

Char is a vector of firm characteristics taken from BJZZ and includes past returns estimated over the prior week ($Ret_{i,w-1}$), prior month ($Ret_{i,m-1}$), and prior two to seven months ($Ret_{i,[m-7,m-2]}$),

[33] The results are robust to extending the window (e.g., 9:30 am on day *t*-1 through 4 pm on day *t*) or shrinking the window (e.g., 4 pm on day *t*-1 through 4 pm on day *t*).

market capitalization (*Size*), monthly turnover (*Turnover*), volatility of daily returns (*Volatility*), and book-to-market (*BM*). We also add indicators for whether trading volume in the stock was in the top or bottom 10% relative to the stock's trading volume in the previous fifty trading days (*High Volume* and *Low Volume). We further include *Retail_OIB* × *Size* and *Inst_OIB* × *Size* to control for the relation between profitability of retail and institutional trading and firm size (BJZZ). With the exception of returns, *High Volume*, and *Low Volume*, 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.

Specification (1) of Table 10 presents the results. Consistent with BJZZ, we find that retail order imbalance is a strong positive predictor of future returns on non-event days. More importantly, order flow is a considerably stronger predictor of future returns on days with Seeking Alpha research. Specifically, a one standard deviation increases in daily retail order imbalance (roughly 0.40) is associated with a 0.036 percentage point increase in 5-days returns on days without SA research, and a 0.125pp (0.036 +0.089) increase on days with SA research.[34] We find modest evidence that retail investors also trade more profitably after other information events, yet the magnitudes are considerably weaker. For example, the incremental informativeness following media articles (0.022pp) or sell-side research (0.023pp) is roughly one quarter of the estimated effect following SA research. This finding supports the view that Seeking Alpha serves a unique role in broadening access to investment research and helping retail investors make more informed trading decisions.[35]

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[34] Following BJZZ (2020), we also decompose *Retail OIB* 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 results of this decomposition, reported in Table IA12 (Section IA.10.4 provides more details), indicate that the increase in the positive association between retail order imbalances and future returns is entirely attributable to informed trading.

[35] In contemporaneous work, Akbas and Subasi (2019) find evidence that retail investors trade profitably following corporate news events, but they do not benchmark their findings to other information sources such as Seeking Alpha or brokerage research.

Specifications (2) and (3) of Table 10 present analogous tests after replacing returns with *Media Tone* and *Revisions*. As in Table 7, we also add controls for *Media Tone* or *Revisions* over day [0], days [-5, -1], and days [-26, -6]. Consistent with the intraday evidence, we find that the ability of retail order imbalances to forecast *Media Tone* or *Revisions* is significantly larger after the release of SA research reports. Specifications (4)-(6) of Table 10 repeat Specifications (1)-(3) after including *Composite Quality*, as defined in Section 5.4.2, and interacting *Composite Quality* with *Retail_OIB* × *SA*. We continue to find that the incremental informativeness of retail trading following SA research reports is concentrated in higher quality reports. Overall, the evidence from the daily analysis is highly consistent with the intraday tests.

6. Fake Research Reports

Investors' increasing reliance on social media for investment information creates incentives to disseminate inaccurate or misleading analysis for the purpose of price manipulation. Seeking Alpha takes steps to prevent fake research, including mandating that contributors disclose investment positions publicly and requiring that pseudonymous contributors disclose their identity to SA.[36] However, recent evidence suggests that a subset of Seeking Alpha research reports are indeed inauthentic and the market is misled by them, as evidenced by an initial reaction followed by a reversal (Kogan, Moskowtiz, Niessner, 2020; Mitts 2020; Dyer and Kim, 2020). Drawing on these studies, we identify potentially fake reports and examine their effects on retail trading intensity, direction, and informativeness. If many retail investors treat fake research reports as authentic, we expect to observe elevated trading as well order imbalances that are directionally consistent with report tone and predictive of short-term but not long-term returns.

[36] Contributors are also not allowed to write under multiple pseudonyms or change from one pseudonym to another. https://seekingalpha.com/page/policy_anonymous_contributors

We identify potentially fake research in two ways. First, we classify research reports by anonymous contributors as potentially fake (Dyer and Kim, 2020). Specifically, a contributor is anonymous if her SA bio includes none of the following: (i) a complete human name (i.e., first and last name); (ii) a human face; (iii) a tag to a company name; (iv) a link to a LinkedIn account; or (v) a link to a Twitter account.[37] We find that 17% of all reports are authored by anonymous contributors, and we classify the remaining 83% as non-fake.

Second, we classify as potentially fake all reports that exhibit linguistic characteristics indicative of deception, as captured by a low authenticity score (Pennebaker, 2011). As in Kogan, Moskowitz, and Niessner (2020), we rely on the Linguistic Inquiry Word Count textual algorithm (LIWC2015) from Pennebaker et al. (2015), which is designed to detect deception.[38] The evidence in Kogan, Moskowtiz, and Niessner (2020) suggests that the relation between authenticity score and the probability of being inauthentic is non-linear. We therefore classify reports whose scores are in the bottom quintile relative to all other reports published in the same month as potentially fake (low authenticity), and the remaining reports as high authenticity.

We re-estimate our main findings for retail trading volume (Specification 2 of Table 3), retail order imbalances (Specification 3 of Table 4), and retail informativeness (Specification 2 of Table 5) after partitioning the sample into potentially fake and non-fake reports. Table 11 reports the results. In Panel A, we find that anonymous reports induce a significant increase in retail trading, report tone influences the direction of retail trades, and that these effects are similar to the effects of non-anonymous reports. More importantly, the predictive ability of retail trading induced

[37] For examples of contributors with different amounts of attributable information, consider the following: Five pieces of biographic information (https://seekingalpha.com/author/donovan-jones#regular_articles); Two pieces of biographic information (https://seekingalpha.com/author/paul-lebo-cfa#regular_articles); and Zero pieces of information included in the bio: (https://seekingalpha.com/author/bull-s-run#regular_articles).
[38] See http://liwc.wpengine.com/

by anonymous reports is economically and statistically significant when the return window is one week (0.378pp) but inconsequential when the holding period is extended to five weeks (0.021pp) or 12 weeks (-0.056pp). We find similar results in Panel B, where we examine reports with low and high authenticity scores, with one exception. The effect of low authenticity reports on retail trading is more than twice the effect of high authenticity reports. Collectively, the fake report analysis suggests that retail investors do not discriminate between fake and non-fake research, and that retail trading following fake reports pushes prices away from fundamentals. Overall, while SA research reports on average leads to more informed retail trading, the average effect masks the presence of a small number of research reports whose effect is to mislead rather than inform.

7. Conclusion

We examine whether social media enhances the informativeness of retail investor trading. Our empirical strategy exploits the editorial delay between Seeking Alpha report submission and publication to identify the effect of social media on retail trading from the effects of earlier events. We use the intraday window immediately after SA report publication to estimate the level of social-network-induced retail trading and the intraday window prior to publication to estimate the counterfactual level of trading.

We find that the level of retail investor trading increases significantly during the intraday post-publication window relative to the pre-publication window, consistent with Seeking Alpha encouraging retail trading. More importantly, we document a substantial increase in the ability of retail order imbalances to predict both future stocks returns and cash flow news, consistent with SA research informing retail trading. The incremental information revealed by post-research retail trading is largely orthogonal to the information revealed by report tone and contributor investment position, consistent with retail investors actively gleaning valuable information from SA research rather than trading quickly on report sentiment. Post-publication trades are especially informative after reports authored by more capable contributors and those that attract more comments, supporting the view of retail investors as capable of sophisticated information processing. These findings suggest that social media can play a positive role in informing retail investors.

We also present evidence that speaks to potentially negative aspects of social media. A small subset of SA research reports, those authored by anonymous contributors or exhibiting linguistic attributes associated with deception, induce retail trading and order imbalances that predict returns measured over one week but not over longer windows. At a minimum, these findings suggest that anonymous reports and those with certain linguistic features deserve extra scrutiny by investors and SA management.

We acknowledge that the documented effects of Seeking Alpha research on retail traders may not generalize to other social media sites, particularly those organized much differently from Seeking Alpha. For example, it is doubtful that retail trade informativeness would similarly increase following tweets on StockTwits, which limits the character length of posts, or posts on SumZero, which limits access to professional analysts. We leave it to future research to identify features of social media that contribute to more informative retail trading.

Appendix A: Variable Definitions

A.1 Outcome Variables

- *SA Coverage* (Table 2) – the number of Seeking Alpha contributors writing a report for a firm during the calendar year. (Source: Seeking Alpha).
- *Retail Volume* (Table 3) – the natural log of 1 + Retail Share Trading Volume. Retail Trading is estimated using the approach outlined in Boehmer et al. (2020). (Source: TAQ).
- *Percent Retail Trading* (Table 3) – retail share volume scaled by total share volume. (Source: TAQ).
- *Retail_OIB* (Table 4) – retail buy volume less retail sell volume, scaled by total retail trading volume. (Source: TAQ).
- *Ret* (Tables 5-11) – the equally-weighted market adjusted return over the subsequent five trading days.
  - In intraday tests, returns are based on the bid-ask average price at the end of half-hour t until the close of trading after five full trading days.
  - In daily tests, returns are based on the bid-ask average price at the end of the trading day until the close of trading after five full trading days.
- *Media Tone* (Tables 7-10) – the sum of the *Adjusted Event Sentiment Score* across all articles written about the firm on days $t+1$ through $t+5$, where the *Adjusted Event Sentiment Score* is the *Event Sentiment (ESS) Score* of each article, after centering the variable at 0 by subtracting 50 from the ESS score reported by RavenPack. (Source: RavenPack).
- *Forecast Revisions* (Tables 7-10) – The number of upward annual and quarterly forecast revisions less the number of downward annual and quarterly forecast revision for a firm over days t+1 through t+5. (Source: IBES).

A.2 Intraday Control Variables (Tables 3-9 and 11)

- *Post_SA* – an indicator equal to one if the trading is measured after the release of an SA research report and zero if trading is measured prior to the release. For example, in intraday tests where the event-window spans the ten half-hours centered around the release of SA research [-5, 5] , *Post_SA* equals one over the [1, 5] window and zero over the [-1, -5] window. (Source: Seeking Alpha).
- $Ret_{i,t-1}$ – the intraday return over the prior 30 minutes (-1), computed using bid-ask midpoints. (Source: TAQ).
- $Ret_{i,[t-5,t-2]}$ – the intraday return over period (-5) through (-2), where each period is 30 minutes long. Returns are computed using bid-ask midpoints. (Source: TAQ).
- *Abs* $Ret_{i,t-1}$ – the absolute value of $Ret_{i,t-1}$. (Source: TAQ).
- *Abs* $Ret_{i,[t-5,t-2]}$ – the absolute value of $Ret_{i,[t-5,t-2]}$. (Source: TAQ).
- *High* $Volume_{i,t-1}$ – an indicator equal to one if the trading volume for firm i in the prior 30 minutes is larger than any of the trading volumes for the same firm during the same half hour interval over the previous 9 trading days. (Source TAQ).
- *High* $Volume_{i,[t-5,t-2]}$ – an indicator equal to one if the trading volume for firm i over period (-5 through (-2), where each period in 30 minutes long, is larger than any of the trading volumes for the same interval over the previous 9 trading days. (Source TAQ).

- *Low Volume*$_{i,t\text{-}1}$ – an indicator equal to one if the trading volume for firm *i* in the prior 30 minutes is smaller than any of the trading volumes for the same firm during the same half hour interval over the previous 9 trading days. (Source TAQ).
- *Low Volume*$_{i,[t\text{-}5,t\text{-}2]}$ – an indicator equal to one if the trading volume for firm *i* over period (-5 through (-2), where each period in 30 minutes long, is smaller than any of the trading volumes for the same interval over the previous 9 trading days. (Source TAQ).
- *Negative (Positive) Tone* – An indicator equal to one when the average fraction of negative (positive) words in the *SA* report exceeds the sample median. (Source: Seeking Alpha). We identify negative and positive words using Loughran and McDonald's (2011) list.
- *Short (Long)*– An indicator equal to one if the contributor discloses a short (long) investment position in the researched company. (Source: Seeking Alpha).
- *Composite Sentiment* – Calculated as (*Long* + *Pos. Tone*) - (*Short* + *Neg. Tone*). (Source: Seeking Alpha).
- *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).
- *Media Tone*$_{[0]}$ – the sum of the *Adjusted Event Sentiment Score* across all articles written about the firm on day *t*. where the *Adjusted Event Sentiment Score* is the *Event Sentiment (ESS) Score* of each article, after centering the variable at 0 by subtracting 50 from the ESS score reported by RavenPack. (Source: RavenPack).
    - *Media Tone*$_{[-5,\,-1]}$ – the sum of the *Adjusted Event Sentiment Score* across all articles written about the firm on days *t*-1 through *t*-5.
    - *Media Tone*$_{[-26,\,-6]}$ – the sum of the *Adjusted Event Sentiment Score* across all articles written about the firm on days *t*-6 through *t*-26.
- *Forecast Revisions*$_{[0]}$ – The number of upward annual and quarterly forecast revisions less the number of downward annual and quarterly forecast revision for a firm on day *t*.
    - *Forecast Revisions*$_{[-5,\,-1]}$ – The number of upward annual and quarterly forecast revisions less the number of downward annual and quarterly forecast revision for a firm computed over days *t*-1 through *t*-5.
    - *Forecast Revisions*$_{[-26,\,-6]}$ – The number of upward annual and quarterly forecast revisions less the number of downward annual and quarterly forecast revision for a firm computed over days *t*-6 through *t*-26.
- *Academic Quality* – An indicator equal to one if the contributor's self-reported bio mentions that the contributor has any of the following: a) a PhD, b) an MBA, or c) a degree from a school in the top 50 of SAT scores based on the 75th percentile, as reported by the 2015 vintage of stateuniversity.com. (Source: https://www.stateuniversity.com/rank/sat_75pctl_rank.html).
- *Unsigned Returns* – An indicator equal to one when the average market reaction to a contributor's last five reports exceeds the yearly median. Market reaction is measured as two-day absolute market-adjusted return. (Source: Seeking Alpha/CRSP).
- *Signed Returns* – An indicator equal to one if the average signed return to a contributor's last five (non-neutral) reports exceeds the yearly median. Signed returns are based on two-day market-adjusted reactions multiplied by the sign of the article, where sign is 1 (-1) for positive (negative) reports. Reports are signed using a two-step procedure. First, we classify reports

with long (short) position disclosures as positive (negative). For remaining reports, we compute the tone of the report as the percentage of negative words in the report (Loughran and McDonald, 2011). We assign reports in the bottom (top) tercile of percent negative relative to the distribution of report tone on the previous day as positive (negative).

- *Comments* – An indicator equal to one when the number of comments on an SA report exceeds the yearly median. We exclude comments made more than 24 hours following report publication. (Source: Seeking Alpha).
- *Composite Report Quality* – a measure of aggregate informativeness defined as: *Academic Quality + Signed Return + Unsigned Return + Comments.* (Source: Seeking Alpha).
- *Anonymous* – an indicator equal to one if a contributors bio includes *none* of the following: (i) a complete human name (i.e., first and last name); (ii) a human face; (iii) a tag to a company name; (iv) a link to a LinkedIn account; or (v) a link to a Twitter account. (Source: Seeking Alpha).
- *Non - Anonymous* – an indicator equal to one if the contributor is not *Anonymous*. (Source: Seeking Alpha).
- *Low Authenticity* – an indicator equal to one if the report is in the bottom quintile of authenticity relative to all other reports issued in the same month, where authenticity is measures using the Linguistic Inquiry Word Court (LIWC) model from Pennebaker et al. (2015). (Source: http://liwc.wpengine.com).
- *High Authenticity* – an indicator equal to one if the report is not classified as *Low Authenticity*.

A.3 Daily and Annual Control Variables (Tables 2 and 10)

- *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 1^{st} and 99^{th} percentile. (Source: CRSP/Compustat).
- *Volatility* – the standard deviation of daily returns during the calendar year (Source: CRSP).
- *Turnover* – the average daily turnover (i.e., share volume scaled by shares outstanding) during the calendar year.
- *Profitability* – EBITDA scaled by book value of assets. Winsorized at the 1^{st} and 99^{th} percentiles. (Source: Compustat).
- $Return_{i,[m\text{-}12,\, m\text{-}1]}$ – the buy-and-hold gross return over the prior 12 months. (Source: CRSP).
    - $Ret_{i,w\text{-}1}$ – the buy-and-hold gross return over the prior one week.
    - $Ret_{i,m\text{-}1}$ – the buy-and-hold gross return over the prior one month.
    - $Ret_{i,[m\text{-}7,\, m\text{-}2]}$ – the buy-and-hold gross return over the prior two to seven months.
- $High\ Volume_{i,t\text{-}1}$ – an indicator equal to one if the firm's trading volume was in the top 10% relative to the firm's trading volume in the previous fifty days. (Source: CRSP).
- $Low\ Volume_{i,t\text{-}1}$ – an indicator equal to one if the firm's trading volume was in the bottom 10% relative to the firm's trading volume in the previous fifty days. (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 forecast 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).
- *SA* – an indicator equal to one if at least one SA research report was published between 1:30 pm on day *t*-1 and 4 pm on day *t.* (Source: Seeking Alpha).
- *Media* – an indicator equal to one if at least one media article was released between 1:30 pm on day *t*-1 and 4 pm on day *t.* (Source: Ravenpack).
- *IBES* – an indicator variable equal to one if an IBES earnings forecast or IBES investment recommendation was released between 1:30 pm on day *t*-1 and 4 pm on day *t.* (Source: IBES).
- *Earnings* – an indicator variable equal to one if earnings were announced between 1:30 pm on day *t*-1 and 4 pm on day *t.* (Source: IBES).

