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The social signal[☆]

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ABSTRACT

We examine social media attention and sentiment from three major platforms: Twitter, StockTwits, and Seeking Alpha. We find that, even after controlling for firm disclosures and news, attention is highly correlated across platforms, but sentiment is not: its first principal component explains little more variation than purely idiosyncratic sentiment. Using market events, we attribute differences across platforms to differences in users (e.g., professionals versus novices) and differences in platform design (e.g., character limits in posts). We also find that sentiment and attention contain different return-relevant information. Sentiment predicts positive next-day returns, but attention predicts negative next-day returns. These results highlight the importance of considering both social media sentiment and attention, and of distinguishing between different investor social media platforms.

1. Introduction

Social media has grown exponentially over the past two decades. Americans spent 3.6 hours per day on some form of social media in 2020 (Forbes, 2021) and increasingly view social media as a primary source of news (Pew, 2021). Financial markets also reflect this: investors frequently post opinions about securities on social media, and firms use it to disclose information and interact with investors (Blankespoor et al., 2014). Despite these trends, investor social media was largely seen as a sideshow until recent social media-fueled trading frenzies, most prominently the 2021 GameStop phenomenon. These events raise questions about the role social platforms play for trading and information in financial markets (Pedersen, 2022), and an emerging line of research has organized around these important questions.

Prior analyses of investor social media have almost exclusively examined data from a single platform, and related papers often draw upon evidence from *different* investor social networks, typically StockTwits, Seeking Alpha, and Twitter.[1] While most of this work considers questions that are not specific to the particular investor social platform studied, these platforms differ in myriad ways.[2] Communication theory

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[1] For example, for StockTwits see Giannini et al. (2019), Cookson et al. (2023a, 2024) and Irvine et al. (2021); for Twitter, Gu and Kurov (2020), Chen et al. (2023), Cookson et al. (2023b), Bianchi et al. (2023) and Bianchi et al. (2024); for Seeking Alpha, Chen et al. (2014), Dim (2024), Chen and Hwang (2022), Farrell et al. (2022) and Kogan et al. (2023).

[2] For example, Seeking Alpha articles are long-form and lightly moderated; Twitter posts are limited to 280 characters, but multiple posts can be threaded together for longer arguments; while StockTwits posts cannot be threaded, they have had a 1,000 character limit since 2019. These platforms also differ in their user bases, recommendation algorithms, how individuals interact through messages and tagging, and many other characteristics. Fig. 1 presents an example post for each platform in our study.

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implies that social media platforms may not be interchangeable because the characteristics of a communication medium affect both the content and impact of messages (e.g., McLuhan, 1975). Because communication is a socially emergent phenomenon, differences in user populations, incentives to post, and ability to engage may lead each platform to have unique informational content.

To examine whether and how these platforms generate differing market-relevant information – the social media *signal* – this paper examines a decade of comprehensive firm-day-level data (2012–2021) from the three most established investor social networks: StockTwits, Twitter, and Seeking Alpha. We first distinguish between two features common to all social networks: *attention* and *sentiment*. We find that over two-thirds of the firm-day attention signal is common across the major social platforms: on a given day, people on different platforms tend to talk about the same firms. By contrast, the common component of sentiment is weak, explaining only slightly more than it would if sentiment across the three platforms were idiosyncratic.

In addition, we show that the common components of social sentiment and attention have opposing return predictions: attention generally predicts negative next day returns, while sentiment predicts positive returns. Exploiting two events – a change in the message character limit on StockTwits and the GameStop (GME) short squeeze – we find that differences in *platform features* (the character-limit event) and differences across *user populations* (the GME event) each contribute to differences in the market-relevant information generated by investor social media.

We now describe our findings in greater detail. We begin by decomposing the social signal generated by all three platforms using principal component analysis (PCA) separately for attention and sentiment. We find that attention has a powerful common component, with the first principal component (PC1) explaining 67% of the variation. Conversely, the PC1 of sentiment explains 39% of the variation in sentiment, only slightly more than the 33% it would explain if the three signals were idiosyncratic. We show that these findings are not driven by news, firm disclosures, stock returns, or persistent firm components by first regressing attention and sentiment from each platform on these variables and firm fixed effects, and then performing a PCA on the residualized signals. This conditional PCA analysis yields very similar patterns to the unconditional PCA we started with, indicating that the common signal in investor social media is distinct from the information in traditional media.[3]

An alternative explanation for the weak cross-platform correlation in sentiment is that the signals from each platform are extracted using different natural language processing algorithms (NLPs). We provide evidence that NLPs cannot explain these differences by comparing different user types within StockTwits, thus holding constant both platform features and NLP. Consistent with our cross-platform results, we find that attention is highly correlated across user types such as influencers, professionals, and novices (i.e., the PC1 explains 84% of the variation), whereas sentiment signals have a weak correlation across user types. Thus, differences in NLPs cannot fully drive our results. Moreover, this evidence suggests that, even if NLPs and all platform features were identical, we would see cross-platform differences in the sentiment signal because of differences in user populations.

The most salient difference across social investor platforms is in the size of the firms they cover. StockTwits focuses more on small-cap firms, whereas Twitter and Seeking Alpha pay greater attention to large-cap firms. When we repeat our conditional PCA separately by firm size bins, we find that attention displays more commonality than sentiment irrespective of firm size. However, large-cap firms display stronger commonality in attention and sentiment than small cap firms. This size-based heterogeneity for sentiment suggests that whether a sentiment-related result in the social finance literature generalizes across platforms may depend on how important small firms are in driving that result.

Next, we explore whether the *informativeness* of sentiment and attention signals differs across platforms. To capture informativeness, we regress next-day abnormal returns on sentiment and attention signals from the three platforms, controlling for news from traditional media, firm announcements, lagged returns and volatility, and Google search volume (Da et al., 2011). The signal from any given platform is a combination of a common component, captured by PC1s of sentiment and attention, and a platform-specific idiosyncratic component. We find that the common component of sentiment predicts *positive* next day abnormal returns and that the common component of attention predicts *negative* next day returns. Looking at signals from each platform separately, we find that informativeness of signals varies substantially across platforms.[4] Overall, StockTwits' signal is better aligned with the common components than Twitter and Seeking Alpha (especially for attention), with respect to next-day returns.[5]

To shed light on the mechanisms behind the informativeness of the social signal, we explore how it relates to same-day returns and to returns out to 20 days. We find that more positive sentiment is associated with higher same-day and day $t+1$ returns, with no reversal in the subsequent 20 days. By contrast, higher attention is associated with higher same-day returns, followed by a partial reversal over the next 10 to 20 days. Digging deeper, we show that net retail buying is positively related to same-day sentiment and attention, but this positive relation only lasts for one to two days. These results help explain our findings on the informativeness of social signal for next-day returns: the positive predictability of sentiment is likely because it contains return-relevant information, while the negative predictability of attention is most consistent with a partial and gradual reversal of an over-reaction on high-attention days.