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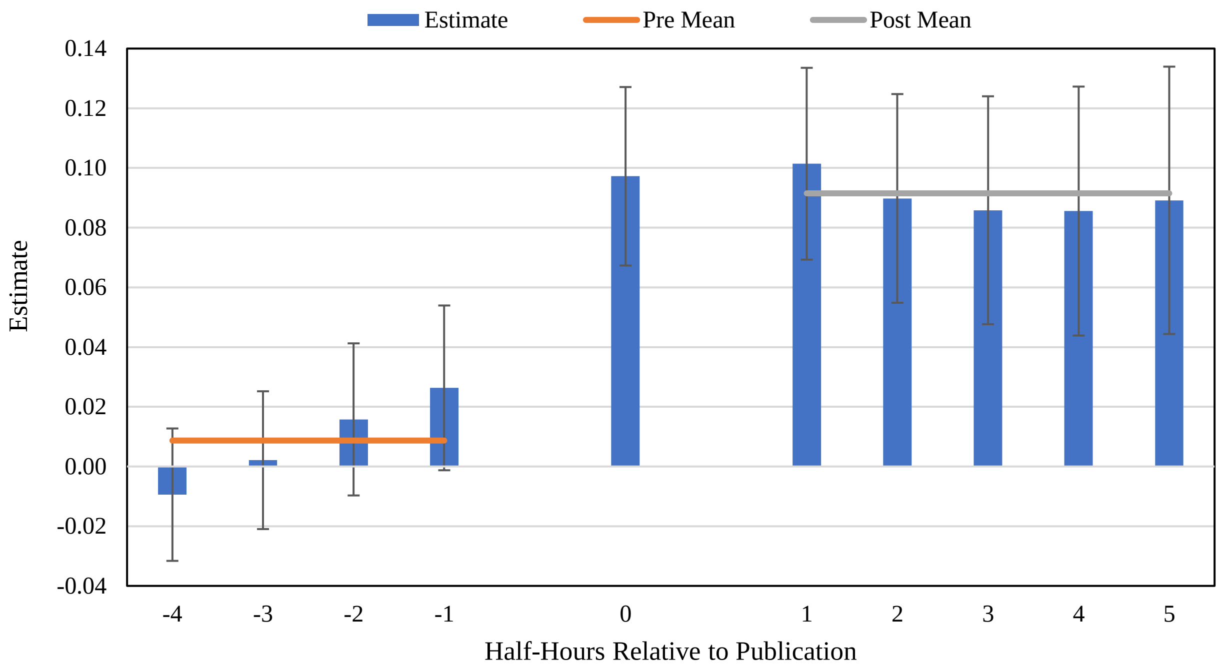

Figure 1. Seeking Alpha Research and the Intensity of Retail Investor Trading: Event Time
This figure plots estimates from Specification (2) of Table 3 after including the half hour publication window and replacing the single post indicator variable with ten indicators marking off event windows [-4] through [5]. The coefficients for each indicator variables are reported as blue bars, and their 95% confidence intervals as error bars. The average of the pre-event and post-event coefficient estimates appear as orange and grey horizontal lines.

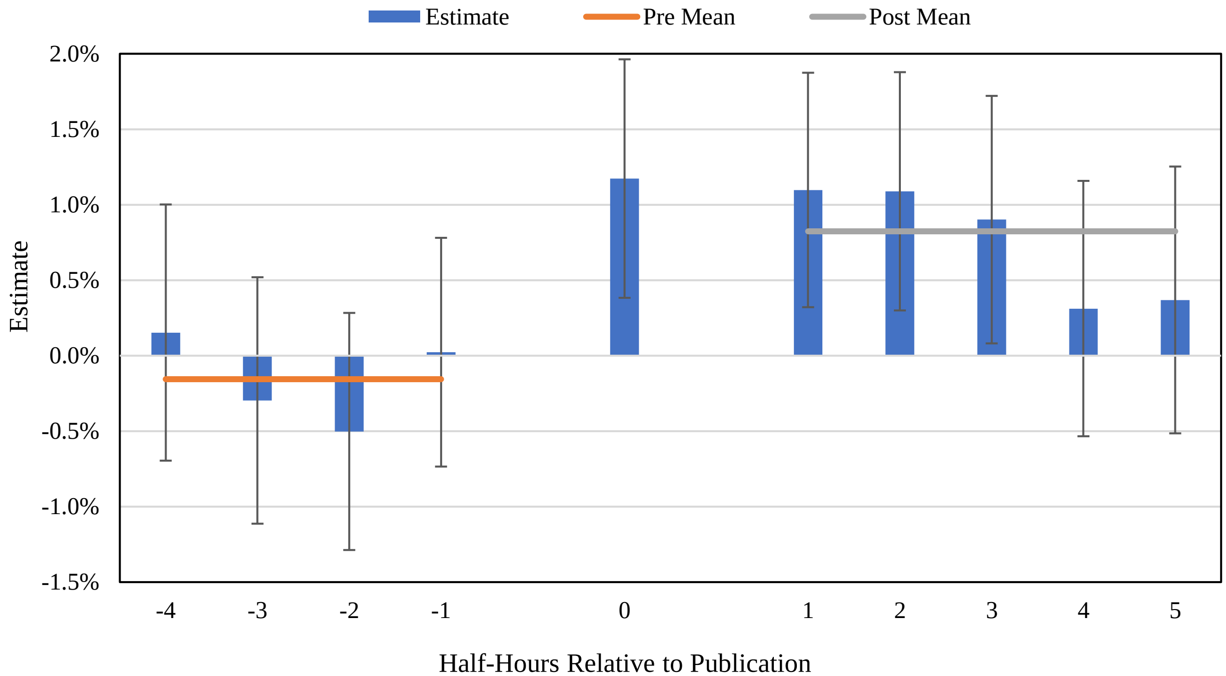

Figure 2. Seeking Alpha Research Sentiment and the Direction of Retail Investor Trading: Event Time
This figure plots estimates from Specification (3) of Table 4 after replacing $Post\_SA \times SA\_Sentiment$ with $SA\_Sentiment$ interacted with ten indicators marking off event windows [-4] through [5]. We report the coefficients on these variables as blue bars, and their 95% confidence intervals as error bars. The average of the pre-event and post-event coefficient estimates appear as orange and grey horizontal lines.

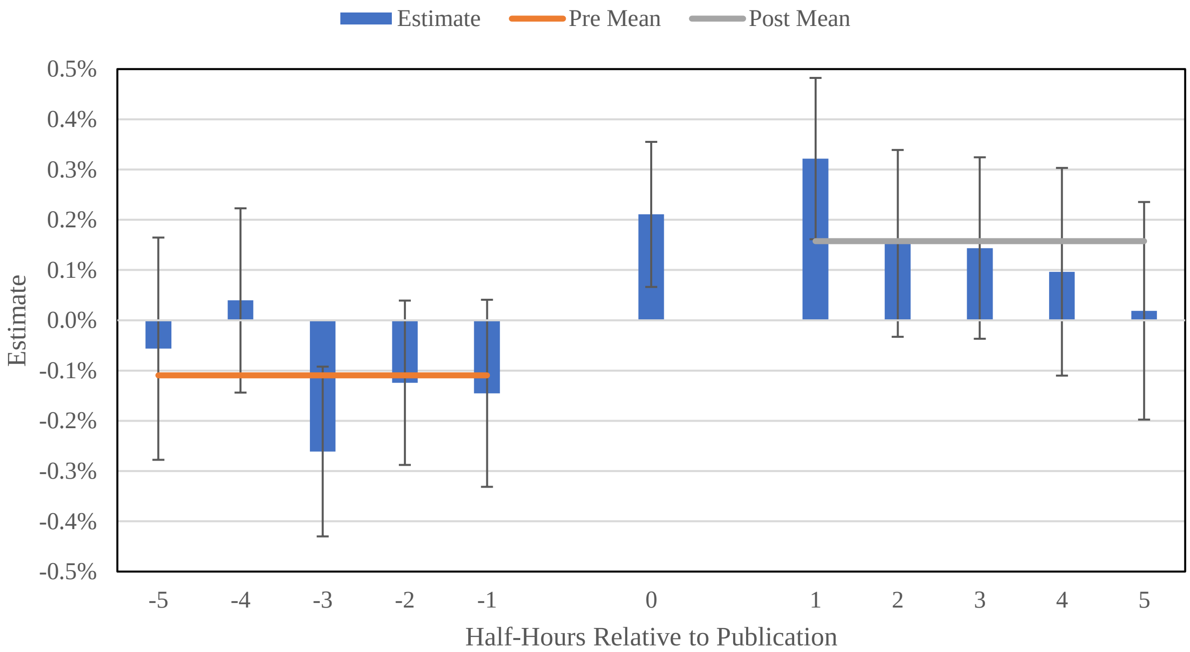

Figure 3. Seeking Alpha Research and the Informativeness of Retail Investor Order Imbalances
This figure plots estimates from Specification (2) of Table 5 after replacing *Retail_OIB* and *Post_SA* × *Retail_OIB*$_{it}$ with *Retail_OIB* interacted with 11 separate indicator variables for each half-hour period ranging from [-5] to [5]. We report the coefficients on these variables as blue bars, and their 95% confidence intervals as error bars. The average of the pre-event and post-event coefficient estimates appear as orange and grey horizontal lines.

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

The table reports information on Seeking Alpha research reports by year. The sample is comprised of 183,969 single-ticker research reports (*SA Reports*) on 4,910 unique firms, contributed by 8,988 unique individuals (*SA Contributors).* The sample is limited to common stocks with available data in in the CRSP-Compustat merged database and TAQ. *Firms Covered by SA* is the number of firms in the sample with at least one single-ticker report on Seeking Alpha. *SA Contributors* is the number of unique research report authors, *Reports per Firm* is the number of reports published for each firm with coverage, and *SA Coverage* is the average number contributors for each firm with coverage. *Intraday SA Reports* is the number of reports that were published between 10:30 am and 3:30pm, and *Intraday Reports No Event* is the subset of intraday reports that is not confounded by other events: media articles, IBES research, or earnings announcements during the ten half-hour intervals surrounding the SA report publication.

Year	*Firms Covered by SA*	*SA Reports (Full Sample)*	*SA Contributors*	*Reports per Firm*	*SA Coverage*	*SA Reports (Intraday)*	*Intraday Reports (No Events)*
2006	724	2,590	228	3.58	2.49	419	304
2007	1,529	8,560	610	5.60	3.31	1,026	664
2008	1,381	7,650	851	5.54	3.31	1,746	1,116
2009	1,296	8,406	776	6.49	3.54	2,424	1,593
2010	1,399	7,721	782	5.52	3.25	2,630	1,635
2011	1,539	11,389	1,150	7.40	4.49	4,499	3,072
2012	1,823	20,504	1,616	11.25	6.56	7,017	4,620
2013	2,503	20,659	2,073	8.25	5.36	7,439	5,605
2014	2,544	25,631	2,216	10.08	5.97	8,097	6,349
2015	2,756	27,101	2,242	9.83	5.76	9,276	7,396
2016	2,512	22,356	2,183	8.90	5.03	8,175	6,154
2017	2,305	21,402	2,091	9.28	5.37	8,534	6,530
Average	1,962	16,489	1,508	8.01	4.57	5,533	4,067
Total	4,910	183,969	8,988	.	.	61,282	45,038

Table 2. Determinants of Seeking Alpha and IBES Coverage

The table presents the results from the estimation of Equation (1):

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

In Specifications (1) and (2), *Coverage* is the natural log of 1 plus the total number of unique Seeking Alpha contributors writing at least one report for the stock during the calendar year (*SA Coverage*). In Specifications (3) and (4), *Coverage* is 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*). *Institutional Ownership* 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 at the end of the previous year. *Char* 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. Standard errors are clustered by firm, with *t*-statistics reported in parentheses.

	SA Coverage		*IBES Coverage*	
	(1)	(2)	(3)	(3)
Institutional Ownership	-0.25	-0.27	0.13	0.14
	(-16.23)	(-17.26)	(13.03)	(13.96)
Breadth of Ownership	0.06	0.07	-0.07	-0.07
	(5.13)	(5.88)	(-9.52)	(-9.98)
Size	0.66	0.57	0.69	0.66
	(23.20)	(19.02)	(44.83)	(41.28)
Book-to-Market	0.02	0.01	0.00	0.00
	(1.40)	(0.85)	(0.11)	(0.02)
Volatility	0.21	0.21	0.05	0.04
	(14.18)	(13.96)	(5.34)	(4.28)
Turnover	0.13	0.09	0.28	0.27
	(10.15)	(6.88)	(23.50)	(23.03)
Return	0.02	0.02	0.04	0.03
	(3.57)	(3.47)	(4.04)	(3.98)
Profitability	0.03	0.03	-0.05	-0.05
	(2.72)	(3.59)	(-8.08)	(-8.43)
Media Coverage	0.06	0.05	0.04	0.03
	(4.49)	(4.03)	(3.96)	(3.68)
IBES Coverage		0.14		
		(8.76)		
SA Coverage				0.06
				(8.18)
Observations	35,261	35,261	35,261	35,261
Year Fixed Effects	Yes	Yes	Yes	Yes
R-squared	42.02%	42.49%	76.50%	76.67%

Table 3. Seeking Alpha Research and the Intensity of Retail Investor Trading

This table presents results from the estimation of Equation (2):

$$Retail\_Trd_{i,t} = \beta_1 Post\_SA_{i,t} + \beta_2 Control_{i,t} + Report_i + HalfHour_t \times Month + \varepsilon_{i,t.}$$

Retail Trd is either *Retail Volume*, defined as log (1 + Retail Volume) in half-hour window *t* around the publication of report *i* or *Percent Retail Trading*, defined as total retail trading volume in half-hour window *t* scaled by total aggregate trading volume in the same window. Trades are classified as retail using the approach of Boehmer et al. (2020). In specifications (1) and (4), the sample includes all intraday SA reports and the event period is [-5, 5]. In Specifications (2) and (5), the sample excludes reports accompanied by media articles, IBES research, or earnings announcements in the event period [-5, 5]. In Specifications (3) and (6), the event period is narrowed to [-1, 1]. *Post_SA* is equal to one for trading in the post-event period and zero for trading in pre-event period. $Controls_{it}$ include lagged returns and lagged absolute returns over the prior period: $Ret_{i,t\text{-}1}$, $AbsRet_{i,t\text{-}1}$, and the prior two to five periods $Ret_{i,[t\text{-}5,t\text{-}2]}$, $AbsRet_{i,[t\text{-}5,t\text{-}2]}$. *Report* denotes SA research report fixed effects and *Half Hour* × *Month* denotes half-hour fixed effects interacted with a monthly fixed effect. All continuous variables are standardized. Standard errors are clustered by date, and *t*-statistics are reported below each estimate.

	Retail Volume			Percent Retail Trading		
	(1)	(2)	(3)	(4)	(5)	(6)
Post_SA	6.00	8.88	7.73	0.17	0.15	0.21
	(6.37)	(8.24)	(8.21)	(5.75)	(3.96)	(4.21)
$Abs\ Ret_{i,t\text{-}1}$	10.55	10.79	8.21	0.24	0.27	0.22
	(31.34)	(26.88)	(12.04)	(13.83)	(11.80)	(4.91)
$Abs\ Ret_{i,[t\text{-}5,t\text{-}2]}$	3.64	3.63	0.17	0.14	0.17	0.13
	(10.89)	(8.66)	(0.25)	(7.99)	(6.86)	(3.07)
$Ret_{i,t\text{-}1}$	1.03	1.06	1.39	0.01	0.01	0.03
	(3.77)	(3.05)	(2.38)	(1.00)	(0.50)	(0.76)
$Ret_{i,[t\text{-}5,t\text{-}2]}$	0.64	1.05	0.60	0.01	0.00	-0.03
	(1.80)	(2.41)	(0.89)	(0.62)	(0.01)	(-0.72)
Observations	485,710	354,755	90,076	485,710	354,755	90,076
SA Reports	Intraday	No Events	No Events	Intraday	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-1, 1]	[-5, 5]	[-5, 5]	[-1, 1]
Report FE	Yes	Yes	Yes	Yes	Yes	Yes
Half Hour × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	81.9%	81.1%	90.5%	50.5%	49.9%	71.7%

Table 4. Seeking Alpha Research Sentiment and the Direction of Retail Investor Trading

This table presents results from the estimation of Equation (3):

$$Retail\ OIB_{i,t} = \beta_1 PostSA \times Sentiment_{i,t} + \beta_2 PostSA_{i,t} + \beta_3 Controls + Report_i + HalfHr_t \times Month + \varepsilon_{i,t.}$$

$Retail\_OIB_{i,t}$ is the retail order imbalance during half-hour t around the publication of report i, computed as the difference between retail buy volume and retail sell volume, scaled by total retail trading volume. In Specifications (1) and (2), the sample includes all intraday SA reports and the event period is [-5, 5]. In Specification (3), the sample excludes reports accompanied by media articles, IBES research, or earnings announcements in the event period [-5, 5]. In Specification (4), the event period is narrowed to [-1, 1]. *Post_SA* is equal to one in the post-event period and zero in the pre-event period. SA Sentiment includes a *Long* (*Short)* indicator equal to one if the contributor discloses a long (short) position, and a *Positive Tone* (*Negative Tone*) indicator equal to one if the fraction of positive (negative) words in the report exceeds the sample median. *Composite Sentiment* is defined as *Long + Positive Tone – Short – Negative Tone. Controls* is a vector that includes lagged returns and lagged absolute returns: $Ret_{i,t-1}$, $AbsRet_{i,t-1}$, $Ret_{i,[t-5,t-2]}$, $AbsRet_{i,[t-5,t-2]}$. See Appendix A for detailed variable definitions. All continuous variables are standardized. Standard errors are clustered by date, and t-statistics are reported below each estimate.

	(1)	(2)	(3)	(4)
Post × SA Long	0.35			
	(1.27)			
Post × SA Short	-1.04			
	(-2.20)			
Post × SA Negative Tone	-1.32			
	(-4.72)			
Post × SA Positive Tone	0.66			
	(2.46)			
Post × SA Composite Sentiment		0.79	0.98	0.90
		(5.20)	(5.21)	(3.10)
Post × SA	0.85	0.32	0.43	1.02
	(3.01)	(1.96)	(2.12)	(3.63)
$Abs\ Ret_{i,t-1}$	0.26	0.26	0.27	0.36
	(3.39)	(3.43)	(2.84)	(1.95)
$Abs\ Ret_{i,[t-5,t-2]}$	0.24	0.25	0.35	0.61
	(2.98)	(3.02)	(3.30)	(3.02)
$Ret_{i,t-1}$	-1.45	-1.45	-1.50	-1.79
	(-21.70)	(-21.72)	(-17.22)	(-10.32)
$Ret_{i,[t-5,t-2]}$	-1.40	-1.40	-1.55	-1.79
	(-17.40)	(-17.43)	(-14.59)	(-8.89)
Observations	485,710	485,710	354,755	90,076
SA Reports	Intraday	Intraday	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-5, 5]	[-1, 1]
Report FE	Yes	Yes	Yes	Yes
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	20.8%	20.8%	20.1%	54.5%

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

This table presents results from the estimation of Equation (4):

$$Ret_{i,[t,t+5d]} = \beta_1 Retail\_OIB_{i,t} + \beta_2 Post\_SA_{i,t} \times Retail\_OIB_{i,t} + \beta_3 Inst\_OIB_{i,t} + \beta_4 Post\_SA_{i,t} \times Inst\_OIB_{i,t} + Controls_{i,t} + HalfHour_t \times Month + \varepsilon_{i,t.}$$

In Specification (1), the sample includes all SA reports and the event period is [-5, 5]. In Specification (2), the sample excludes reports accompanied by media articles, IBES research, or earnings announcements in the event period [-5, 5]. In Specification (3), the event period is narrowed to [-1, 1]. $Ret_{i,[t,t+5d]}$ is the five-day market-adjusted return, computed from the bid-ask average price at the end of half-hour *t* and the closing price at the end of day 5, with the publication day being day 0. $Retail\_OIB_{i,t}$ is the retail order imbalance during half-hour *t* around the publication of report *i*, computed as the difference between retail buy volume and retail sell volume, scaled by total retail trading volume. *Post_SA* is equal to one in the post-event period and zero in the pre-event period. $InstOIB_{i,t}$ is non-retail buy volume less non-retail sell volume in window *t*, scaled by non-retail trading volume. All other control variables are defined in Appendix A. All continuous variables are standardized. Standard errors are clustered by month and *t*-statistics are reported below each estimate.

	(1)	(2)	(3)
Retail_OIB	-0.054	-0.105	-0.116
	(-1.36)	(-2.11)	(-1.22)
Retail_OIB × *Post_SA*	0.213	0.256	0.422
	(3.50)	(3.51)	(3.54)
Institutional_OIB	0.128	0.182	0.070
	(1.37)	(1.74)	(0.42)
Institutional_OIB × *Post_SA*	0.193	0.233	0.382
	(1.58)	(1.67)	(1.76)
$Abs\ Ret_{i,t-1}$	0.003	-0.024	0.002
	(0.05)	(-0.48)	(0.03)
$Abs\ Ret_{i,[t-5,t-2]}$	-0.060	-0.068	-0.094
	(-1.07)	(-1.01)	(-1.36)
$Ret_{i,t-1}$	0.024	0.028	0.045
	(1.06)	(1.06)	(1.06)
$Ret_{i,[t-5,t-2]}$	0.068	0.046	0.000
	(1.90)	(1.01)	(0.00)
$High\ Volume_{i,t-1}$	0.030	0.028	-0.105
	(0.51)	(0.40)	(-1.11)
$High\ Volume_{i,[t-5,\ t-2]}$	-0.126	-0.289	-0.251
	(-1.35)	(-2.28)	(-1.29)
$Low\ Volume_{i,t-1}$	0.012	0.010	-0.118
	(0.30)	(0.22)	(-1.70)
$Low\ Volume_{i,[t-5,\ t-2]}$	-0.092	-0.125	-0.043
	(-0.83)	(-1.07)	(-0.28)
Observations	484,244	353,557	89,774
SA Reports	Intraday	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-1, 1]
Half Hour × Month FE	Yes	Yes	Yes
R-squared	1.09%	1.16%	2.64%

Table 6. SA Research and the Informativeness of Retail Investor Trading: Longer Horizon Evidence
This table repeats Specification (2) of Table 5 after replacing the dependent variable (one-week ahead returns) with returns over longer horizons. For reference, Specification 1 repeats the one-week analysis reported in Table 5. Specifications 2 through 5 replace one-week ahead returns with returns over weeks 2 through 5, respectively. The week 2 return is computed based on the buy-and-hold return over the six to ten trading days after the report releases, and other weekly returns are defined analogously. Specifications 6 and 7 report the cumulative buy-and-hold return over the 5-week and 12-week holding periods.

	Week 1 (1)	Week 2 (2)	Week 3 (3)	Week 4 (4)	Week 5 (5)	Weeks (1-5) (6)	Wks (1-12) (7)
Retail_OIB	-0.105	0.033	0.060	-0.014	-0.062	-0.088	-0.027
	(-2.11)	(0.78)	(1.30)	(-0.28)	(-1.37)	(-0.93)	(-0.14)
Retail_OIB × *Post_SA*	0.256	-0.010	-0.062	0.007	0.099	0.291	0.224
	(3.51)	(-0.15)	(-1.40)	(0.10)	(1.67)	(2.30)	(1.00)
Inst_OIB	0.182	0.098	-0.024	-0.076	0.104	0.283	0.596
	(1.74)	(1.15)	(-0.31)	(-0.75)	(1.09)	(1.42)	(1.52)
Inst_OIB × *Post_SA*	0.233	-0.063	-0.054	0.223	0.115	0.452	0.400
	(1.67)	(-0.57)	(-0.47)	(1.75)	(0.95)	(1.82)	(0.71)
Abs $Ret_{i,t-1}$	-0.024	-0.012	0.008	-0.064	-0.014	-0.103	-1.046
	(-0.48)	(-0.31)	(0.12)	(-1.42)	(-0.36)	(-0.72)	(-3.14)
Abs $Ret_{i,[t-5,t-2]}$	-0.068	-0.038	-0.068	-0.056	-0.056	-0.282	-1.436
	(-1.01)	(-0.76)	(-1.36)	(-1.04)	(-1.24)	(-1.69)	(-3.24)
$Ret_{i,t-1}$	0.028	-0.030	-0.011	0.021	0.006	0.014	0.172
	(1.06)	(-1.70)	(-0.51)	(1.05)	(0.25)	(0.28)	(2.04)
$Ret_{i,[t-5,t-2]}$	0.046	0.002	-0.035	0.053	-0.038	0.027	0.351
	(1.01)	(0.06)	(-0.95)	(1.55)	(-1.02)	(0.34)	(1.80)
High $Volume_{i,t-1}$	0.028	-0.019	-0.064	-0.090	-0.024	-0.171	0.226
	(0.40)	(-0.42)	(-0.93)	(-1.83)	(-0.55)	(-1.21)	(0.75)
High $Volume_{i,[t-5, t-2]}$	-0.289	-0.302	-0.096	-0.047	0.034	-0.694	-1.060
	(-2.28)	(-2.74)	(-0.85)	(-0.42)	(0.32)	(-3.21)	(-1.90)
Low $Volume_{i,t-1}$	0.010	-0.080	-0.065	0.013	0.027	-0.093	-0.151
	(0.22)	(-1.83)	(-1.67)	(0.30)	(0.69)	(-0.98)	(-0.90)
Low $Volume_{i,[t-5, t-2]}$	-0.125	-0.048	-0.034	0.236	0.097	0.129	0.101
	(-1.07)	(-0.38)	(-0.28)	(2.08)	(0.78)	(0.49)	(0.22)
Observations	353,557	353,557	353,557	353,557	353,557	353,557	353,557
Sample	No Events	No Events	No Events	No Events	No Events	No Events	No Events
Window	[-5,5]	[-5,5]	[-5,5]	[-5,5]	[-5,5]	[-5,5]	[-5,5]
Half Hour×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	1.16%	1.00%	1.11%	0.81%	0.76%	1.91%	1.99%

Table 7. SA Research and the Informativeness of Retail Investor Trading: Predicting Cash Flow News

This table reports results from the estimation of Equation (5):

$$CFNews_{i,[t,t+5d]} = \alpha + \beta_1 Retail\ OIB_{i,t} + \beta_2 PostSA_{i,t} \times Retail\ OIB_{i,t} + \beta_3 Inst\ OIB_{i,t} + \beta_4 Inst\ OIB_{i,t} + Controls_{i,t} + HalfHour_t \times Month + \varepsilon_{i,t.}$$

CFNews is *Media Article Tone*, defined as the sum of the Adjusted Event Sentiment Score (ESS) across all stock-focused media articles in the five-day period following the day of SA report publication, or *Forecast Revisions*, defined as the number of upward forecast revisions less the number of downward forecast revisions over the same period. SA reports that are not followed by any media articles or any forecast revisions within five days are dropped. *Controls* include all Table 5 control variable, as well as *Media Article Tone* and *Forecast Revisions* calculated over daily intervals [0], [-5, -1], and [-26, -6]. In Specifications (1) and (4), the sample includes all SA reports and the event period is [-5, 5]; in Specifications (2) and (5), the sample is limited to SA reports unaccompanied by media articles, IBES research, or earnings announcements in the event period; and in Specifications (3) and (6), the sample is further limited to event period [-1, 1]. All other variables are as defined as Table 5. Standard errors are clustered by month and *t*-statistics are reported below each estimate.

	Media Article Tone			Forecast Revisions		
	(1)	(2)	(3)	(4)	(5)	(6)
Retail_OIB	1.42	0.91	0.68	0.09	0.01	-0.04
	(3.89)	(2.34)	(1.13)	(1.29)	(0.09)	(-0.33)
Retail_OIB × *Post_SA*	1.21	1.04	0.56	0.11	0.20	0.31
	(2.97)	(2.27)	(0.77)	(1.20)	(1.99)	(2.23)
Institutional_OIB	0.25	0.63	-0.54	0.17	0.32	0.46
	(0.38)	(1.01)	(-0.57)	(1.12)	(1.75)	(1.83)
Institutional_OIB × *Post_SA*	0.12	0.19	0.67	0.03	0.18	-0.08
	(0.16)	(0.23)	(0.58)	(0.20)	(0.92)	(-0.22)
$Abs\ Ret_{i,t\text{-}1}$	-1.83	-1.94	-1.84	-0.13	-0.12	-0.11
	(-7.82)	(-8.87)	(-6.41)	(-4.54)	(-3.94)	(-2.47)
$Abs\ Ret_{i,[t\text{-}5,t\text{-}2]}$	-2.39	-2.71	-2.43	-0.21	-0.24	-0.25
	(-9.37)	(-10.44)	(-7.67)	(-5.97)	(-5.98)	(-5.44)
$Ret_{i,t\text{-}1}$	0.29	0.14	-0.04	0.09	0.07	0.05
	(2.90)	(1.29)	(-0.18)	(5.48)	(3.44)	(1.24)
$Ret_{i,[t\text{-}5,t\text{-}2]}$	0.13	-0.04	0.12	0.14	0.10	0.14
	(0.66)	(-0.21)	(0.47)	(5.42)	(2.51)	(2.80)
$High\ Volume_{i,t\text{-}1}$	1.61	3.41	4.04	0.18	0.25	0.20
	(3.74)	(6.03)	(4.41)	(2.57)	(2.62)	(1.58)
$High\ Volume_{i,[t\text{-}5,\ t\text{-}2]}$	-2.98	1.14	-0.25	-0.17	-0.01	0.01
	(-3.25)	(1.05)	(-0.20)	(-1.26)	(-0.07)	(0.06)
$Low\ Volume_{i,t\text{-}1}$	-2.68	-2.61	-2.69	-0.19	-0.22	-0.27
	(-7.21)	(-6.94)	(-4.31)	(-2.67)	(-3.30)	(-2.17)
$Low\ Volume_{i,[t\text{-}5,\ t\text{-}2]}$	-5.05	-4.88	-4.78	-0.28	-0.35	-0.20
	(-5.26)	(-5.33)	(-4.27)	(-1.53)	(-1.72)	(-0.93)
$Media\ Tone\ /\ Forecast\ Rev_{[0]}$	1.04	1.86	1.76	1.01	1.75	1.68
	(2.29)	(3.19)	(3.08)	(22.93)	(10.32)	(10.39)
$Media\ Tone\ /\ Forecast\ Rev_{[-5,-1]}$	2.37	1.43	1.41	0.65	0.59	0.59
	(5.94)	(3.86)	(3.72)	(11.63)	(10.99)	(11.08)
$Media\ Tone\ /\ Forecast\ Rev_{[-26,-6]}$	8.03	7.28	7.23	0.89	0.83	0.82
	(13.40)	(12.51)	(12.58)	(9.12)	(8.62)	(8.80)
Observations	396,314	276,097	70,195	238,905	157,680	40,058
SA Reports	Intraday	No Events	No Events	Intraday	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-1, 1]	[-5, 5]	[-5, 5]	[-1, 1]
Half-Hour × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	7.87%	7.40%	9.13%	13.46%	13.40%	15.73%

Table 8. Retail Investor Trading Informativeness Tests: Controlling for Seeking Alpha Research Sentiment

In this table, we re-estimate Specification (2) in Table 5 and Specifications (2) and (4) in Table 7 after including a measure of SA Research Sentiment (*Composite Sentiment)*: computed as *Long* + *Positive Tone* – *Short* – *Negative Tone,* where *Long* (*Short*) is an indicator equal to one if the contributor discloses a long (short) positions and *Positive (Negative) Tone* is an indicator equal to one if the fraction of positive (negative) words in the report exceeds the sample median. Standard errors are clustered by month and *t*-statistics are reported below each estimate.

	Returns	Media Article Tone	Forecast Revisions
	(1)	(2)	(3)
Composite Sentiment	0.289	0.74	0.27
	(6.20)	(2.05)	(3.96)
Retail_OIB	-0.114	0.90	0.00
	(-2.28)	(2.31)	(-0.02)
Retail_OIB × *Post_SA*	0.254	1.02	0.20
	(3.48)	(2.22)	(1.98)
Institutional_OIB	0.188	0.63	0.33
	(1.79)	(1.01)	(1.78)
Institutional_OIB × *Post_SA*	0.195	0.17	0.16
	(1.41)	(0.21)	(0.86)
Abs $Ret_{i,t\text{-}1}$	-0.010	-1.91	-0.11
	(-0.16)	(-8.79)	(-3.59)
Abs $Ret_{i,[t\text{-}5,t\text{-}2]}$	-0.048	-2.68	-0.22
	(-0.71)	(-10.32)	(-5.65)
$Ret_{i,t\text{-}1}$	0.020	0.13	0.06
	(0.74)	(1.17)	(3.20)
$Ret_{i,[t\text{-}5,t\text{-}2]}$	0.029	-0.06	0.09
	(0.63)	(-0.34)	(2.35)
High $Volume_{i,t\text{-}1}$	0.034	3.42	0.25
	(0.48)	(6.05)	(2.60)
High $Volume_{i,[t\text{-}5,\ t\text{-}2]}$	-0.287	1.14	-0.01
	(-2.25)	(1.04)	(-0.06)
Low $Volume_{i,t\text{-}1}$	0.014	-2.60	-0.22
	(0.31)	(-6.94)	(-3.26)
Low $Volume_{i,[t\text{-}5,\ t\text{-}2]}$	-0.121	-4.86	-0.35
	(-1.03)	(-5.31)	(-1.70)
Media Tone / Forecast $Rev_{[0]}$		1.39	1.74
		(3.77)	(10.26)
Media Tone / Forecast $Rev_{[-5,-1]}$		7.24	0.58
		(12.40)	(10.75)
Media Tone / Forecast $Rev_{[-26,-6]}$		1.83	0.81
		(3.14)	(8.44)
Observations	353,557	276,097	157,680
SA Reports	No Events	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-5, 5]
Half-Hour × Month FE	Yes	Yes	Yes
R-squared	1.23%	7.42%	13.51%

Table 9. Retail Investor Trading Informativeness Tests: Conditioning on Seeking Alpha Report Quality

In this table, we augment Specification (2) in Table 5 and Specifications (2) and (4) in Table 7 to include the following terms: *Retail_OIB × Report Quality* and *Retail_OIB ×Post_SA × Report Quality*. *Report Quality* is the sum of *Academic Quality, Signed Return, Unsigned Return, and Comments* (all defined in Appendix A). All continuous variables are standardized. Standard errors are clustered by month, and *t*-statistics are reported below each estimate.