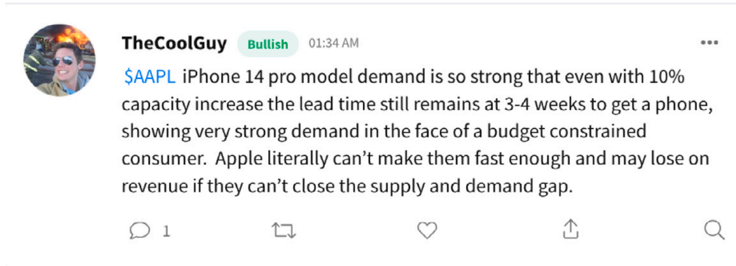
We next examine two events which provide insight into whether platform-specific features and user groups contribute to the differences in the informativeness of sentiment and attention. First, we examine changes in the informativeness of the social signal around May 8, 2019, when StockTwits increased its character limit per message from 140 to 1,000 characters. We find that StockTwits sentiment became more predictive of next-day stock returns after this change. Moreover, this effect is driven by sentiment when messages are longer; the informativeness of shorter messages and attention were unchanged. We find that professionals' messages are more informative on average, and that after the character limit increase they write longer messages, suggesting a possible mechanism. Consistent with the fact that Twitter and Seeking Alpha were unaffected by StockTwits' character limit increase, we find no change in the informativeness of signals from these platforms. These results indicate that a within-platform change to users' ability to communicate can affect the market-relevant information encoded in the social media signal, in line with communication theory. These findings also suggest that structural differences across investor social media platforms contribute to the differences we find in the signal they generate.

Second, we examine how the informativeness of sentiment and attention changed around the January 2021 GME phenomenon. In 2020, the number of U.S. retail brokerage accounts increased rapidly and StockTwits saw an influx of new users, both likely a result of COVID

[3] The PC1 data on sentiment and attention are available to researchers on our websites and in the replication materials for this article.

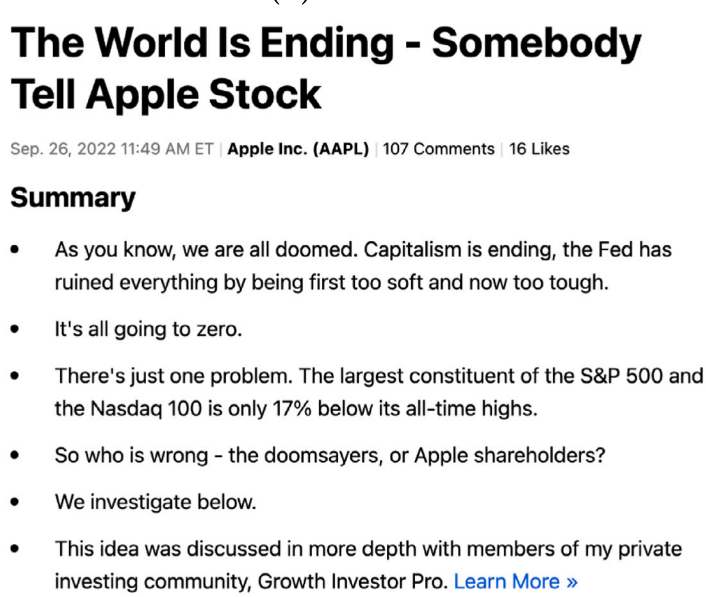
[4] When we examine the signals from Reddit WallStreetBets (WSB) starting in 2018, we find no link between sentiment and next day returns and a positive loading on attention. We also show that the inclusion of WSB signals in the conditional PCA does not change our findings.

[5] Because these platforms focus on different-sized firms, we examine heterogeneity in informativeness by firm size. The informativeness of sentiment does not appear to differ by firm size, either across or within platforms. However, StockTwits attention is more informative for small and mid-size firms than it is for large firms.



(a) StockTwits

(b) Twitter



(c) Seeking Alpha

Fig. 1. Examples of posts across three social media platforms. *Note:* This figure presents example posts for StockTwits, Twitter, and Seeking Alpha. For ease of direct comparison, all three examples are about Apple stock (AAPL) on the same day (September 28, 2022). Only the summary is presented for the Seeking Alpha post; the full post is much longer.

stay-at-home orders coupled with the introduction of no-fee trading at many brokerages. Bradley et al. (2024) shows that Reddit retail trading based on WSB "due diligence" reports became less informative in the wake of the GME short squeeze. We show that the informativeness of sentiment across all platforms deteriorated significantly after the GME short squeeze: returns became less sensitive to sentiment. Moreover, the drop in informativeness is concentrated among messages by new users, as the informativeness of the signal extracted from more established users (who joined before 2020) did not change after January 2021. These findings emphasize the importance of changing user populations and new narratives in shaping the information content of the social signal.

Related literature. Our paper makes several contributions to the literature on retail investors, sentiment, attention, and the informativeness of novel data sources in financial markets. Our core contribution is to quantify the information content, similarities and differences across the three most-established investor social media platforms over the last decade. With the rising significance of social media platforms as a forum for communicating investor beliefs, a literature has emerged to study their information content. Investors discuss financial ideas on myriad online forums, but analyses typically focus on a single platform and employ different data (e.g., Chen et al., 2014; Cookson and Niessner, 2020; Gu and Kurov, 2020; Irvine et al., 2021).[6] Divergent findings may stem from examining different parts of the investor social media space. In this paper, we show how cross-platform differences matter for the informativeness and retail trading implications of sentiment and attention. In addition, we illustrate how specific features of social media platforms (character limits and differing user-bases) shape the informativeness of the social signal.