	Returns	Media Article Tone	Forecast Revisions
	(1)	(2)	(3)
Retail_OIB	0.063	1.21	0.08
	(0.72)	(2.10)	(0.47)
Retail_OIB × Report Quality	-0.113	-0.24	-0.05
	(-1.68)	(-0.59)	(-0.48)
Retail_OIB × Post_SA	-0.263	-0.45	-0.37
	(-2.30)	(-0.65)	(-1.80)
Retail_OIB × Post_SA × Rep. Quality	0.347	1.01	0.37
	(3.89)	(1.94)	(3.07)
Report Quality	-0.032	1.95	0.08
	(-0.62)	(6.69)	(1.29)
Institutional_OIB	0.186	0.62	0.30
	(1.78)	(0.99)	(1.65)
Institutional_OIB × Post_SA	0.216	0.21	0.16
	(1.56)	(0.26)	(0.82)
Abs Ret$_{i,t\text{-}1}$	-0.022	-2.08	-0.13
	(-0.44)	(-9.42)	(-4.06)
Abs Ret$_{i,[t\text{-}5,t\text{-}2]}$	-0.065	-2.89	-0.25
	(-0.99)	(-10.96)	(-6.22)
Ret$_{i,t\text{-}1}$	0.028	0.14	0.06
	(1.06)	(1.30)	(3.47)
Ret$_{i,[t\text{-}5,t\text{-}2]}$	0.046	-0.04	0.09
	(1.00)	(-0.20)	(2.34)
High Volume$_{i,t\text{-}1}$	0.026	3.47	0.26
	(0.37)	(6.06)	(2.73)
High Volume$_{i,[t\text{-}5,\ t\text{-}2]}$	-0.287	1.17	0.08
	(-2.24)	(1.07)	(0.45)
Low Volume$_{i,t\text{-}1}$	0.012	-2.60	-0.20
	(0.26)	(-6.89)	(-3.11)
Low Volume$_{i,[t\text{-}5,\ t\text{-}2]}$	-0.127	-4.73	-0.31
	(-1.09)	(-5.22)	(-1.51)
Media Tone / Forecast Revisions$_{[0]}$		1.99	1.81
		(3.48)	(10.21)
Media Tone / Forecast Revisions$_{[-5,-1]}$		1.41	0.57
		(3.79)	(10.98)
Media Tone / Forecast Revisions$_{[-26,-6]}$		7.20	0.82
		(12.32)	(8.56)
Observations	353,557	276,097	157,680
SA Reports	No Events	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-5, 5]
Half Hour × Month FE	Yes	Yes	Yes
R-squared	1.17%	7.53%	13.44%

Table 10. Retail Investor Trading Informativeness Tests: Daily Analysis

This table presents the results from the estimation of Equation (6):

$$Y_{i,[t+1,t+5]} = \alpha + \beta_1 Retail\_OIB_{i,t} + \beta_2 Retail\_OIB_{i,t} \times Event_{i,t} + \beta_3 Retail\_OIB_{i,t} \times Log(Size)_{i,y-1} + \beta_4 Inst\_OIB_{i,t} + \beta_5 Inst\_OIB_{i,t} \times Event_{i,t} + \beta_6 Inst\_OIB_{i,t} \times Log(Size)_{i,t} + \beta_7 Event_{i,t} + \beta_8 Char_{i,t} + Day_t + \varepsilon_{i,t,}$$

where $Y_{i,[t+1,t+5]}$ is stock *i*'s return from the close of day *t* to the close of day *t+5 (Stock Returns)*, the sum of the Adjusted Event Sentiment Score (ESS) across all media article over the same period (*Media Article Tone*), or the number of upward forecast revisions less the number of downward forecast revisions over the same period (*Forecast Revisions*). $Retail\_OIB_{it}$ is the total retail buy volume for stock *i* on day *t* minus the respective sell volume, scaled by total retail trading volume. $Event_{i,t}$ is a vector of indicator variables: $SA_{i,t}$, $IBES_{i,t}$ $Media_{i,t}$, and $Earnings_{i,t}$. $SA_{i,t}$ is equal to one if an SA research report on stock *i* is published between 1:30 pm on day *t*-1 and 4 pm on day *t*. $IBES_{i,t}$, $Media_{i,t}$, and $Earnings_{i,t}$ indicate the release of an IBES report, media article, and earnings, and are defined analogously. *Inst_OIB* is non-retail buy volume less non-retail sell volume scaled by non-retail trading volume. *Char* is a vector of the following firm characteristics: past returns estimated over the prior week ($Ret_{i,w-1}$), prior month ($Ret_{i,m-1}$), and prior two to seven months ($Ret_{i,[m-7,m-2]}$), market capitalization (*Size*), monthly turnover (*Turnover*), volatility of daily returns (*Volatility*), book-to-market (*BM*), and indicators for whether trading volume in the stock was the top or bottom 10% relative to the stock's trading volume in the previous fifty trading days (*High Volume* and *Low Volume)*. When the dependent variable is *Media Article Tone* (*Forecast Revisions*), *Char* also includes *Media Tone* (*Revisions*) calculated over daily intervals [0], [-5, -1], and [-26, -6]. In Specifications (4)-(6), we include report *Quality* and interact *Quality* with *Retail_OIB* × *SA.* Detailed variable definitions appear in Appendix A. All continuous variables are standardized. Standard errors are clustered by month, and *t*-statistics are reported in parentheses.

	Stock Returns (1)	Media Article Tone (2)	Forecast Revisions (3)	Stock Returns (4)	Media Article Tone (5)	Forecast Revisions (6)
Retail_OIB	0.036	0.28	0.01	0.037	0.28	0.01
	(7.68)	(9.38)	(2.38)	(7.69)	(9.41)	(2.39)
Retail_OIB × SA	0.089	1.29	0.11	-0.022	0.43	-0.01
	(3.30)	(6.91)	(2.46)	(-0.45)	(1.49)	(-0.13)
Retail_OIB ×SA× Quality				0.079	0.58	0.08
				(1.96)	(2.94)	(2.01)
Retail_OIB × Media	0.022	0.03	-0.02	0.022	0.03	-0.02
	(2.51)	(0.62)	(-1.56)	(2.51)	(0.61)	(-1.57)
Retail_OIB × IBES	0.023	0.48	0.01	0.023	0.47	0.01
	(1.69)	(7.01)	(0.83)	(1.68)	(6.97)	(0.81)
Retail_OIB × Earnings	0.066	0.07	-0.07	0.066	0.06	-0.07
	(1.45)	(0.39)	(-2.49)	(1.43)	(0.34)	(-2.53)
Retail_OIB × Size	-0.028	0.21	0.00	-0.028	0.21	0.00
	(-5.46)	(7.24)	(0.26)	(-5.45)	(7.24)	(0.26)
Institutional_OIB	-0.051	0.06	0.02	-0.051	0.06	0.02
	(-7.32)	(1.97)	(2.12)	(-7.32)	(1.97)	(2.12)
Institutional_OIB × SA	0.035	0.26	0.08	0.035	0.26	0.08
	(1.24)	(1.45)	(2.43)	(1.23)	(1.45)	(2.43)
Institutional_OIB ×Media	0.019	-0.07	-0.03	0.019	-0.07	-0.03
	(1.77)	(-1.60)	(-2.45)	(1.77)	(-1.61)	(-2.45)
Institutional_OIB × IBES	0.008	0.16	-0.02	0.008	0.16	-0.02
	(0.52)	(1.84)	(-1.18)	(0.52)	(1.82)	(-1.18)
Inst_OIB × Earnings	0.022	-0.28	0.04	0.022	-0.28	0.04
	(0.53)	(-1.25)	(1.41)	(0.53)	(-1.25)	(1.42)
Institutional_OIB × Size	0.006	0.10	0.00	0.006	0.10	0.00
	(1.12)	(3.45)	(0.48)	(1.12)	(3.44)	(0.47)
$Ret_{i,w-1}$	-0.092	-0.66	0.17	-0.092	-0.66	0.17
	(-3.78)	(-10.34)	(20.01)	(-3.78)	(-10.34)	(20.01)
$Ret_{i,m-1}$	-0.040	-0.88	0.27	-0.040	-0.88	0.27

	(-1.25)	(-11.05)	(21.59)	(-1.25)	(-11.04)	(21.59)
$Ret_{i,[m-7,\, m-2]}$	-0.003	0.34	0.34	-0.003	0.34	0.34
	(-0.08)	(4.02)	(20.13)	(-0.08)	(4.04)	(20.13)
$Turnover_{i,m-1}$	-0.048	-1.53	-0.04	-0.048	-1.54	-0.04
	(-1.90)	(-17.34)	(-2.78)	(-1.91)	(-17.43)	(-2.80)
$Volatility_{i,m-1}$	0.062	-0.04	-0.03	0.062	-0.05	-0.03
	(1.53)	(-0.46)	(-1.68)	(1.52)	(-0.54)	(-1.68)
Log (Size)	-0.002	2.94	0.07	-0.002	2.94	0.07
	(-0.07)	(14.32)	(2.81)	(-0.07)	(14.31)	(2.81)
Log (BM)	0.016	0.52	-0.10	0.016	0.52	-0.10
	(0.59)	(6.64)	(-8.64)	(0.59)	(6.65)	(-8.64)
$High\ Volume_{i,t-1}$	0.198	0.92	0.01	0.197	0.91	0.01
	(6.80)	(7.94)	(0.52)	(6.80)	(7.84)	(0.51)
$Low\ Volume_{i,t-1}$	-0.125	-0.34	-0.07	-0.125	-0.33	-0.07
	(-5.31)	(-3.25)	(-4.11)	(-5.31)	(-3.23)	(-4.10)
SA	0.005	3.67	0.08	-0.010	1.76	0.08
	(0.13)	(12.99)	(2.47)	(-0.16)	(4.77)	(1.57)
Media	0.017	-1.13	-0.01	0.008	-1.13	-0.01
	(1.60)	(-11.88)	(-0.93)	(0.20)	(-11.91)	(-0.93)
IBES	-0.025	0.51	-0.01	0.017	0.51	-0.01
	(-0.94)	(4.89)	(-0.66)	(1.60)	(4.87)	(-0.65)
Earnings	-0.072	-9.81	-0.13	-0.025	-9.83	-0.13
	(-1.30)	(-15.99)	(-3.01)	(-0.94)	(-16.02)	(-3.01)
Quality				-0.072	1.24	0.00
				(-1.30)	(6.54)	(0.08)
$Media\ /\ Revisions_{[0]}$		0.11	0.48		0.11	0.48
		(25.21)	(95.89)		(25.15)	(95.96)
$Media\ /\ Revisions_{[-5,\, -1]}$		0.05	0.12		0.05	0.12
		(14.61)	(30.72)		(14.61)	(30.73)
$Media\ /\ Revisions_{[-26,-6]}$		0.04	0.07		0.04	0.07
		(25.51)	(19.55)		(25.45)	(19.55)
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,216,191	2,928,492	1,220,545	4,216,191	2,928,492	1,220,545
SA Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
R-squared	15.57%	5.49%	10.58%	15.57%	5.49%	10.58%

Table 11. Fake Seeking Alpha Reports

This table repeats the retail trading volume tests (Specification 2 of Table 3); retail order imbalance tests (Specification 3 of Table 4); one-week retail trading informativeness test (Specification 2 of Table 5), and the five-week and 12-week retail trade informativeness tests (Specifications 6 and 7 of Table 6) after partitioning the sample into reports that are more or less likely to be fake. In Panel A, our proxy for fake reports is author anonymity. We define a contributor as anonymous if her SA bio includes none of the following: (i) a complete human name (i.e., first and last name); (ii) a human face; (iii) a tag to a company name; (iv) a link to a LinkedIn account; or (v) a link to a Twitter account. All other contributors are classified as non-anonymous. In Panel B, our proxy for fake reports is the authenticity score of Pennebaker, 2011. We classify a report as low (high) authenticity if its authenticity score in the bottom 20 (top 80%) relative to all other reports issued during the same calendar month. We also test whether the coefficients for the fake reports are significantly different from non-fake reports by estimating the results for the full sample and interacting the main variable of interest with a fake report indicator. Standard errors are clustered by time and t-statistics are reported below each estimate.

	Obs.	Retail Volume	Percent Retail	Retail OIB	Return 1-Week	Return 5-weeks	Return 12-weeks
		[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Anonymous Contributors							
Anonymous	58,729	7.38%	0.11%	1.70%	0.378%	0.021%	-0.056%
		(3.12)	(1.08)	(3.67)	(2.48)	(0.06)	(-0.09)
Non-Anonymous	293,386	9.06%	0.15%	0.81%	0.229%	0.431%	0.305%
		(8.02)	(3.82)	(3.91)	(2.69)	(2.83)	(1.32)
Anonymous Interaction Term		-1.57%	-0.05%	0.88%	0.155%	-0.461%	-0.342%
		(-0.64)	(-0.49)	(1.74)	(0.86)	(-1.24)	(-0.49)
Panel B: Authenticity Score							
Low Authenticity	73,965	18.19%	0.18%	1.60%	0.405%	0.117%	-0.578%
		(9.64)	(1.96)	(3.78)	(2.91)	(0.39)	(-1.14)
High Authenticity	279,423	6.24%	0.14%	0.83%	0.200%	0.388%	0.427%
		(5.17)	(3.50)	(3.96)	(2.60)	(2.40)	(1.74)
Low Authenticity Interaction Term		12.06%	0.05%	0.78%	0.232%	-0.293%	-1.078%
		(5.72)	(0.54)	(1.66)	(1.61)	(-0.82)	(-1.94)

Internet Appendix for:

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

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

In this appendix, we tabulate and discuss results from select robustness and supplementary analyses referenced in the paper. The set of figures and tables are as follows:

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IA.1 Characteristics of Stocks Covered by Seeking Alpha

Table IA1 provides summary statistics on the characteristics of stocks covered in Seeking Alpha reports. We consider the following attributes: market capitalization (*Size*), book-to-market (*BM*), daily return volatility (*Volatility*), daily share turnover *(Turnover)*, past one-year return ($Return_{m\text{-}12,m\text{-}1}$), past one-year profitability (*Profitability*), the number of sell-side analysts covering the firm in the prior year (*IBES Coverage*), the number of unique media articles mentioning the firm in the prior year (*Media Coverage*), the percentage of the firm's shares held by institutional investors in the prior year (*Inst Ownership*), and the number of common shareholders in the prior year (*Breadth of Ownership*). Appendix A of the paper provides more detailed definitions.

For each year (2006-2017), we compute the mean, median, standard deviation, and 25th and 75th percentiles of each firm attribute across all reports. Table IA1 reports the time-series average of each statistic. As a benchmark, we also report the means of the firm attributes across all stocks in the CRSP-Compustat merged sample, where we either equally weight each firm (*EW Market*) or value-weight each firm by its market capitalization at the end of the prior year *(VW Market*). We find that the average size of a firm covered by an SA report is roughly $61.0 billion, which is smaller than the corresponding size of the value-weighted market average ($89.3 billion), but considerably larger than the equal-weighted market average ($4.6 billion). Relative to the *VW Market*, we also find that SA Coverage tilts towards more volatile firms, more liquid firms, firms with stronger past returns, and firms with lower institutional ownership. However, the *VW Market* attribute almost always falls within the interquartile range of the SA attribute, suggesting that SA coverage is not dramatically different from the market portfolio.

IA.2 Seeking Alpha Report Timing and the Timing of Major Information Events

An important identifying assumption is that other confounding events that influence retail trading are just as likely to occur during the pre-publication window as in the post-publication window. This assumption could in principle be violated if Seeking Alpha's editorial team systematically seeks to release reports immediately before or after the arrival of important information events. While this seems unlikely, we empirically address this possibility by examining the distribution of earnings announcements, analyst reports, and media articles in the pre- and post-publication windows. Finding that these events are equally likely to occur in the pre- and post-periods will help validate our assumption that differences in retail trading between the pre- and post- periods do not reflect differences in the arrival of other information.

We estimate the following linear probability model:

$$Event_{i,t} = \alpha + \beta_1 Post\_SA_{i,t} + Report_i + HalfHour_t \times Month + \varepsilon_{i,t}, \qquad \text{(IA.1)}$$

where $Event_{i,t}$ is equal to one if firm *i* event occurs in half-hour *t*, and zero otherwise. *Event* is either *Earnings Announcement*, *IBES Research*, or *Media Article* (defined in Appendix A). $Post\_SA_{i,t}$ equals one if *t* is in the interval [1, 5], and zero if *t* is in the interval [-5, -1]. $Report_i$ is a report fixed effect, which makes β_1 an estimate of the change in the probability of an information event occurring in the post-event window relative to the pre-event window. We include calendar half-hour fixed effects to control for intraday variation in the arrival of information, and we allow the loadings on these fixed effects to vary over the sample period (i.e., *Half Hour* × *Month* fixed effects). We cluster standard errors by date.

In Specifications (1)-(3) of Table IA2, we tabulate results when *Event* is *Earnings Announcement*, *IBES research*, or *Media Article*. In each specification, the coefficient on *Post_SA* is economically small and statistically insignificant, inconsistent with the idea that information disseminated by SA coincides with the dissemination of information from other sources. In the remaining specifications, we seek to provide more granular evidence by replacing the single post-event indicator *Post_SA* with five post-event indicators: *SA*[1]…*SA*[5], four pre-event indicators: *SA*[-4]…*SA*[-1], and the event publication indicator *SA*[0]. The corresponding coefficients reflect changes in event probabilities relative to the first half hour in the event period [-5]. The coefficient estimates are insignificant and exhibit no systematic pattern. The absence of a relation in the timing of SA research reports relative to earnings announcements, sell-side research reports, and media articles, helps build confidence that any changes in retail trading immediately after SA research can, on average, be attributed to Seeking Alpha rather than the arrival of other information.

IA.3 The Distribution of SA Reports during the Trading Day

Figure IA1 examines the intraday distribution of SA reports published between 10:30 am and 3:30 pm for two samples: 1) all 61,282 reports and 2) 45,038 reports that have no earnings announcements, media articles, or sell-side research reports over the [-5, 5] event window ("No Event" reports). We observe that SA reports are uniformly distributed. For example, in the full sample, the median number of reports in a 30-minute window is 5,986, with a maximum of 7,016 (11:30-11:59) and a minimum of 5,451 (12:30-12:59).

IA.4 SA Research and the Intensity of Retail Investor Trading: Stale Reports

The results in Tables 3 and 4 suggest that SA research reports induce significant amounts of retail trading that is directionally consistent with the sentiment of the report. One potentially important attenuating factor is that some contributors may post their research reports on alternative websites, including their own personal sites, prior to posting on Seeking Alpha. Thus, attentive investors may be able to trade on some SA reports before the report is posted to Seeking Alpha, and our approach would underestimate the influence of SA research.

To explore the impact of "stale" reports on retail trading, we visit each contributor's author page to identify whether the author links a website to his author page. We find that roughly 41% of contributors provide a link to a website. For any author with both a website and at least ten reports, we visit the linked website and search for whether any SA research posts are available on the website.[IA1] In some cases, we find that the authors most recent SA reports are on their website while older reports are not. We classify an author as having a "matched blog" if we find any SA reports on their linked webpage, and we classify all reports authored by contributors with matched blogs as "stale". This classification is conservative in the sense that we are likely overestimating the fraction of stale reports. Even with this more conservative classification, we find that only 5.2% of reports are stale. Our investigation suggests that most authors write their research reports solely for Seeking Alpha, consistent with SA providing compensation only for reports that are exclusive to their website.[IA2]

Specifications (1) and (2) of Table IA3 of the Internet Appendix repeat Specification (2) of Table 3 for authors (with at least ten reports) with and without a matched blog. Similarly, Specifications (3) and (4) repeat Specification (3) of Table 4 for the same subsamples. We find the increase in *Retail* Volume is roughly 30% larger for authors for non-stale reports (6.58% versus 5.12%).[IA3] Similarly, retail order imbalances are roughly 40% more correlated with report sentiment for non-stale reports (0.97% versus 0.68%). Overall, the evidence is consistent with stale

[IA1] Authors with fewer than ten reports account for roughly 55% of the sample but just 15% of all reports. Thus, excluding contributors who issue fewer than ten reports great simplifies the data collection effort and is unlikely to meaningfully impact our estimates. We define matched blog as undefined for any author with fewer than ten reports (including authors without websites) to ensure that our comparison of authors with and without matched blogs is not biased by differences in reporting frequency.
[IA2] For more details on exclusive articles see: https://seekingalpha.com/page/premium-partnership-faq
[IA3] The estimates for each subsample are smaller than our overall estimate in Table 3 (8.88%). This is because both samples exclude contributors who issue fewer than ten reports. The aggregate estimate for contributors who issue at least ten (less than ten) reports is 6.49% (18.06%).

SA reports inducing weaker retail trading responses.[IA4] However, because stale reports are so infrequent their inclusion does not meaningfully alter our main findings.

IA.5 Institutional Trading Intensity and Order Imbalances around SA Research

Section 4.1 shows that retail investor trading intensity increases sharply following SA research, and Section 4.2 shows that retail order imbalances become more strongly correlated with the sentiment of SA research report. In this section, we conduct analogous tests after replacing retail trading measures with institutional trading measures.

Table IA4 reports the institutional trading intensity results when we replace *Retail Vol* in Equation (2) with *Inst. Vol*, defined as log (1 + Total Volume – Retail Volume). We find institutional trading volume significantly increases following the release of SA reports. For example, Specification (1) of Table IA4 indicate that institutional volume increases by 4.40% ($e^{0.043}$ -1) in the [1, 5] post-event window relative to the [-5, -1] pre-event window. The point estimate is roughly 70% of the magnitude of the corresponding estimate for *Retail Vol* (6.00%).

We next replicate the order imbalance analysis after replacing *Retail_OIB* in Equation (3) with *Inst_OIB*. The results, tabulated in Table IA5, indicate that *Inst_OIB* is correlated with the sentiment of SA research reports. For example, *Inst_OIB* significantly increases for reports where the contributor discloses a long position and significantly declines for reports with more negative tone. Specification (2) shows that a one unit increase in *Composite Sentiment* is associated with a 0.23 percentage point increase in *Inst_OIB*. The estimate, while statistically significant, is only about 30% of the magnitude of the corresponding *Retail_OIB* estimate (0.79pp) reported in Table 4. Overall, the evidence suggests that institutional investors respond to SA research, but not as

[IA4] The estimates of the effects of stale reports are relatively imprecise, however. We cannot reject the null that they differ from those of non-stale reports or from zero.

strongly as the reaction from retail investors. This is consistent with the evidence in Table 2 that SA research caters to retail investors, who have access to fewer alternative information sources.

IA.6 SA Research and the Informativeness of Retail Investor Trading - Sensitivity Tests

Table IA6 presents robustness checks for the informativeness evidence in Table 5. All specifications are based on Specification (2) of Table 5, and for brevity we focus on the coefficients on *Retail_OIB* × *Post_SA*. Specification (1) of Table IA6 presents the baseline result from Table 5 (0.256). In Specification (2), we explore the impact of stale reports. Specifically, we repeat the analysis after excluding reports authored by contributors with an identified matched blog (as defined in Section IA.4), and we find that the estimate on Post_SA × Retail_OIB increases slightly to 0.259pp.[IA5]

Our analysis in Table 5 includes specifications which exclude confounding events over the [-5,5] half-hour window. However, it does not address reports that are issued the day after earnings announcements. While reported earnings are generally available to all investors in the day after earnings releases, it is possible that the initial set of information increases (e.g., through earnings conference calls), which suggests that retail trading during the post-event window might be more informed even in the absence of SA reports. We address this concern by excluding reports issued one day after earnings announcements, which comprise 2.2% of all observations. In Specification (3) of Table IA6, we observe that the coefficient on *Post_SA* × *Retail_OIB* remains virtually unchanged (0.265pp). We also consider the impact of reports issued one day prior to earnings announcements (representing 6.0% of the sample), which could potentially break firm news. Excluding these reports results in a slightly reduction on the coefficient on Post_SA × Retail_OIB,

[IA5] We also separately examine contributors with an identified matched blog. The estimate for this subgroup is -0.0491% (*t*=-0.17). Thus, SA reports that were previously disseminated do not enhance retail trade informativeness.

but the estimates remains economically large (0.235pp) and highly significant in Specification (4).[IA6]

In our main tests, we limit the sample to reports issued between 10:30 am and 3:30 pm. While this filter is useful is minimizing the impact of confounding events (see Section 3), it does considerably reduce the sample size. We therefore also repeat the analysis using all Seeking Alpha reports. As in all the previous tests, we continue to impose the filter that there is no confounding information event over the [-5,5] window. The results of this analysis, reported in Specification (5), are similar to our baseline estimates.

Finally, we examine the stability of our results over time. We begin by estimating Equation (4) monthly from January 2007 through December 2017. We plot the cumulative coefficient on $Post\_SA \times Retail\_OIB$ from Specifications (2) of Table 5 in Figure IA2. We observe a jump in the second half of 2008 consistent with SA research being particularly valuable during the financial crisis, and a stable positive drift over the remainder of the 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 (Specification (6) of Table IA6), and continue to find that the coefficient on $Post\_SA \times Retail\_OIB$ is statistically significant. We also separately estimate the results for the first third (January 2007 – August 2010), middle third (September 2010-April 2014), and last third (May 2014-December 2017) of the sample period. The estimates from all three periods, reported in Specifications (7)-(9), are at least marginally significant ($p < 0.10$), consistent with the results being relatively stable over time.

[IA6] In the next section, we also separately examine trade informativeness for reports issued immediately prior to or following an earnings announcement and we consider longer pre- and post-earnings announcement windows.

IA.7 SA Research and the Informativeness of Retail Investor Trading around Earnings Announcements

In this section, we examine whether post-earnings SA research reports are associated with significantly larger (or smaller) changes in retail trade informativeness. We define the post-earnings period as day +1 and for robustness as the window [1, 3]. We then augment Specification (2) of Table 5 to include an indicator for reports issued in the post-earnings period, *Earn Indicator*, and its interaction with *Retail OIB* × *Post SA.*

Panel A of Table IA7 reports the estimates on *Retail OIB* × *Post SA* and *Retail OIB* × *Post SA* × *Earn Indicator*, as well as the fraction of SA reports occurring during the post-earnings periods. We find that a relatively small fraction of SA reports are issued after earnings announcements (2.2% for day +1 and 9.1% for days [1,3]). For either definition of post-earnings SA reports, the coefficient on *Retail OIB* × *Post SA* × *Earn Indicator* is statistically insignificant, whereas the coefficient on *Retail OIB* × *Post SA*, which captures the informativeness of all other reports, is highly significant and qualitatively similar to our baseline estimate of 0.256 pp, reported in Specification 2 of Table 5. We conclude that SA reports after earnings announcements are a relatively small portion of the sample, with no distinct effect on retail trade informativeness.

Panel B of Table IA7 presents analogous results for SA reports issued prior to earnings announcements. We observe that SA reports are more common in the days prior to earnings announcements (e.g., 6.0% for day -1 vs 2.21% for day +1). Furthermore, these reports are associated with significantly greater increases in retail trade informativeness. For example, SA reports published in the [-1,-3] window increase retail trade informativeness by an additional 0.822pp (t=2.21). We note that the coefficient on *Retail OIB* × *Post_SA* remains economically and statistically significant (0.182 pp, t=2.68), suggesting SA research published on other days still increases retail trade informativeness.

IA.8 SA Research, Retail Investor Trading, and Future Cash Flow News – Event Time

Figure IA3 repeats Specifications (2) and (5) of Table 7 after replacing *Retail_OIB* and $Post\_SA \times Retail\_OIB_{it}$ with *Retail_OIB* interacted with 11 separate measures of retail order imbalance for each half-hour period ranging from –5 to 5. Panel A reports the results for *Media Tone*. The figure shows that there is no obvious pre-trend in the period before publication. In addition, there is a noticeable and immediate spike upwards in the estimates during the post-event window. In particular, the estimates over the post-event window range from 1.29 to 2.70, each exceeding the pre-period mean of 0.93. Panel B of Figure IA3 reveals similar results for *Forecast Revisions*.

IA.9 SA Report Quality by Component

Table 9 of the paper shows that the increase in retail trading informativeness following SA research is greater among higher quality reports, where composite report quality is defined as the sum of four components. In Table IA8, we report the results separately for each measure of contributor skill. *Academic Quality* is an indicator equal to one if the contributor author's bio mentions that she has a PhD, an MBA, or graduated from a school in the top 50 of average SAT scores based on the 75th percentile, as reported in the 2015 vintage of stateuniversity.com. Our second measure our contributor skill is *Comments*, which is an indicator variable equal to one if the number of comments elicited by the report within 24 hours of the report release exceeds the yearly median.

We also consider two measures of skill based on past market reaction to reports. *Signed Returns* is an indicator variable that is equal to one if the average signed return to a contributor's last five (non-neutral) reports exceeds the yearly median. Signed returns are based on two-day market-adjusted reactions multiplied by the sign of the report, where sign is 1 (-1) for positive (negative) reports. Following Farrell, Jame, and Qiu (2020), reports are signed using a two-step procedure. First, reports with long (short) position disclosures are classified as positive (negative). For remaining reports, we compute the tone of the report as the percentage of negative words in the report (Loughran and McDonald, 2011), and we assign reports in the bottom (top) tercile of percent negative relative to the distribution of report tone on the previous day as positive (negative). Since signing reports is measured with error and excludes roughly 25% reports that are classified as neutral, we also consider *Unsigned Returns*, which equals one if the average absolute two-day market-adjusted reaction to a contributor's last five reports exceeds the yearly median and zero otherwise. We find the correlation between *Signed Returns* and *Unsigned Returns* is low (ρ =0.05), suggesting that both may contain independently useful information.

Panel A of Table IA8 reports the results when five-day ahead returns are the dependent variable. We find that the coefficients on *Post_SA* × *Retail_OIB* × *Quality* are positive and three of the four are statistically significant at a 5% level, and the remaining variable (*Comments*) is significant at a 10% level. The individual quality measures are less robust predictors of cash flow news. None of the four triple interaction terms are significant in isolation when *Media Tone* is the dependent variable in Panel B, and only two of the four predictors are significant at the 10% level (or better) for *Forecast Revisions* in Panel C.

IA.10 Daily Analysis of Seeking Alpha Research

In Section 5.5, we acknowledge that while our intraday analysis is well-suited for estimating the causal effects of SA research on retail trading, it has some limitations such as small sample size and poor ability to benchmark SA research publication events to other information events. In this section, we re-examine the effects of SA on retail trading intensity and retail order imbalances using a daily framework.

IA.10.1 Daily Estimates of Retail Trading Intensity

We estimate the effects of Seeking Alpha research on retail investor trading using the following daily panel regression:

$$Retail\_Trd_{i,t} = \alpha + \beta_1 Event_{i,t} + \beta_2 Char_{i,t} + Day_t + Firm_i \times Year + \varepsilon_{i,t.} \qquad \text{(IA.2)}$$

where *Retail_Trd* is *Retail Turnover* or *Percentage Retail Turnover*. $Event_{i,t}$ is a vector of event indicators: $SA_{i,t}$, $IBES_{i,t}$, $Media_{i,t}$, and $Earnings_{i,t}$. $\text{SA}_{i,t}$ is an indicator equal to one if there was at least one SA research report published between 1:30 pm on day *t*-1 and 4 pm on day *t*, and zero otherwise. We define all other events (i.e., *IBES*, *Media*, and *Earnings*) analogously.

We also control for time-series variation in aggregate retail trading activity with calendar day fixed effects, and firm-specific and time-varying retail trading intensity with *Firm* × *Year* fixed effects. The inclusion of *Firm* × *Year* fixed effects also controls for firm characteristics that are stable within a firm-year (e.g., *Size*, *Book-to-Market*, *Institutional Ownership*, *Volatility*, *Turnover*, *Return*, *Profitability*, *IBES Coverage*, and *Media Coverage)*. Char is a vector of time-varying firm characteristics, including returns estimated over the prior week ($Ret_{i,w-1}$), prior month ($Ret_{i,m-1}$) and prior two to seven month ($Ret_{i,[m-7,-m-2]}$), absolute returns estimated over the same intervals ($AbsRet_{i,w-1}$, $AbsRet_{i,m-1}$, and $AbsRet_{i,[m-7,-m-2]}$), and retail trading over the prior week ($RetailTurnover_{i,w-1}$ *or* $Percent\ Retail_{i,w-1}$). All continuous independent variables are standardized to have mean zero and unit variance, and standard errors are clustered by firm.

Specifications (1) and (2) of Table IA9 report the results for *Retail Turnover* and *Percent Retail*, respectively. We find that the estimate for *Retail Turnover* is a highly significant 6.70% on days with SA research. This effect is larger than the estimated effect for *Media* (3.70%) and similar to the effect for IBES research (7.10%). We also find that retail trading increases by more than institutional trading. Specifically, *Percent Retail* increased by 0.24 percentage points. This effect is substantially larger than the estimated effects for Media or IBES (both 0.03pp), further corroborating the importance of SA as a source of investment analysis for retail investors.