We also contribute to the social economics literature (Akçay and Hirshleifer, 2021; Hirshleifer, 2020; Kuchler and Stroebel, 2021) and especially research on the economics of social media (Pedersen, 2022). Connections on social media have been shown to shape political disagreements, amplify anti-minority sentiment, and even influence house price expectations (Bailey et al., 2018a; Levy, 2021; Lu and Sheng, 2022). In this broader literature, some have used connections on a single social media platform as a proxy for social connections in general (e.g., Bailey et al., 2018b; Hirshleifer et al., 2023), while other research presents evidence that a specific platform has economic impacts (e.g., Müller and Schwarz, 2022). The market events we examine provide some support to both approaches. Our findings around the message limit change to StockTwits support the view that social media is not interchangeable, as platform-specific features significantly impact the information each platform generates. However, the evidence from the GME event also illustrates how events on one platform spill over onto others, showing strong common effects of a sufficiently large change in the social media space.

Our results also contribute to the literature on retail attention and sentiment (e.g., Da et al., 2011; Sicherman et al., 2016; Gargano and Rossi, 2018). Existing work with investor social media either focuses on aspects of investor attention (e.g., Giannini et al., 2018; Cookson et al., 2023a; Irvine et al., 2021) or on sentiment and optimism (e.g., Antweiler and Frank, 2004; Renault, 2017; Cookson et al., 2020). Outside of social media, research on sentiment (e.g., Tetlock, 2007; Garcia, 2013) and attention (e.g., Barber and Odean, 2008; Da et al., 2011) has also typically focused on only one of the two. As a result, a seemingly conflicting body of evidence has emerged in which sentiment is typically informative of future returns, but retail attention appears strongly misinformed. The literature has partly resolved this tension by showing that different kinds of attention have different return implications (Ben-Rephael et al., 2017; Da et al., 2022; Barber et al., 2022). By examining sentiment and attention together across multiple platforms, we show that there is a striking difference in the informativeness of sentiment vs. attention.

We also contribute to the literature on the role of new entrants to financial markets and their implications for markets (e.g., Bradley et al. (2024)). In early work, Chen et al. (2014) shows that Seeking Alpha recommendations are informative. With the advent of new firm-day retail trading measures (Boehmer et al., 2021), the literature has examined how retail trading relates to social media activity, with a primary focus on Seeking Alpha (e.g., Farrell et al., 2022). This research has also shown that retail investor activity has important implications for market quality, particularly driven by new retail traders on Robinhood (e.g., Eaton et al., 2022). Relative to this literature, our results connect social media, retail traders, and market outcomes, and we show that new entrants lead to much of the decline in informativeness of social media signal following the GME phenomenon.[7] This finding highlights how the content of previously informative signals can change upon the arrival of new participants, and that this is a general phenomenon that is not confined to one social platform.

2. Data and summary statistics

2.1. Social media sentiment and attention data

Our data come from three investor social media platforms: Twitter, Seeking Alpha, and StockTwits. We obtain firm-day data on financially-oriented Twitter posts (tweets) from Social Market Analytics (SMA), a firm that provides sentiment information to professional investors. Specifically, we use daily 4:00 pm snapshots of the number of tweets and average sentiment over the prior 24-hour period for each firm.

For Seeking Alpha, we obtain article-level sentiment from Ravenpack 1.0, keeping all articles with a relevance score above 75, which Ravenpack considers to be "significantly relevant". To measure sentiment, we use the Event Sentiment Score (ESS) calculated by Ravenpack, which ranges between −1 and 1, with 0 indicating neutral sentiment and positive (negative) values indicating positive (negative) sentiment.

For the investor social platform StockTwits, we obtain comprehensive message-level data. Like Twitter, StockTwits allows users to publicly post short messages (henceforth "tweets") with a limited number of characters — 140 before May 8, 2019, and 1,000 thereafter. Unlike Twitter, StockTwits is primarily focused on financial markets. By including a "cashtag", a dollar sign ($) followed by a ticker symbol, StockTwits users can specify that their post refers to a specific firm or security. We limit our analysis to messages that mention exactly one company, so we can accurately assign sentiment to the company. We have data on all single-firm tweets from 2010 through 2021: 150 million tweets from over 800,000 users. Similar to Cookson et al. (2023a), we drop users posting over 1,000 tweets in a day, and we restrict our sample to the top 1,500 firms by the number of tweets posted between 2010 and 2021.

StockTwits allows users to attach a sentiment tag to their tweet indicating if their tweet reflects "bullish" or "bearish" sentiment. We assign +1 to self-labeled "bullish" tweets and −1 to self-labeled "bearish" tweets. We also obtain a sentiment score for each tweet ranging from −1 (extremely bearish) to +1 (extremely bullish) which is calculated by StockTwits using a proprietary text classification algorithm called MarketLex.[8]

To aggregate sentiment at the firm-day level ($Sentiment_{i,t}$) for StockTwits and Seeking Alpha, we compute average sentiment across all tweets (or articles) about a firm i from 4:00 pm (close) on date $t-1$ to 4:00 pm on date t. These firm-day sentiment measures are thus comparable to the Twitter firm-day sentiment measure provided by SMA. Similarly, we compute firm-day message volume ($Messages_{i,t}$) for StockTwits and Seeking Alpha by counting the number of messages (tweets or articles) about each firm over the same period. We then define a firm-day measure of attention, $Attention_{i,t}$, for each platform

[6] Recent work on earnings forecasts from Estimize has examined similar questions about information transmission and social influence – e.g., Da and Huang (2020) and Jame et al. (2016) study aspects of the wisdom of crowds, and Da et al. (2021) shows how Estimize analysts extrapolate their beliefs from past experience.

[7] In connecting social media and retail trading, we also relate to the literature that studies motivations for retail trade (Liu et al., 2020). Prior work shows how peer interactions lead to excessive trading and exacerbate behavioral biases (Heimer, 2016), and emphasizes the role of overconfidence (Barber and Odean, 2001; Daniel and Hirshleifer, 2015), particularly about the precision of one's information (e.g., Daniel et al., 1998).

[8] According to StockTwits, this methodology uses lexical and semantic rules based on a custom-built lexicon for social finance, constructed from a combination of words and phrases from 4 million messages with user-provided bullish or bearish tags and manual human supervision.

by dividing the firm-day number of messages by the total number of messages on that platform in a day[9]:

$$\text{Attention}_{i,t} = \frac{Messages_{i,t}}{\sum_i Messages_{i,t}} \quad (1)$$

StockTwits users can voluntarily declare their level of experience using the options provided when filling out their user profile. StockTwits also provides information on how many followers each user has. Thus, for StockTwits, we can separate sentiment and attention into distinct series by user profile or follower base: Professionals, Intermediates, Novices, No experience label, and Influencers (>99th percentile by number of followers). We also produce a separate series for self-classified sentiment (explicit bullish or bearish declarations), as opposed to StockTwits' sentiment measure based on MarketLex.