IA.10.2 Daily Estimates of Retail Order Imbalances

We estimate the effects of Seeking Alpha research sentiment on retail investor order imbalances using the following daily panel regression:

$$Retail\_OIB_{i,t} = \alpha + \beta_1 Event_{i,t} + \beta_2 Event\_Sentiment_{i,t} + \beta_3 Char_{i,t} + Day_t + Firm_i \times Year + \varepsilon_{i,t}. \quad \text{(IA.3)}$$

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). *Event*$_{i,t}$ is a vector of event indicators: *SA*$_{i,t}$, *IBES*$_{i,t}$, *Media*$_{i,t}$, and *Earnings*$_{i,t}$. *SA*$_{i,t,}$ as defined in Equation IA.2. *Event_Sentiment*$_{i,t}$ is the sentiment score associated with the *Event*. We classify SA research as having positive (negative) sentiment when the fraction of positive (negative) words in the SA report is above the sample median (using the word list in Loughran and McDonald's, 2011 as in Chen et al. 2014). 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). We consider each individual measure separately, as well as a measure of *Composite Sentiment*, defined as the sum of the four measures of SA Sentiment (i.e., *Long* + *Pos. Tone* – *Short* – *Neg. Tone*).[IA7] *Media Sentiment* equals one if

[IA7] If multiple SA reports are released for the same firm *i* and day *t*, each sentiment measure (i.e., *Long*, *Short*, *Neg. Tone*, *Pos. Tone*, and *Composite* Sentiment) is computed as the average value of the sentiment measure across all reports.

the ESS (RavenPack sentiment score) for the article exceeds 50 (the ESS score assigned to neutral articles), *IBES sentiment* is an indicator equal to one if the IBES research report contained a recommendation upgrade or upward forecast revision, and *Earnings Sentiment* is an indicator equal to one if the earnings surprise is positive relative to the consensus forecast and zero otherwise. Char includes a vector of time-varying firm characteristics including returns estimates over the prior week ($Ret_{i,w-1}$), prior month ($Ret_{i,m-1}$) and prior two to seven month ($Ret_{i,[m-7,m-2]}$), absolute returns estimated over the same intervals ($AbsRet_{i,w-1,}$ $AbsRet_{i,m-1,}$ and $AbsRet_{i,[m-7,m-2]}$), and retail order imbalances over the prior week ($Retail\_OIB_{i,w-1}$). As in Equation (IA.2), the regressions also include *Day* and *Firm* × *Year* fixed effects.

The results are reported in Table IA10. We find robust evidence that Seeking Alpha research sentiment predicts retail order imbalances. For example, Specification (1) reports that retail order imbalance increases (decreases) by 1.13 percentage points (-2.21pp) when an SA contributor discloses a long (short) investment position and 0.33pp (-0.86pp) when the report's positive (negative) tone is above the median, and Specification (2) indicates that a one unit increase in *Composite Sentiment* is associated with a 0.80pp increase in retail order imbalance. We also find that retail order imbalances are correlated with the sentiment of sell-side research and media articles, but the magnitudes are considerably smaller than for SA research reports.

IA.10.3 Retail Informativeness in the Days Around Seeking Alpha Research

For robustness, we examine the dynamics of retail trade informativeness around the release of the SA report. We modify Equation (6) by interacting $Retail\_OIB_{i,t}$ with dummy variables that indicate days -2, -1, +1, and +2 relative to SA publication day. In Table IA11, we find that the coefficients on these interactions terms are positive but statistically insignificant, which suggests that retail trading on these SA publication-adjacent days is at least as informed as retail trading on a typical day.

IA.10.4 Decomposing Retail Trading into Price Pressure, Liquidity Provision, and Informed Trading

The positive association between retail order imbalances and future returns following Seeking Alpha research is consistent with informed trading, but it could also be related to liquidity provision or price pressure. The evidence that retail order imbalances forecast future cash flows news suggests that informed trading contributes to at least *some* of the return predictability following SA research, but does not speak to the relative importance of each of the three hypotheses. In this section, we use the daily return decomposition of BJZZ to estimate the relative importance of informed trading, price pressure, and liquidity provision after SA research reports.

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: $Retail\_OIB_{i,t} = \alpha + \beta_1 Retail\_OIB_{i,w-1} + \beta_2 Ret_{i,w-1} + \varepsilon_{i,t}$, where *OIB Persistence* $= \hat{\beta}_1 Retail\ OIB_{i,w-1}$; *OIB Contrarian* $= \hat{\beta}_2 Ret_{i,w-1}$; and *OIB Other* $= \hat{\varepsilon}_{i,t}$. We then estimate Equation (6) in the text after replacing *Retail_OIB* (total retail order imbalance) with *OIB Persistence, OIB Contrarian,* or *OIB Other (Informed).*

Specifications (1)-(3) of Table IA12 report the results. We find that the coefficient on *OIB Persistence* × *SA* and *OIB Contrarian* × *SA* are statistically insignificant and economically small. In contrast, the coefficient on *OIB Other* × *SA* is highly significant and virtually identical to the estimate reported in Specification (1) of Table 10. The decomposition evidence suggests that the increase in the positive association between retail order imbalances and future returns is entirely attributable to informed trading, rather than liquidity provision or price pressure.

Internet Appendix References:

Boehmer, E., Jones, C., Zhang, X., and Zhang, X., 2020. Tracking retail investor activity. *Journal of Finance*, forthcoming.

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.

Farrell, M., Jame, R., Qiu, T., 2020. The cross-section of non-professional analyst skill. Working paper.

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.

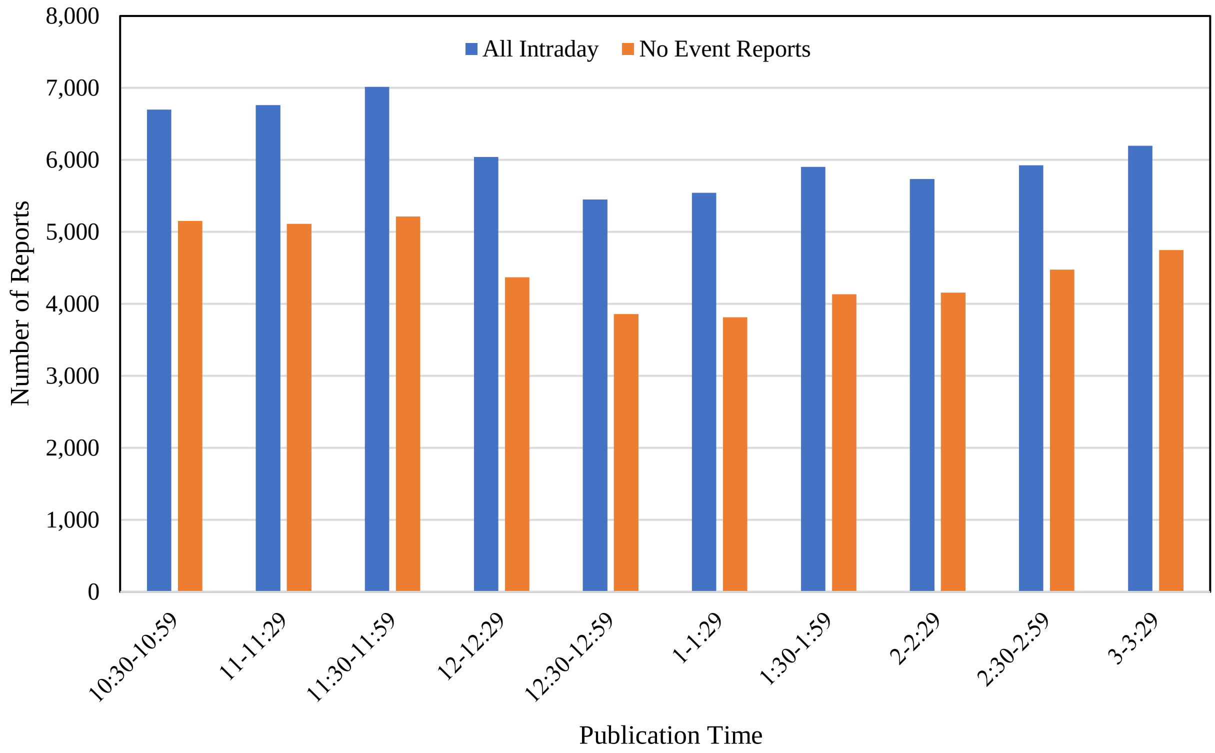


Figure IA1. Distribution of Intraday Seeking Alpha Reports.
This figure plots the distribution of report publication times for SA reports published between 10:30 am and 3:30 pm (*All Intraday*). *No Event Reports* denotes the subset of intraday reports that are not confounded by other media articles, IBES research, or earnings announcements during the ten half-hour intervals surrounding the SA report publication.

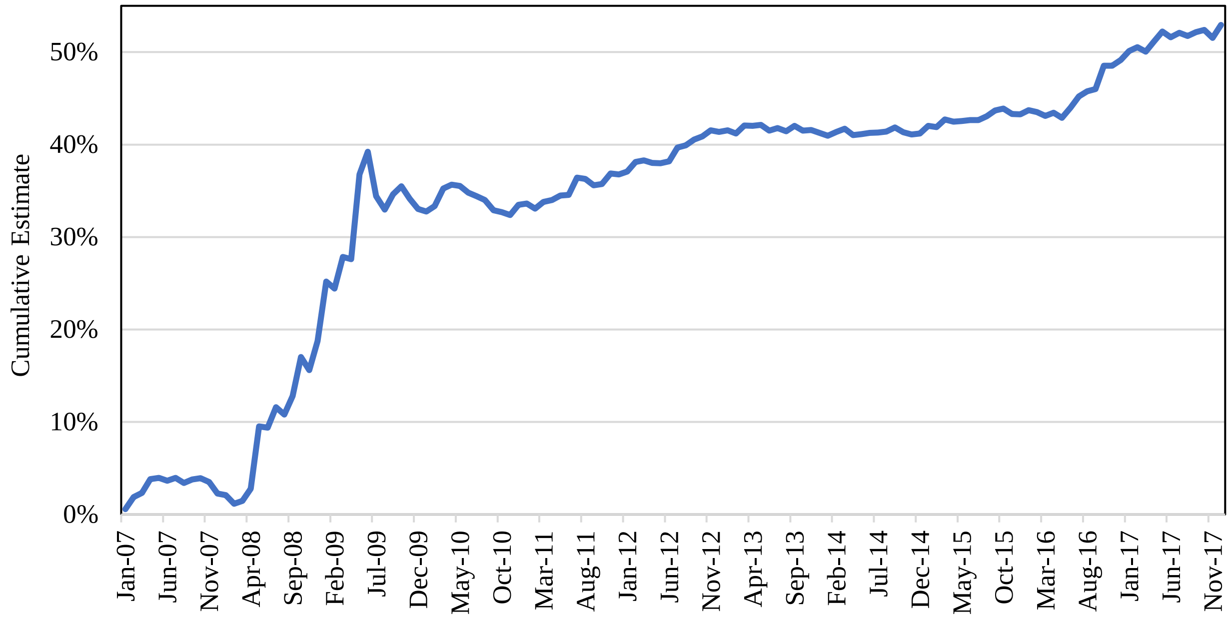
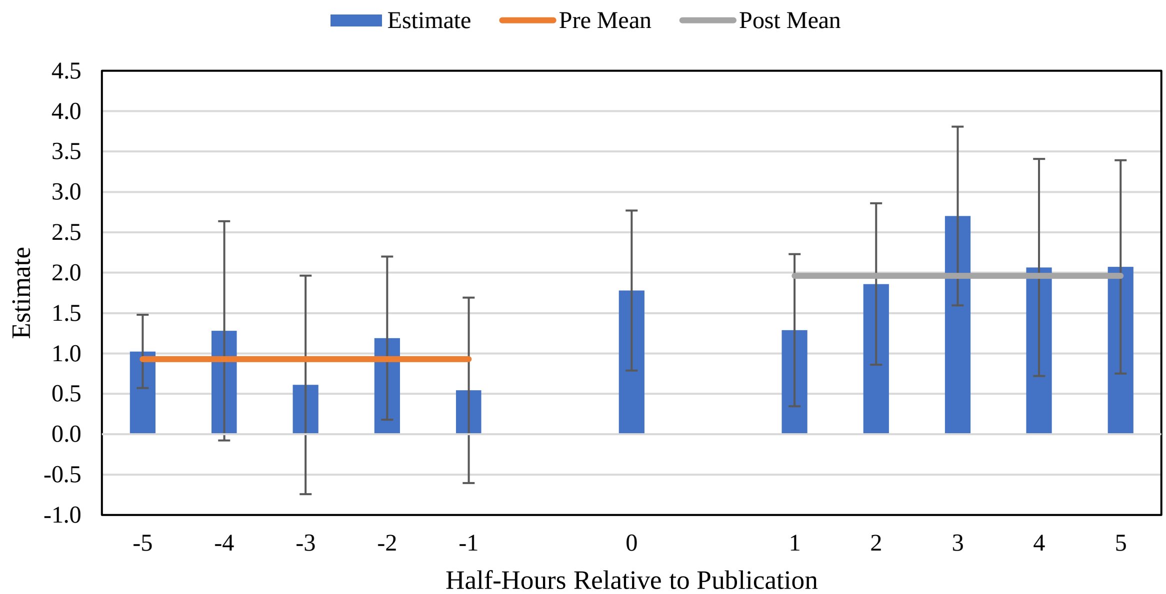


Figure IA2. SA Research and the Informativeness of Retail Order Imbalances over Time
We estimate Specification (2) of Table 5 for each month from January 2007 through December 2017. The blue line plots the *cumulative* coefficient on *Retail_OIB* × *Post_SA* for each month over the sample period.

Panel A: Media Articles



Panel B: Forecast Revisions

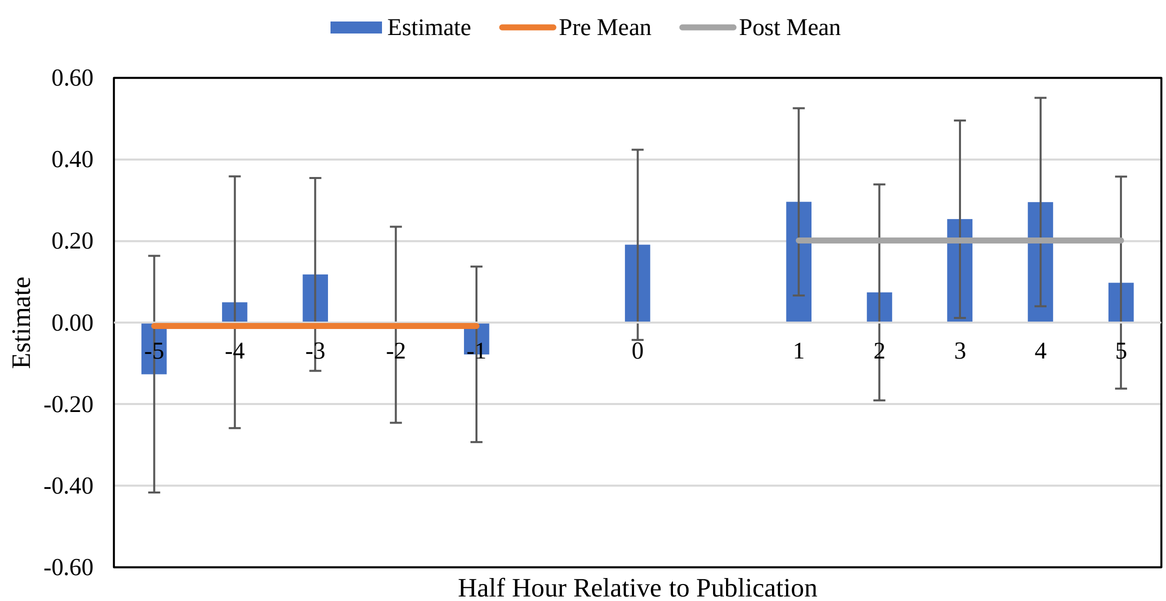


Figure IA3. SA Research and the Informativeness of Retail Trading: Predicting Future Cash Flow News – Event Time. The figures in Panel A and Panel B plot estimates from Specification (2) and (4) of Table 7 after replacing *Retail OIB* and *PostSA* × *Retail OIB*$_{it}$ with 11 separate retail order imbalance variables for each half-hour period ranging from [-5] to [5]. We report the coefficients on these variables as blue bars, and their 95% confidence intervals as error bars. The average of the pre-event and post-event coefficient estimates appear as orange and grey horizontal lines.

Table IA1. Characteristics of Stocks Covered by Seeking Alpha

The table reports the time-series average of annual cross-sectional summary statistics. The *Seeking Alpha Reports* sample includes all reports issued by Seeking Alpha over the 2006-2017 sample period. Across all SA reports in a year, we compute the mean, median, standard deviation, and the 25th and 75th percentiles of the following firm attributes: market capitalization (*Size*), book to market (*BM*), daily return volatility (*Volatility*), daily share turnover *(Turnover)*, past one-year return ($Return_{m-12,m-1}$), past one-year profitability (*Profitability*), the number of sell-side analysts covering the firm in the prior year (*IBES Coverage*), the number of unique media articles mentioning the firm in the prior year (*Media Coverage*), the percentage of the firm's shares held by institutional investors in the prior year (*Inst Ownership*), and the number of common shareholders in the prior year (*Breadth of Ownership*). We also report the means of the firm attributes across all stocks in the CRSP-Compustat merged sample, where we either equally weight each firm (*EW Market*) or value-weight each firm by its market capitalization at the end of the prior year *(VW Market)*.

	Seeking Alpha Reports					Market Portfolio	
	Mean	Median	Standard Deviation	25th	75th	VW Market Mean	EW Market Mean
Size ($Bil)	61.03	13.92	13.50	2.10	85.67	89.30	4.60
BM	0.55	0.33	0.12	0.18	0.63	0.46	0.82
Volatility	2.46%	2.15%	0.16%	1.62%	2.99%	1.79%	2.98%
Turnover	13.31%	9.48%	1.96%	5.70%	16.58%	8.00%	6.60%
$Return_{[m-12, m-1]}$	14.91%	8.39%	7.35%	-14.18%	33.44%	10.56%	11.81%
Profitability	13.58%	14.48%	2.43%	6.38%	23.69%	16.05%	6.37%
IBES Coverage	24.50	24.18	1.86	13.27	34.27	25.54	9.32
Media Coverage	250.19	206.32	24.08	101.91	352.64	272.66	84.20
Institutional Ownership	66.58%	68.71%	2.78%	57.48%	81.40%	68.92%	55.84%
Breadth of Ownership	103.25	9.28	70.36	1.14	57.83	176.39	21.35

Table IA2. The Relation Between Seeking Alpha Report Timing and the Timing of Major Information Events

Specifications (1)-(3) report the results from the estimation of Equation (IA.1):

$$Event_{i,t} = \alpha + \beta_1 Post\_SA_{i,t} + Report_i + HalfHour_t \times Month + \varepsilon_{it}.$$

$Event_{i,t}$ indicates the occurrence of an event (earnings announcement, IBES report, or media article) in a half-hour window *t* around the publication of an SA report *i*. *Post_SA*, is equal to one when *t* is in the interval [1, 5] and zero when it is the interval [-5, -1]. In Specifications (4)-(6), we include the half-hour publication window 0 and replace the *Post_SA* indicator with ten indicators representing individual event windows -4 through 5. *Report* denotes report fixed effects and *Half Hour* × *Month* denotes fixed effects for each half-hour of the trading interacted with month fixed effects. Standard errors are clustered by date, with *t*-statistics reported in parentheses.

	Earnings	IBES Research	Media Articles	Earnings	IBES Research	Media Articles
	(1)	(2)	(3)	(4)	(5)	(6)
Post_SA	0.00%	0.05%	-0.06%			
	(-0.21)	(0.84)	(-0.77)			
SA[-4]				0.00	0.06	-0.09
				(-0.68)	(0.69)	(-0.80)
SA[-3]				0.01	-0.05	-0.04
				(1.38)	(-0.58)	(-0.32)
SA[-2]				0.00	0.04	-0.10
				(-0.36)	(0.49)	(-0.93)
SA[-1]				0.00	0.07	-0.05
				(-0.11)	(0.85)	(-0.49)
SA[0]				-0.01	0.08	-0.07
				(-0.88)	(0.87)	(-0.60)
SA[1]				0.00	0.01	-0.13
				(0.43)	(0.11)	(-1.10)
SA[2]				0.00	0.16	-0.16
				(0.02)	(1.67)	(-1.30)
SA[3]				0.00	0.11	-0.10
				(0.04)	(1.15)	(-0.74)
SA[4]				-0.01	0.07	-0.11
				(-1.42)	(0.66)	(-0.79)
SA[5]				-0.01	0.06	-0.14
				(-0.99)	(0.57)	(-0.98)
Observations	485,710	485,710	485,710	546,992	546,992	546,992
Report and Half Hour × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Period	[-5,5]	[-5,5]	[-5,5]	[-5,5], Include 0	[-5,5], Include 0	[-5,5], Include 0
R-squared	12.5%	25.1%	14.8%	11.2%	24.1%	13.5%

Table IA3. SA Research and the Intensity of Retail Investor Trading: Stale Reports

Specifications 1 and 2 of this table reports the estimates from Specification 2 of Table 3 after partitioning the sample into reports authored by contributors with matched blogs (Specification 1) and reports authored by contributors without matched blogs (Specification 2). Specifications 3 and 4 reports the estimates from Specification 3 of Table 4 after conducting the same partition. The sample is limited to contributors who author at least 10 reports. We identify a contributor as having a matched blog if the contributor provides a link on her SA bio page to a personal webpage, and we find at least one of her SA reports on her personal webpage.

	Log (Retail Volume)		Retail OIB	
	Stale Reports	Not Stale Reports	Stale Reports	Not Stale Reports
	[1]	[2]	[3]	[4]
Post × SA Composite Sentiment			0.68%	0.97%
			(0.69)	(4.53)
Post_SA	5.12%	6.58%	-0.31%	0.25%
	(1.30)	(5.64)	(-0.29)	(1.12)
Abs $Ret_{i,t\text{-}1}$	8.51%	10.24%	-0.20%	0.26%
	(5.28)	(22.69)	(-0.39)	(2.42)
Abs $Ret_{i,[t\text{-}5,t\text{-}2]}$	4.07%	3.27%	1.12%	0.32%
	(2.31)	(6.84)	(2.03)	(2.75)
$Ret_{i,t\text{-}1}$	2.92%	1.16%	-1.13%	-1.62%
	(1.81)	(3.12)	(-2.49)	(-16.59)
$Ret_{i,[t\text{-}5,t\text{-}2]}$	5.11%	0.82%	-2.22%	-1.58%
	(2.66)	(1.69)	(-4.69)	(-13.29)
Observations	14,528	267,697	14,528	267,697
SA Reports	No Events	No Events	No Events	No Events
Event Period	[-5,5]	[-5,5]	[-5,5]	[-5,5]
Report FE	Yes	Yes	Yes	Yes
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	81.97%	80.76%	20.03%	20.53%

Table IA4. Seeking Alpha Research Publication and Institutional Investor Trading

This table repeats the intraday panel regressions reported in Table 3 of the paper after replacing *Retail Volume* with *Institutional Volume* defined as log (1 + Total Trading Volume – Retail Volume).

	(1)	(2)	(3)
Post_SA	4.30%	6.64%	5.32%
	(4.30)	(5.82)	(6.48)
$Abs\ Ret_{i,[t-1]}$	6.71	6.80	5.06
	(21.10)	(18.29)	(8.55)
$Abs\ Ret_{i,[t-5,t-2]}$	1.76	1.65	-0.28
	(5.27)	(3.90)	(-0.45)
$Ret_{i,[t-1]}$	0.60	0.62	1.29
	(2.38)	(1.97)	(2.61)
$Ret_{i,[t-5,t-2]}$	0.28	0.90	0.45
	(0.78)	(2.10)	(0.76)
$High\ Volume_{i,t-1}$	11.84	11.34	6.64
	(14.59)	(10.92)	(4.06)
$High\ Volume_{i,[t-5,\ t-2]}$	-9.26	-11.26	-26.84
	(-5.27)	(-4.71)	(-9.63)
$Low\ Volume_{i,t-1}$	-6.48	-5.62	-0.90
	(-4.29)	(-3.72)	(-0.49)
$Low\ Volume_{i,[t-5,\ t-2]}$	13.20	15.26	30.07
	(4.81)	(5.23)	(8.04)
Observations	485,710	354,755	90,076
SA Reports	All Intraday	No Events	No Events
Event Period	[-5, 5]	[-5, 5]	[-1, 1]
Report FE	Yes	Yes	Yes
Half Hour × Month FE	Yes	Yes	Yes
R-squared	80.4%	81.1%	91.2%

Table IA5. Seeking Alpha Research Sentiment and Institutional Investor Order Imbalances

This table repeats the intraday panel regressions reported in Table 4 of the paper after replacing *Retail_OIB* with *Institutional_OIB*, defined as non-retail buy volume less non-retail sell volume scaled by non-retail trading volume, where non-retail buy (sell) volume is total buy (sell) volume less retail buy (sell) volume.

	(1)	(2)	(3)	(4)
Post × SA Long	0.34			
	(2.05)			
Post × SA Short	-0.01			
	(-0.03)			
Post × SA Negative Tone	-0.48			
	(-3.03)			
Post × SA Positive Tone	-0.01			
	(-0.04)			
Post × SA Composite Sentiment		0.23	0.36	0.57
		(2.69)	(3.41)	(3.48)
Post × SA	0.30	0.06	0.16	0.32
	(1.86)	(0.66)	(1.45)	(2.13)
$Abs\ Ret_{i,t-1}$	0.04	0.04	0.04	-0.10
	(0.82)	(0.86)	(0.72)	(-0.85)
$Abs\ Ret_{i,[t-5,t-2]}$	0.10	0.10	0.15	0.16
	(1.90)	(1.99)	(2.29)	(1.27)
$Ret_{i,t-1}$	-0.39	-0.39	-0.44	-0.93
	(-9.57)	(-10.03)	(-8.60)	(-9.23)
$Ret_{i,[t-5,t-2]}$	-0.93	-0.93	-1.08	-1.74
	(-18.52)	(-19.62)	(-17.22)	(-14.21)
$High\ Volume_{i,t-1}$	0.23	0.23	0.16	0.32
	(2.00)	(2.11)	(1.12)	(1.16)
$High\ Volume_{i,[t-5,\ t-2]}$	0.09	0.11	0.11	0.33
	(0.51)	(0.61)	(0.44)	(0.71)
$Low\ Volume_{i,t-1}$	-0.11	-0.11	-0.24	0.19
	(-0.77)	(-0.77)	(-1.40)	(0.59)
$Low\ Volume_{i,[t-5,\ t-2]}$	0.18	0.18	-0.06	-0.35
	(0.64)	(0.66)	(-0.19)	(-0.57)
Observations	485,710	485,710	354,755	90,076
SA Reports	All Intraday	All Intraday	No Events	No Events
Half-Hour Event Window	[-5, 5]	[-5, 5]	[-5, 5]	[-1, 1]
Report FE	Yes	Yes	Yes	Yes
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	22.6%	22.6%	22.4%	56.6%

Table IA6. SA Research and the Informativeness of Retail Investor Trading: Robustness

The table presents the results of variations of the retail trade informativeness results reported in Table 5. Row 1 reports the results from the baseline result from Specification 2 of Table 5. Row 2 excludes reports issued by contributors with matched blogs (as defined in Table IA.3). Rows 3 and 4 exclude reports that are issued the day after or the day before an earnings announcement. Row 5 repeats the analysis after including reports issued during non-trading hours. Row 6 excludes reports issued during the financial crisis (July 2008-December 2008). Rows 7, 8, and 9 report the results for reports issued in the first third, middle third, and last third of our sample.

	Observations	Estimate	*t*-statistic
1. Baseline	353,557	0.256	(3.51)
2. Exclude Stale Reports	268,689	0.259	(3.64)
3. Exclude Post-Earnings Reports	345,711	0.265	(3.58)
4. Exclude Pre-Earnings Reports	334,401	0.235	(3.46)
5. Include Overnight Reports	593,470	0.175	(2.71)
6. Exclude Financial Crisis (July - Dec 2008)	347,601	0.230	(3.25)
7. First third of sample (Jan 2007 - Aug 2010)	36,176	0.721	(1.83)
8. Middle third of sample (Sep 2010- April 2014)	124,764	0.168	(1.91)
9. Last third of sample (May 2014 - Dec 2017)	192,617	0.217	(2.42)

Table IA7. SA Research and the Informativeness of Retail Trading around Earnings Announcements

This table repeats Specification (2) of Table 5 after including an indicator for reports issued near an announcement and interacting this indicator with *Retail OIB × Post_SA*. Panel A reports the results when the earning indicator is defined as either the day after earnings [1], or one to three days after earnings [+1, +3]. Panel B reports analogous results for reports issued prior to earnings announcements. In the interest of brevity, we only report the estimates on *Retail OIB × Post SA* and *Retail OIB × Post SA × Earn Indicator*. We also report the fraction of total SA reports that occur over each earnings event window.

Panel A: Post Earnings SA Reports

		Retail OIB × Post SA		*Retail OIB × Post SA × Earn Indicator*	
Earnings Day	*Fraction of Repots*	*Estimate*	*t-stat*	*Estimate*	*t-stat*
+1	2.21%	0.263	(3.56)	-0.400	(-1.07)
[+1, +3]	9.11%	0.228	(3.15)	0.350	(1.27)

Panel B: Pre-Earnings SA Reports

		Retail OIB × Post SA		*Retail OIB × Post SA × Earn Indicator*	
Earnings Day	*Fraction of Repots*	*Estimate*	*t-stat*	*Estimate.*	*t-stat*
-1	6.02%	0.233	(3.42)	0.436	(0.83)
[-1, -3]	10.18%	0.182	(2.68)	0.822	(2.21)

Table IA8. SA Research and Retail Order Informativeness: Components of Report Quality

This table repeats the intraday panel regressions from Table 9 of the paper after replacing *Report Quality* with either *Academic Quality*, *Unsigned Return*, *Signed Return*, or *Comments*. Half Hour × Month fixed effects are included. Detail variable definitions are in Appendix A.

Panel A: Stock Returns

	Academic Quality	*Unsigned Return*	*Signed Return*	*Comments*
Retail_OIB	-0.054%	-0.048%	-0.069%	-0.096%
	(-1.05)	(-0.78)	(-0.95)	(-1.88)
Retail_OIB × Quality	-0.389%	-0.106%	-0.073%	-0.027%
	(-2.04)	(-1.00)	(-0.70)	(-0.20)
Retail_OIB × Post_SA	0.181%	0.083%	0.056%	0.167%
	(2.53)	(0.96)	(0.60)	(2.22)
Retail_OIB × Post_SA × Quality	0.569%	0.327%	0.395%	0.285%
	(2.14)	(2.29)	(2.80)	(1.72)
Report Quality	0.112%	-0.158%	0.122%	-0.077%
	(1.02)	(-2.08)	(1.43)	(-0.74)
Institutional_OIB	0.179%	0.183%	0.181%	0.180%
	(1.71)	(1.75)	(1.74)	(1.72)
Institutional_OIB × Post	0.237%	0.227%	0.233%	0.225%
	(1.69)	(1.64)	(1.67)	(1.62)
Abs $Ret_{i,[t-1]}$	-0.023%	-0.017%	-0.024%	-0.023%
	(-0.47)	(-0.35)	(-0.49)	(-0.46)
Abs $Ret_{i,[t-5,t-2]}$	-0.067%	-0.060%	-0.068%	-0.066%
	(-1.00)	(-0.90)	(-1.01)	(-0.99)
$Ret_{i,[t-1]}$	0.028%	0.028%	0.029%	0.028%
	(1.06)	(1.05)	(1.07)	(1.06)
$Ret_{i,[t-5,t-2]}$	0.046%	0.046%	0.046%	0.046%
	(1.00)	(0.99)	(1.00)	(1.00)
High $Volume_{i,t-1}$	0.025%	0.025%	0.025%	0.025%
	(0.36)	(0.37)	(0.36)	(0.37)
High $Volume_{i,[t-5, t-2]}$	-0.288%	-0.282%	-0.289%	-0.290%
	(-2.24)	(-2.20)	(-2.25)	(-2.26)
Low $Volume_{i,t-1}$	0.012%	0.011%	0.011%	0.012%
	(0.28)	(0.24)	(0.25)	(0.28)
Low $Volume_{i,[t-5, t-2]}$	-0.124%	-0.131%	-0.123%	-0.124%
	(-1.05)	(-1.12)	(-1.05)	(-1.06)
Observations	353,557	353,557	353,557	353,557
SA Sample	No Event	No Event	No Event	No Event
Event Period	[-5,5]	[-5,5]	[-5,5]	[-5,5]
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	1.16%	1.17%	1.16%	1.16%

Table IA8. SA Research and Retail Order Informativeness: Components of Report Quality (continued)