2.2. Firm news data

In addition to social media sentiment and attention, we also control for firm news events. Specifically, we collect information on coverage and sentiment of traditional news media from the *Wall Street Journal* and the *Dow Jones Newswire*. These measures come from Ravenpack 1.0, which provides information on the number of articles by firm-day as well as article-level sentiment. We keep all articles with a relevance score above 75 and use the Ravenpack Event Sentiment Score, aggregating the article-level sentiment to the firm-day level by averaging firm-specific sentiment across articles within a day.

To capture other sources of news, we collect information on 8-K filing dates (unscheduled firm-specific news) and earnings announcement dates. The 8-K filing dates are collected from the SEC Analytics Suite by WRDS, and the earnings announcement dates are from IBES.

2.3. Returns data

We compute daily abnormal returns by subtracting the value-weighted market return from the firm's daily return using CRSP data.

2.4. Sample characteristics

To allow accurate measurement of the social signal, our sample focuses on the 1,500 firms with the most single-firm tweets about them on StockTwits between 2010 and 2021. Although this reduces the number of firms in our sample from more than 9,000 to 1,500, it only reduces the number of StockTwits messages by about 20% (from 150 million to 120 million). We also restrict attention to firm-days for which there are at least 10 single-firm tweets on StockTwits. Because Twitter and Seeking Alpha data are sparsely populated before 2012, we begin our analysis sample in 2012. After merging the social media data with Ravenpack for traditional news media information and market data for return reactions, we obtain a final sample of roughly 815,000 firm-day observations.

Sample summary statistics are reported in Table 1. Panel A presents statistics on activity across the three platforms. For the average firm-day, the number of messages on StockTwits is a multiple of the number on Twitter or Seeking Alpha. Despite this substantial difference in message volume, the three platforms cover a similar number of firms (i.e., StockTwits mentions cover 1,497 firms in our final sample compared with just under 1,300 for Twitter, and Seeking Alpha). Thus, even if individual messages on StockTwits were to contain less information than a Seeking Alpha post, the greater volume of messages on StockTwits could aggregate into an informative firm-day signal. In Panel B, we present the same statistics for subgroups of StockTwits investors. This decomposition highlights that there is significant activity within each subgroup (the average number of posts ranges from 5.87 to 13.37).

Panel C illustrates how platforms differ in terms of the size of firms they pay attention to. The first three columns show the size distribution of the top 1,500 most talked-about firms on each platform, split into small-cap, mid-cap and large-cap bins. The three firm size bins each capture about a third of the most popular firms on Twitter and Seeking Alpha, while two-thirds of firms most discussed on StockTwits are small-cap. The second three columns present the share of messages discussing firms in each size bin. Large firms typically attract the most messages: around 60% of messages on Twitter and Seeking Alpha, despite accounting for a much smaller share of the firm-level coverage. By contrast, StockTwits still shows a small-cap focus at the message-level, with comparatively little difference between the shares of messages and of firms in each bin.

Panel D shows how restricting our sample to firm-days with at least 10 StockTwits messages affects the observation count in the sample. The firm-day sample size falls from nearly 2.8 million to roughly 822,000 observations. Additional sample filters (e.g., requiring data on controls or returns) have a negligible impact on our observation count.

2.5. Platform features and users

Communication theory (e.g., McLuhan, 1975) holds that the characteristics of a communication medium affect both the content and impact of its message. Thus, differences between platforms – in user populations, incentives to post, and ability to engage – may lead to important differences in the information each platform attracts and aggregates. Fig. 1 presents three messages about Apple Stock ($AAPL), one from each investor social media platform, in order to illustrate cross-platform differences.

The most immediate difference in Fig. 1 is that Seeking Alpha content consists of long-form articles (the screenshot displays only the title and summary), in contrast to the short posts on StockTwits and Twitter. There are many other platform feature differences. For example, although StockTwits and Twitter both allow "cashtags", only on StockTwits can posts be flagged as bullish or bearish by the poster. Moreover, StockTwits is an investment-specific platform, while Twitter covers an unrestricted variety of topics. Other differences include the recommendation algorithms and the ability to thread tweets. Each of these can contribute to important discrepancies across platforms in both the social signal (sentiment and attention measures) as well as how the social signal relates to market outcomes. We exploit a change in one of these dimensions – when StockTwits increased their message character limit from 140 to 1,000 characters – to examine how platform features impact the information content on the platform.

Another major difference across social media platforms is that they attract different users. Seeking Alpha posters are much more selected than Twitter or StockTwits users, which are open to anyone who signs up for an account. StockTwits has historically attracted users aiming to build reputation via their posts: deletion of past posts is not possible. Moreover, interest in these platforms has shifted and grown markedly over time, as is clear from Appendix Figure A1. To explore the importance of user composition, we test whether newer StockTwits users provide a less informative signal around a notable market event: the GME short squeeze of early 2021. We also use our within-StockTwits decomposition of different user types to examine how each type contributes to the social signal.

3. Decomposing the social signal

This section describes the commonalities and differences in the signals drawn from different social media investing platforms and across StockTwits investor types. Here, we distinguish between two key dimensions of the social signal: sentiment and attention.

[9] Our results are robust to using an alternate firm-day measure of attention: the deviation from its median number of messages over the preceding 10 days. See Appendix Tables A2 and A7.

Table 1
Summary statistics.

Panel A: Statistics by social media platform

	Daily sentiment				# messages (daily)				# of firms		Firm-day observations	
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	Ever mentioned	All	Mentioned	All
StockTwits	0.10	0.14	−0.97	0.97	132.40	734.97	10	138,280	1,497	1,500	815,980	815,980
Twitter	0.02	0.06	−0.80	0.94	18.84	62.69	0	7,160	1,271	1,500	522,284	815,980
Seeking Alpha	0.02	0.12	−1	1	0.46	1.75	0	150	1,283	1,500	137,018	815,980

Panel B: Statistics by user type on StockTwits

	Daily sentiment				# messages (daily)				Users		Firm-day observations	
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max	#	Share	Non-zero	All
Top 1%	0.07	0.29	−1	1	5.97	34.04	0	4,212	7,173	0.01	512,549	815,980
Professional	0.09	0.30	−1	1	7.89	28.92	0	2,405	20,073	0.02	591,383	815,980
Intermediate	0.09	0.29	−1	1	13.37	50.88	0	5,439	45,156	0.05	687,993	815,980
Novice	0.07	0.29	−1	1	5.87	26.18	0	3,645	34,118	0.04	514,773	815,980
No label	0.10	0.18	−0.99	0.99	105.27	658.60	0	127,243	730,164	0.88	810,614	815,980

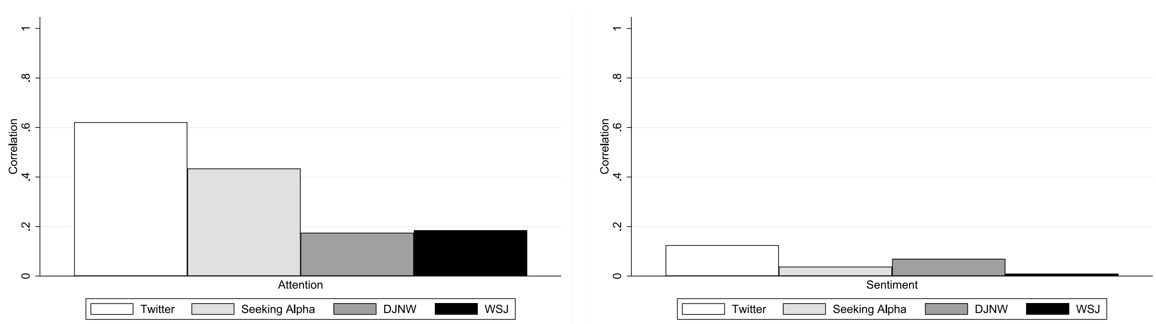
Panel C: Stock characteristics by social media platform

	Share of firms (%)			Share of messages (%)		
	StockTwits	Twitter	Seeking Alpha	StockTwits	Twitter	Seeking Alpha
Small-cap	68.60	30.07	30.67	54.27	16.13	18.27
Mid-cap	15.13	36.20	37.27	15.41	22.21	24.65
Large-cap	16.27	33.73	32.07	30.32	61.66	57.09

Panel D: Firm-day observations satisfying sample restriction

Sample restriction	# obs.	# dropped obs.
Full sample	2,795,852	–
At least 10 StockTwits messages	821,534	1,974,318
Non-missing controls data	815,980	5,554
Non-missing controls + returns	814,646	1,334

Note: Panel A reports statistics on the firm-day level sentiment and attention by social media platform for all observations with at least 10 StockTwits messages. The sample time frame is Jan. 1, 2012 to Dec. 31, 2021 for StockTwits, Twitter, and Seeking Alpha. "# of firms - Ever mentioned" refers to the # of firms ever mentioned on a platform during our sample period; "# of firms - All" refers to the # firms included in our analysis sample (with the sentiment of firms not mentioned replaced by zeros). "Firm-day observations - Mentioned" refers to the # of firm-day observations with non-zero attention; "firm-day observations - All" refers to the # of firm-day observations in our analysis sample. Panel B provides similar statistics by user type on StockTwits. "Users - # (or Share)" refers to the # (or share) of StockTwits users of a certain type; Panel C reports the share of the 1,500 most talked-about firms on each platform that are in each of three market capitalization bins (first three columns), and the share of messages about firms in each bin (columns 4–6). "Small-cap," "mid-cap," and "large-cap" refer to stocks with market capitalizations below 2 billion, between 2 and 10 billion, and above 10 billion. Panel D shows how sample restrictions reduce the # of firm-day observations to arrive at our analysis sample.



(a) Attention signal **(b)** Sentiment signal

Fig. 2. Cross-platform correlation of social signals. *Note:* This figure reports the bivariate correlations of attention and sentiment signals between StockTwits and other platforms or news sources at the firm-day level. Attention is measured as the fraction of messages, reports, or articles about a firm across all firms on a platform in a day. Sentiment is measured as the average sentiment of all messages about a firm on a platform in a day.

3.1. Are social signals common across platforms?

We begin by examining how much commonality there is in the social signal across StockTwits, Twitter, and Seeking Alpha. Fig. 2 and Panel A of Table 2 present the correlations of attention and sentiment between StockTwits and corresponding measures on Twitter and Seeking Alpha at the firm-day level. As a benchmark, we also present the correlations of StockTwits with traditional news coverage and sentiment from the Dow Jones Newswire (DJNW) and the Wall Street Journal (WSJ). The correlation between attention series on social platforms is relatively high at 0.621 between StockTwits and Twitter attention, and 0.434 between StockTwits and Seeking Alpha. By comparison, the correlations with coverage by traditional news media are much weaker: 0.184 for the WSJ and 0.175 for the DJNW. These correlations suggest that attention across social investing platforms contains a strong common component that is not well explained by news media coverage.

In contrast to the attention correlations, we observe much weaker correlations in sentiment series across different platforms. The correlation of StockTwits with Twitter sentiment is only 0.125, whereas the correlation with Seeking Alpha sentiment is 0.038. The correlation with news sentiment is also low, at 0.010 for the WSJ and 0.069 for the DJNW. This suggests that sentiment is more idiosyncratic across

Table 2
How common is sentiment and attention across platforms?

Panel A: Correlations with the StockTwits signal				
	Twitter	Seeking Alpha	DJNW	WSJ
StockTwits attention	0.595	0.398	0.220	0.163
StockTwits sentiment	0.125	0.038	0.032	0.010

Panel B: PCA of all platform-level signals						
	PC1	PC2	PC3	PC4	PC5	PC6
Attention:						
StockTwits	0.548	−0.130	−0.188	0.047	0.638	0.488
	(0.052)	(0.107)	(0.292)	(0.069)	(0.155)	(0.076)
Twitter	0.605	−0.033	−0.098	−0.009	0.048	−0.788
	(0.013)	(0.050)	(0.126)	(0.016)	(0.142)	(0.025)
Seeking Alpha	0.548	−0.007	0.052	0.084	−0.745	0.368
	(0.017)	(0.047)	(0.180)	(0.021)	(0.212)	(0.117)
Sentiment:						
StockTwits	−0.031	0.644	−0.345	0.682	0.017	−0.014
	(0.014)	(0.011)	(0.337)	(0.010)	(0.056)	(0.006)
Twitter	0.082	0.647	−0.225	−0.720	−0.008	0.071
	(0.046)	(0.041)	(0.282)	(0.013)	(0.035)	(0.024)
Seeking Alpha	0.160	0.384	0.885	0.087	0.190	0.008
	(0.070)	(0.021)	(0.737)	(0.040)	(0.221)	(0.051)
Fraction	35.6%	19.3%	15.9%	14.5%	9.2%	5.5%
	(4.284)	(0.124)	(0.482)	(0.085)	(2.240)	(1.638)