Panel B: Media Tone

	Academic Quality	*Unsigned Return*	*Signed Return*	*Comments*
Retail_OIB	1.07	0.75	0.72	1.10
	(3.14)	(1.73)	(1.34)	(2.38)
Retail_OIB × Quality	-1.32	0.27	0.38	-0.61
	(-0.96)	(0.41)	(0.51)	(-0.82)
Retail_OIB × Post_SA	0.71	0.55	1.06	0.61
	(1.71)	(1.11)	(1.65)	(1.20)
Retail_OIB × Post_SA × Quality	2.17	0.87	-0.09	1.32
	(1.31)	(1.11)	(-0.10)	(1.36)
Report Quality	6.07	2.95	0.39	0.20
	(5.44)	(4.81)	(0.68)	(0.27)
Institutional_OIB	0.63	0.55	0.60	0.62
	(1.00)	(0.87)	(0.96)	(1.00)
Institutional_OIB × Post	0.26	0.28	0.27	0.22
	(0.32)	(0.35)	(0.33)	(0.28)
$Abs\ Ret_{i,[t-1]}$	-1.94	-2.07	-1.95	-1.95
	(-8.90)	(-9.27)	(-8.98)	(-9.10)
$Abs\ Ret_{i,[t-5,t-2]}$	-2.70	-2.87	-2.73	-2.74
	(-10.48)	(-10.85)	(-10.54)	(-10.75)
$Ret_{i,[t-1]}$	0.12	0.14	0.13	0.13
	(1.12)	(1.30)	(1.23)	(1.23)
$Ret_{i,[t-5,t-2]}$	-0.06	-0.05	-0.06	-0.06
	(-0.32)	(-0.26)	(-0.31)	(-0.30)
$High\ Volume_{i,t-1}$	3.42	3.45	3.46	3.46
	(6.00)	(6.05)	(6.04)	(6.07)
$High\ Volume_{i,[t-5,\ t-2]}$	1.15	1.08	1.19	1.20
	(1.06)	(0.98)	(1.09)	(1.10)
$Low\ Volume_{i,t-1}$	-2.54	-2.58	-2.59	-2.60
	(-6.82)	(-6.87)	(-6.88)	(-6.92)
$Low\ Volume_{i,[t-5,\ t-2]}$	-4.79	-4.72	-4.85	-4.85
	(-5.31)	(-5.18)	(-5.30)	(-5.29)
$Media\ Tone_{[0]}$	0.07	0.07	2.00	0.07
	(3.65)	(3.48)	(3.49)	(3.50)
$Media\ Tone_{[-5,-1]}$	0.03	0.03	1.41	0.03
	(3.89)	(3.85)	(3.79)	(3.79)
$Media\ Tone_{[-26,\ -6]}$	0.07	0.07	7.28	0.07
	(12.46)	(12.61)	(12.42)	(12.41)
Observations	276,097	276,097	276,097	276,097
SA Sample	No Event	No Event	No Event	No Event
Event Period	[-5,5]	[-5,5]	[-5,5]	[-5,5]
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	7.58%	7.49%	7.40%	7.40%

Table IA8. SA Research and Retail Order Informativeness: Components of Report Quality (continued)

Panel C: Forecast Revisions

	Academic Quality	*Unsigned Return*	*Signed Return*	*Comments*
Retail_OIB	0.02	0.03	0.08	0.00
	(0.22)	(0.31)	(0.65)	(-0.01)
Retail_OIB × Quality	-0.09	-0.05	-0.14	0.05
	(-0.37)	(-0.35)	(-0.85)	(0.30)
Retail_OIB × Post_SA	0.14	0.00	-0.10	0.12
	(1.41)	(0.03)	(-0.67)	(0.94)
Retail_OIB × Post_SA × Quality	0.35	0.37	0.61	0.21
	(1.07)	(1.77)	(2.69)	(1.06)
Report Quality	0.72	0.20	0.06	-0.34
	(3.98)	(1.94)	(0.47)	(-3.01)
Institutional_OIB	0.30	0.30	0.30	0.29
	(1.64)	(1.63)	(1.64)	(1.60)
Institutional_OIB × Post	0.17	0.17	0.17	0.16
	(0.89)	(0.86)	(0.88)	(0.83)
$Abs\ Ret_{i,[t-1]}$	-0.12	-0.13	-0.13	-0.12
	(-3.99)	(-4.19)	(-4.01)	(-3.98)
$Abs\ Ret_{i,[t-5,t-2]}$	-0.24	-0.25	-0.24	-0.23
	(-6.04)	(-6.33)	(-6.15)	(-6.06)
$Ret_{i,[t-1]}$	0.06	0.06	0.06	0.06
	(3.40)	(3.48)	(3.45)	(3.44)
$Ret_{i,[t-5,t-2]}$	0.09	0.09	0.09	0.09
	(2.29)	(2.33)	(2.32)	(2.28)
$High\ Volume_{i,t-1}$	0.26	0.26	0.26	0.26
	(2.67)	(2.73)	(2.74)	(2.69)
$High\ Volume_{i,[t-5,\ t-2]}$	0.08	0.08	0.08	0.06
	(0.42)	(0.41)	(0.44)	(0.33)
$Low\ Volume_{i,t-1}$	-0.20	-0.20	-0.20	-0.20
	(-3.08)	(-3.11)	(-3.12)	(-3.08)
$Low\ Volume_{i,[t-5,\ t-2]}$	-0.31	-0.31	-0.31	-0.31
	(-1.49)	(-1.48)	(-1.52)	(-1.51)
$Revisions_{[0]}$	0.60	0.59	1.81	0.60
	(10.22)	(10.20)	(10.21)	(10.21)
$Revisions_{[-5,-1]}$	0.10	0.10	0.57	0.10
	(11.06)	(10.95)	(10.95)	(10.97)
$Revisions_{[-26,-6]}$	0.08	0.08	0.82	0.08
	(8.59)	(8.54)	(8.56)	(8.57)
Observations	157,680	157,680	157,680	157,680
SA Sample	No Event	No Event	No Event	No Event
Event Period	[-5,5]	[-5,5]	[-5,5]	[-5,5]
Half Hour × Month FE	Yes	Yes	Yes	Yes
R-squared	13.51%	13.42%	13.40%	13.45%

Table IA9. Seeking Alpha Research Coverage and the Intensity of Retail Investor Trading (Daily)
The table presents the results from the following daily panel regression:

$$Retail\ Trade_{i,t} = \beta_1 SA_{i,t-1} + \beta_2 Event_{i,t} + \beta_3 Char_{i,t} + Day_t + Firm_i \times Year_t + \varepsilon_{i,t.}$$

Retail Trade is either *Retail Vol* defined as log (1 + Retail Volume) for stock *i* on day *t* or *Percent Retail Trading* defined as total retail trading volume in stock *i* on day *t* scaled by total aggregate trading volume in stock *i* on day *t*. Trades are classified as retail using the approach of Boehmer et al. (2020). $SA_{i,t}$ is an indicator equal to one if at least one SA research report on stock *i* is published between 1:30 pm on day *t*-1 and 4 pm on day *t*. $Event_{i,t}$ is a vector of indicators for $Media_{i,t}$, $IBES_{i,t}$, and $Earnings_{i,t}$, defined analogously to $SA_{i,t}$. *Char* includes the return and the absolute return over the previous week ($Ret_{i,w\text{-}1}$, $AbsRet_{i,w\text{-}1}$), the previous month ($Ret_{i,m\text{-}1}$, $AbsRet_{i,m\text{-}1}$), the previous two to seven month ($Ret_{i,[m\text{-}7,m\text{-}2]}$, $AbsRet_{i,[m\text{-}7,m\text{-}2]}$), and the lag of the dependent variable measured over the previous five trading days ($Retail\ Turnover_{i,w\text{-}1}$ or $Percent\ Retail\ Trading_{i,w\text{-}1}$). All continuous independent variables are standardized to have mean zero and unit variance. Day_t denotes calendar day fixed effects and $Firm_i \times Year_t$ denotes fixed effects for each firm interacted with year fixed effects. Standard errors are clustered by date, and *t*-statistics are reported below each estimate.

	Log (Retail Turnover)	*Percent Retail Trading*
	(1)	(2)
SA	6.70	0.24
	(69.71)	(23.63)
Media	3.70	0.03
	(83.97)	(5.16)
IBES	7.10	0.03
	(120.10)	(5.54)
Earnings	40.60	0.60
	(116.62)	(25.30)
$Ret_{i,w\text{-}1}$	0.40	-0.01
	(10.31)	(-2.39)
$Ret_{i,m\text{-}1}$	0.20	-0.04
	(4.02)	(-5.50)
$Ret_{i,[m\text{-}7,m\text{-}2]}$	0.10	-0.08
	(0.46)	(-4.75)
$Abs\ Ret_{i,w\text{-}1}$	5.90	0.19
	(121.65)	(35.42)
$Abs\ Ret_{i,m\text{-}1}$	-0.20	0.12
	(-3.49)	(17.59)
$Abs\ Ret_{i,[m\text{-}7,m\text{-}2]}$	-0.40	0.05
	(-4.67)	(3.28)
$Log\ Retail\ Turnover_{i,w\text{-}1}$	20.30	
	(51.80)	
$Percent\ Retail\ Trading_{i,w\text{-}1}$		-0.04
		(-10.03)
Day Fixed Effects	Yes	Yes
Firm × Year Fixed Effects	Yes	Yes
Observations	4,222,189	4,222,189
SA Sample	Full Sample	Full Sample
R-squared	72.76%	59.35%

Table IA10. Seeking Alpha Research Coverage and the Direction of Retail Investor Trading (Daily)
The table presents the results from the following daily panel regression:

$$Retail\_OIB_{i,t} = \alpha + \beta_1 Event_{i,t} + \beta_2 Event\_Sentiment_{i,t} + \beta_3 Char_{i,t} + Day_t + Firm_i \times Year + \varepsilon_{i,t}.$$

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. (2020). *SA×Sentiment* is a vector of four variables: *Long (Short)*, a dummy equal to one if the author discloses a long (short) position and *Negative Tone (Positive Tone)*, a dummy equal to one if the fraction of negative (positive) words in the report exceeds the median. *Positive Tone*, a dummy equal to one if the fraction of positive words in the report exceeds the median. In Specification (2), *Composite Sentiment is* defined as: *Long + Pos Tone – Short – Neg Tone*. $SA_{i,t}$ is an indicator equal to one if at least one SA research report on stock *i* is published between 1:30 pm on day *t*-1 and 4 pm on day *t*. In cases where there are multiple SA reports for the same day, we take the average of SA × Sentiment across all reports. $Event_{i,t}$ is a vector of indicators for $Media_{i,t}$, $IBES_{i,t}$, and $Earnings_{i,t}$, defined analogously to $SA_{i,t}$. *Event×Sentiment* measures the sentiment of *Media*, *IBES*, and Earnings. *Media × Sentiment* equals one (negative one) if the ESS score for a media articles for firm *i* on day *t* is greater (less) than 50 (the score assigned to a neutral article) and equals 0 if the ESS score is 50. *IBES × Sentiment* equals one (negative one) if the IBES report includes a recommendation upgrade or upward forecast revision (downgrade or downward revision). *Media × Sentiment (IBES × Sentiment*) are averaged across all media articles (IBES reports) for the same firm day. *Earnings Sentiment* equals one (negative one) if the earnings surprise is positive (negative) relative to the consensus forecast. *Char* includes the return and the absolute return over the previous week ($Ret_{i,w-1}$, $AbsRet_{i,w-1}$), the previous month ($Ret_{i,m-1}$, $AbsRet_{i,m-1}$), the previous two to seven month ($Ret_{i,[m-7,m-2]}$, $AbsRet_{i,[m-7,m-2]}$), and the lag of the dependent variable measured over the previous five trading days ($Retail\_OIB_{i,w-1}$). All continuous independent variables are standardized to have mean zero and unit variance. Day_t denotes calendar day fixed effects and $Firm_i \times Year_t$ denotes fixed effects for each firm interacted with year fixed effects. Standard errors are clustered by date, and *t*-statistics are reported below each estimate.

	(1)	(2)
SA × Long	1.13	
	(7.54)	
SA × Short	-2.21	
	(-6.69)	
SA × Negative Tone	0.33	
	(2.48)	
SA × Positive Tone	-0.86	
	(-6.47)	
SA × Composite Sentiment		0.80
		(10.29)
SA	1.31	1.09
	(10.61)	(13.60)
Media × Sentiment	0.39	0.39
	(11.24)	(11.24)
Media	0.26	0.26
	(5.76)	(5.77)
IBES × Sentiment	0.32	0.32
	(3.68)	(3.68)
IBES	0.37	0.37
	(7.39)	(7.36)
Earnings × Sentiment	0.07	0.07
	(0.62)	(0.61)
Earnings	-1.12	-1.13
	(-8.38)	(-8.43)
$Ret_{i,w-1}$	-0.81	-0.81
	(-36.85)	(-36.85)

$Ret_{i,m-1}$	-0.69	-0.69
	(-30.05)	(-30.06)
$Ret_{i,[m-7,\ m-2]}$	-0.42	-0.42
	(-13.39)	(-13.41)
$Abs\ Ret_{i,w-1}$	0.46	0.46
	(23.12)	(23.12)
$Abs\ Ret_{i,m-1}$	0.30	0.30
	(13.65)	(13.65)
$Abs\ Ret_{i,[m-7,\ m-2]}$	0.26	0.26
	(8.71)	(8.72)
$Retail\_OIB_{\ i,w-1}$	2.29	2.29
	(66.08)	(66.09)
Day Fixed Effects	Yes	Yes
Firm × Year Fixed Effects	Yes	Yes
Observations	4,174,881	4,174,881
SA Sample	Full Sample	Full Sample
R-squared	2.15%	2.15%

Table IA11. Retail Investor Trading Informativeness: Daily Analysis (Before and After Report Publication)
This table repeats Table 10 after replacing the single *Retail_OIB × SA* interaction term with *Retail OIB* interacted with five separate indicators denoting separate trading days around the publication of the SA report. For example, day -2 (day +2) indicates that trade occurred two trading days prior to (after) the release of the SA report. All controls are included but omitted for brevity.

	Coefficient	*t-stat*
Retail_OIB	0.04	7.18
Retail_OIB × SA_{-2}	0.02	0.68
Retail_OIB × SA_{-1}	0.03	1.03
Retail_OIB × SA_{-0}	0.07	2.48
Retail_OIB × SA_{+1}	0.05	1.63
Retail_OIB × SA_{+2}	-0.02	-0.64

Table IA12. SA Research and the Informativeness of Retail Order Imbalances: Decomposition Analysis
The table presents coefficients from the estimation of Specification (1) of Table 10 when retail trading is replaced with one of its three components: *Persistence* (a proxy for price pressure), *Contrarian* (a proxy for liquidity provision), or *Other* (a proxy for informed trading). These components are estimated as the fitted values from the panel regression:

$$Retail\_OIB_{i,t} = \alpha + \beta_1 Retail\_OIB_{i,w-1} + \beta_2 Ret_{i,w-1} + \varepsilon_{i,t},$$

where $\widehat{OIB}_{i,t}^{Persistence} = \hat{\beta}_1 OIB_{i,w-1}$; $\widehat{OIB}_{i,t}^{Contrarian} = \hat{\beta}_2 Ret_{i,w-1}$; and $\widehat{OIB}_{i,t}^{Other} = \hat{\varepsilon}_{i,t}$, respectively. All continuous variables are standardized. Standard errors are clustered by month, and *t*-statistics are reported in parentheses.

	Persistence	**Contrarian**	**Other (Informed)**
	(1)	(2)	(3)
Retail_OIB	0.057	0.030	0.030
	(7.05)	(1.25)	(7.25)
Retail_OIB × SA	0.002	-0.031	0.092
	(0.06)	(-1.04)	(3.49)
Retail_OIB × Media	-0.001	0.025	0.019
	(-0.12)	(1.27)	(2.32)
Retail_OIB × IBES	0.004	-0.046	0.024
	(0.29)	(-2.10)	(1.89)
Retail_OIB × Earnings	0.001	-0.054	0.066
	(0.03)	(-0.71)	(1.51)
Retail_OIB × Size	-0.037	-0.002	-0.024
	(-4.58)	(-0.17)	(-5.12)
Institutional_OIB	-0.053	-0.053	-0.051
	(-7.65)	(-7.57)	(-7.39)
Institutional_OIB × SA	0.032	0.033	0.035
	(1.14)	(1.17)	(1.24)
Institutional_OIB × Media	0.019	0.019	0.019
	(1.73)	(1.74)	(1.74)
Institutional_OIB × IBES	0.007	0.006	0.009
	(0.48)	(0.38)	(0.60)
Inst_OIB × Earnings	0.020	0.018	0.021
	(0.47)	(0.44)	(0.51)
Institutional_OIB × Size	0.005	0.004	0.006
	(0.88)	(0.73)	(0.99)
$Ret_{i,w-1}$	-0.093	-0.079	-0.090
	(-3.84)	(-3.29)	(-3.72)
$Ret_{i,m-1}$	-0.037	-0.041	-0.039
	(-1.16)	(-1.28)	(-1.23)
$Ret_{i,[m-7,\ m-2]}$	-0.002	-0.003	-0.002
	(-0.06)	(-0.08)	(-0.06)
$Turnover_{i,m-1}$	-0.050	-0.047	-0.049
	(-2.01)	(-1.88)	(-1.95)
$Volatility_{i,m-1}$	0.060	0.062	0.061
	(1.49)	(1.52)	(1.50)
Log (Size)	-0.001	-0.002	0.000
	(-0.03)	(-0.06)	(0.01)
Log (BM)	0.017	0.016	0.016
	(0.62)	(0.57)	(0.60)
$High\ Volume_{i,t-1}$	0.197	0.203	0.198
	(6.76)	(7.02)	(6.80)
$Low\ Volume_{i,t-1}$	-0.127	-0.128	-0.129

	(-5.49)	(-5.44)	(-5.60)
SA	0.009	0.010	0.004
	(0.26)	(0.31)	(0.12)
Media	0.016	0.017	0.016
	(1.57)	(1.62)	(1.51)
IBES	-0.026	-0.024	-0.026
	(-0.96)	(-0.90)	(-0.95)
Earnings	-0.080	-0.079	-0.071
	(-1.45)	(-1.41)	(-1.29)
Day Fixed Effects	Yes	Yes	Yes
Observations	4,216,191	4,216,191	4,216,191
SA Sample	Full Sample	Full Sample	Full Sample
R-squared	15.71%	15.57%	15.70%