Panel C: PCA of platform-level attention or sentiment signals						
	Attention signal			Sentiment signal		
	PC1	PC2	PC3	PC1	PC2	PC3
StockTwits	0.565	−0.665	0.489	0.611	−0.464	0.642
	(0.027)	(0.592)	(0.073)	(0.006)	(0.021)	(0.010)
Twitter	0.614	−0.057	−0.787	0.662	−0.147	−0.735
	(0.029)	(0.075)	(0.020)	(0.003)	(0.015)	(0.002)
Seeking Alpha	0.551	0.745	0.376	0.435	0.874	0.217
	(0.022)	(0.620)	(0.109)	(0.009)	(0.009)	(0.024)
Fraction	67%	18.9%	11.1%	38.8%	32.3%	29%
	(9.336)	(6.033)	(3.360)	(0.170)	(0.069)	(0.144)

Note: This table reports the correlations and principal component analyses of social signals across platforms. Panel A reports the bivariate correlations of attention and sentiment between StockTwits and another platform. Panel B reports the principal components of attention and sentiment signals in one analysis, while panel C reports the principal components separately for attention (columns 1–3) and for sentiment (columns 4–6). Standard errors in parentheses are double clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

social investing platforms, and as Fig. 2 highlights, the difference in the magnitudes of the correlations for attention and sentiment is striking.

A priori, there are various plausible hypotheses about how the six signals we analyze could be cross-correlated. For example, sentiment and attention signals could have a strong correlation with one another under the theory that people pay attention to what they feel strongly about. Alternatively, people with similar outlooks could cluster within platforms, leading to correlation within platform between attention and sentiment. It is also not clear that the strongest cross-correlations are positive. If disagreement across platforms in sentiment or attention were the norm, we would expect to see negative cross-platform correlations. In the following analysis, our main finding is that the strongest cross-correlations are attention across platforms and sentiment across platforms, with little within-platform clustering or correlation between attention and sentiment signals.

To systematically describe the cross-correlation of the six signals (attention and sentiment for each of the three platforms), we employ principal components analysis (PCA). PCA provides a convenient way to describe the multivariate correlations across attention and sentiment signals on the social platforms. The first principal component (PC1) from a PCA yields the linear combination of the signals that explain the most variation across the six signals. The second principal component (PC2) is the linear combination that explains the most of the remaining variation, and so on. Thus, if the loadings on the underlying signals are large within a principal component, these signals are mutually correlated. In other words, the loadings identify the clustering of signals within the data. Further, a standard output from PCA is the fraction of variation explained by each principal component. This is a useful summary statistic of how much cross-correlation there is in each principal component for the signals that matter most to it.

To gauge the extent to which sampling variability determines our ability to draw conclusions about PC loadings and explained variation, we compute standard errors for the loadings and the fraction of variation explained by each PC by conducting a block bootstrap procedure that clusters standard errors by firm and by date. To do this, we separately conduct a block bootstrap by firm and by date, drawing 1000 replications from each. Then, we follow the formula in Thompson (2011) to compute the double clustered variance–covariance matrix from each single clustered variance–covariance matrix. Throughout our analysis, we obtain relatively small standard errors, indicating that the statistics we focus on from the PCA are sufficiently precise. For table legibility, we suppress the reporting of standard errors on the PC loadings in later tables.

Panel B of Table 2 presents the PCA across the six signals we consider in this paper (i.e., sentiment and attention across the three platforms at the firm-day level). PC1 explains 35.6% of the variation across the six signals, which is nearly twice the variation explained in PC2. Moreover, PC1 is roughly an equal-weighted average of attention signals, with low loadings on sentiment signals. Almost a mirror of PC1, PC2 is roughly an equal weighted average of sentiment signals, with low loadings on attention signals. This structure implies that sentiment and attention have a low correlation, and motivates our subsequent approach of using *separate* PCAs for attention signals and for sentiment signals.

Next, we describe the common variation between social media signals in PCAs for attention, and separately for sentiment. These PCAs are summarized in Panel C of Table 2. Consistent with the view that attention is common across investors on various social media platforms, PC1 of attention explains 70% of the variation across platforms. Further, all three attention signals are given similar positive weights in this first PC, suggesting a natural interpretation that the common component of attention is manifested in all three social media platforms. PC2 captures differences in attention across Seeking Alpha and StockTwits since it places positive weight on Seeking Alpha and negative weight on StockTwits (with roughly zero weight on Twitter). However, these differences in attention across platforms captured by the second PC only explain 18.9% of the variation in attention.

Turning to the sentiment PCA, the first PC only explains 38.8% of sentiment variation across platforms. This is a weak common component, because purely idiosyncratic variation in the three series would result in a first PC explaining 33.3%. Like the attention PCA, the second PC of sentiment mostly captures the difference between Seeking Alpha (positive weight, $w = 0.874$) and StockTwits (negative weight, $w = -0.464$) since the Twitter sentiment series has a much smaller weight ($w = -0.147$). The fact that the second PC explains 32.3% of the variation implies that differences across platforms in sentiment capture approximately as much variation across platforms as similarities. These results suggest that, for any given firm or day, attention-related results from the social finance literature are more likely to generalize than results concerning sentiment.

3.2. Conditional PCAs to account for confounding effects of news and firm characteristics

The results in the prior PCA are unconditional, and therefore could be driven by many omitted variables. For example, news coverage or firm announcements could drive attention and sentiment to co-vary across platforms. Naturally, we want to control for this. One approach would be to regress a signal on the other signals, while controlling for news controls and firm fixed effects. However, this does not isolate the

Table 3
How common is the social signal across platforms? *Conditional on news and firm fixed effects.*

Panel A: PCA of residualized attention signals									
	Residualize news			Residualize news & firm			Residualize news, firm, & returns		
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
StockTwits	0.582	−0.548	0.601	0.608	−0.421	0.674	0.606	−0.427	0.671
Twitter	0.616	−0.185	−0.766	0.627	−0.266	−0.732	0.626	−0.266	−0.733
Seeking Alpha	0.531	0.815	0.230	0.487	0.867	0.103	0.492	0.864	0.106
Fraction	66.4%	21%	12.7%	63.4%	24.1%	12.5%	63.5%	23.9%	12.6%
	(8.768)	(5.200)	(3.666)	(7.898)	(4.449)	(3.536)	(8.151)	(4.513)	(3.716)
Panel B: PCA of residualized sentiment signals									
	Residualize news			Residualize news & firm			Residualize news, firm, & returns		
	PC1	PC2	PC3	PC1	PC2	PC3	PC1	PC2	PC3
StockTwits	0.639	−0.376	0.671	0.660	−0.288	0.694	0.660	−0.289	0.694
Twitter	0.675	−0.144	−0.724	0.676	−0.174	−0.716	0.676	−0.173	−0.716
Seeking Alpha	0.369	0.915	0.162	0.327	0.942	0.080	0.327	0.942	0.081
Fraction	38.2%	32.7%	29.2%	38.2%	32.8%	29.1%	38.1%	32.8%	29.2%
	(0.159)	(0.054)	(0.142)	(0.134)	(0.038)	(0.125)	(0.134)	(0.038)	(0.125)

Note: This table repeats the principal component analysis in Table 2 using the *residualized* social signal. The residualized signal in columns 1–3 refers to the residual from regressing a signal on DJNW sentiment (lagged 0 through 7 days), DJNW attention (lagged 0 through 7 days), dummies for earnings announcements (lagged 0 through 7 days), dummies for 8-k filings (lagged 0 through 7 days); in columns 4–6, we also residualize out firm fixed effects; in columns 7–9, we further residualize out lagged return volatility (previous five trading days) and lagged cumulative abnormal returns (previous five trading days and the 25 days before that). Standard errors in parentheses are double clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

correlations across platforms that are of interest to us: for example, in a regression of Stocktwits sentiment on Twitter and Seeking Alpha sentiment, the coefficient on Twitter sentiment holds constant Seeking Alpha sentiment, which is not the variation we are interested in. Thus, we adopt a *conditional* PCA approach. In a conditional PCA, the input signals are first regressed on controls and fixed effects to orthogonalize the signal with respect to confounding variation. We run regressions of the following form for each of the six signals:

$$Signal^{P}_{i,t} = \Gamma^{P} X_{i,t} + \gamma^{P}_{i} + \epsilon^{P}_{it}, \tag{2}$$

where $Signal^{P}_{i,t}$ is either attention or sentiment on a platform P for firm i on day t; $X_{i,t}$ are controls for traditional news for firm i on day t; γ^{P}_{i} are firm fixed effects. Then, we extract the residual from each signal series and perform the PCA on the 6 residualized signals.

Table 3 Panels A and B first residualize by news only, that is, traditional media coverage of firm i on date t drawn from RavenPack. RavenPack provides both the number of articles about firm i on date t, as well as the sentiment of those articles. We control for both sentiment and number of articles. We also include an indicator variable for whether there is an earnings announcement on date t for firm i, as well as lags of up to 7 days; we do the same for 8-K disclosures. The aim is to flexibly control for news in the residualization step. In the next three columns of both panels, we residualize by news and also add firm fixed effects to control for any unobserved and time-invariant firm characteristics. Finally, in the last three columns of both panels, we further residualize by lagged return volatility and cumulative abnormal returns.

As Table 3 shows, our controls for news, time-invariant firm characteristics, and lagged returns do not change the qualitative conclusion that attention is highly correlated across social media platforms, while sentiment has a more modest correlation. Instead of the first PC of attention explaining 67% of the variation across platforms, residualized attention explains 63 to 66% of the variation. Sentiment is even more insensitive to controlling for news and firm fixed effects. Relative to the 38.8% in the unconditional PCA of sentiment, the conditional PCA results in a first PC that explains 38.1 to 38.2% of the variation across platforms. More than showing robustness to controlling for news and other confounding factors, these findings indicate that there is a strong cross-correlation in the information shared on social media platforms that is largely independent of news.[10] That is, the information on social media is not simply a reflection of traditional news, firm disclosures, and recent market conditions.

To ensure that these results are not driven by the way we define social media attention in Eq. (1), Appendix Table A2 reproduces the analyses in Tables 2 and 3 using an alternate firm-day attention measure: the deviation from the median number of messages over the preceding 10 days ("abnormal attention"). The PCA loadings are very similar, and fraction of variation explained by each PC shows the same pattern, albeit with PC1's share falling to around 50%. To further alleviate this concern, we construct an extensive margin measure of attention: whether a stock is mentioned on a platform ("coverage"). Appendix Table A3 shows that the cross-platform correlations for coverage are lower, at around half the level shown for our main attention measure. However, despite this being an extensive margin measure, the PCA shows similar results to those for abnormal attention.[11]

3.3. Heterogeneity by firm size

There are clear differences in coverage across platforms by firm size: StockTwits over-represents small stocks relative to Twitter and Seeking Alpha. Thus, we explore heterogeneity by firm size by performing a separate PCA for firms within different size bins: small (below $2 billion in market cap), medium (between $2 billion and $10 billion), and large (above $10 billion). For clarity, the heterogeneity analysis reports only the first PC; our main interest is in evaluating this component's strength, loadings, and how it varies by firm size.

Table 4 reports the results. We find that large firms have more commonality in both attention and sentiment signals than do medium and small firms. Moreover, within each size bucket, the main conclusion of the PCA holds: attention is more correlated than is sentiment. However, there is meaningful heterogeneity across the size distribution in the strength of the first PC. Panels A and B present the unconditional PCA results. For attention, the first PC explains 49.5% of variation for small firms, but this increases to 72.5% for large firms. Sentiment's first PC

[10] When social media posts are not talking about firm news, what do they talk about? There are many potential non-news topics. Typical examples include how national or international events affect the focal firm, or how news about competitors does.

[11] In Appendix Table A4 we include Reddit's WallStreetBets (WSB) sentiment and attention as additional signals in the conditional PCA. Our findings are unchanged: PC1 of attention explains approximately double the baseline variation (51.1% vs. 25%), while PC1 of sentiment remains barely above the baseline.

Table 4
How common is the social signal across platforms? *Heterogeneity in first principal component (PC1) by firm size*.

Panel A: PC1 of attention signals by firm size						
	Small		Medium		Large	
StockTwits	0.577		0.620		0.566	
Twitter	0.653		0.652		0.615	
Seeking Alpha	0.490		0.436		0.549	
Fraction of variation	49.5%		58.9%		72.5%	
	(1.225)		(1.009)		(10.168)	
Panel B: PC1 of sentiment signals by firm size						
	Small		Medium		Large	
StockTwits	0.637		0.659		0.643	
Twitter	0.661		0.665		0.670	
Seeking Alpha	0.397		0.352		0.372	
Fraction of variation	36.3%		40.1%		42.4%	
	(0.129)		(0.258)		(0.288)	
Panel C: PC1 of residualized attention signals by firm size						
	Residualize news			Residualize news & firm FEs		
	Small	Medium	Large	Small	Medium	Large
StockTwits	0.634	0.664	0.577	0.647	0.671	0.609
Twitter	0.668	0.675	0.618	0.672	0.681	0.627
Seeking Alpha	0.390	0.321	0.534	0.360	0.293	0.485
Fraction of variation	46%	54.4%	69.4%	45.7%	54.4%	68.1%
	(1.167)	(1.047)	(9.060)	(1.139)	(0.798)	(7.651)
Panel D: PC1 of residualized sentiment signals by firm size						
	Residualize news			Residualize news & firm FE		
	Small	Medium	Large	Small	Medium	Large
StockTwits	0.656	0.671	0.656	0.669	0.673	0.659
Twitter	0.674	0.678	0.682	0.679	0.680	0.680
Seeking Alpha	0.338	0.299	0.323	0.300	0.291	0.320
Fraction of variation	36%	39.6%	41.7%	36.2%	39.4%	41.2%
	(0.122)	(0.274)	(0.274)	(0.110)	(0.248)	(0.210)

Note: This table reports heterogeneity in the first principal components from Table 2 panel C and Table 3 columns 1–6. The sample is split into three groups by firm size: "small" refers to stocks whose market capitalization is below 2 billion; "medium" those between 2 and 10 billion; "large" those above 10 billion. Standard errors in parentheses are double clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

is stronger for large firms (42.4%) than for small firms (36.3%). Panels C and D present the results of the conditional PCA. Similar to our main findings, residualizing attenuates the strength of the first PC slightly, but it does not change the qualitative conclusion. Notably, differences in news and time-invariant firm characteristics do not explain the heterogeneity across the size distribution, which remains pronounced in the conditional PCA.

3.4. Similarities and differences in the social signal across user types

A potential explanation for the weak correlation of sentiment across platforms is that the different natural language processing (NLP) algorithms used for each platform may produce different measures from the same underlying text. We test whether NLPs are a major driver of the low correlation in sentiment signals by focusing on messages *within* StockTwits *across* types of users. The StockTwits data allow us to construct attention and sentiment signals separately for different investor subgroups. In this section, we disaggregate the StockTwits signal to separately consider the sentiment and attention of influencers (those in the top 1% by number of followers), professional users, intermediate users, novice users, and users who do not indicate an experience category ("no label").

Panel A of Table 5 presents the correlation of attention for each user subset on StockTwits with its complement at the firm-day level; for example, we compare the attention of the top 1% of users by followers with the remaining 99% in the first column. The correlations of attention across user groups on StockTwits range from 0.805 (top 1%) to 0.947 ("no label" users). In contrast to the high correlations for attention, those for sentiment are weak: correlations range from 0.166 (no label) to 0.088 (novices). These weak correlations in sentiment across user subgroups suggest that differences across user *types* are an important driver of differences in social media sentiment, because this analysis holds constant the NLP and platform features.

In Panels B and C, we repeat the conditional PCA using the signals from StockTwits subgroups. For brevity, these panels only report the first five PCs.[12] Consistent with our cross-platform PCA, we see that attention contains a strong common component (84.3% of the variation captured by PC1) while sentiment's common component is weaker, capturing only 27.6%. The second PCs capture differences in attention or sentiment between the more sophisticated investors (top 1% and professionals) and the rest. In the attention PCA, PC3 and higher explain very little variation. In contrast, these components explain a non-trivial share of variation for sentiment. Thus, differences in NLPs across platforms cannot fully drive our results. Moreover, this within-StockTwits evidence suggests that, even if NLPs and all platform features were identical, we would see cross-platform differences in the sentiment signal due to differences in user populations.

3.5. Are social signals persistent?

We now examine the persistence of attention and sentiment over time by computing the partial autocorrelation function (PACF) for each platform's attention and sentiment signal. In Appendix Figure A2, we compute the PACF for each series out to 20 lags (days). Attention (dashed lines) tends to have high autocorrelations at lag 1 (around 0.8) that decay to near zero after lag 5. By contrast, sentiment has low autocorrelations at lag 1 (between 0.1 and 0.25) and decays more rapidly to zero.

This constitutes another difference between attention and sentiment signals: attention exhibits a much greater and more persistent autocorrelation than does sentiment. We account for these underlying differences when we relate attention and sentiment to returns by controlling for 10 lags of each.

4. Informativeness of social media signals

In the second part of this paper we examine how the social signal relates to two outcomes typically studied by the literature: returns and retail order imbalance.

We first explore the informativeness for future returns of the attention and sentiment signals from each social media platform. Note that the signals from each platform are a combination of a *platform-specific* or idiosyncratic component, and a *common* social signal component. For example, a coefficient in a regression between an outcome and only the Twitter signal captures the relation between the outcome and a combination of (i) a common social media component and (ii) a Twitter-specific component. In contrast, in a regression with signals from all three platforms, coefficients on signals from each platform reflect only how each platform-specific component relates to the outcome. The contrast between the coefficients from these two regressions captures how the common component of a particular platform's signal relates to returns. Moreover, the informativeness of the common and idiosyncratic components of each platform's signal may be aligned (i.e., they have the same sign and approximate magnitude) or misaligned. Importantly, cases of misalignment can generate differences in informativeness between the platform-specific signal and the common social signal.

[12] Appendix Table A1 presents results from the unconditional PCA analysis.

Table 5
How common is the social signal across user types? *Evidence from users groups on StockTwits.*

Panel A: Correlations within StockTwits					
	Top 1%	Professional	Intermediate	Novice	No label
StockTwits attention	0.805	0.860	0.948	0.914	0.947
StockTwits sentiment	0.095	0.108	0.118	0.088	0.166

Panel B: PC1 of residualized attention signals					
	PC1	PC2	PC3	PC4	PC5
Top 1%	0.415	0.800	0.432	0.003	−0.023
Professional	0.443	0.195	−0.783	0.372	0.121
Intermediate	0.466	−0.193	−0.124	−0.490	−0.700
Novice	0.445	−0.464	0.423	0.632	−0.094
No label	0.465	−0.263	0.081	−0.471	0.698
Fraction of variation	84.3%	7.2%	4.6%	2.3%	1.5%
	(2.607)	(1.131)	(0.883)	(0.405)	(0.278)

Panel C: PC1 of residualized sentiment signals	PC1	PC2	PC3	PC4	PC5
Top 1%	0.572	−0.182	−0.128	0.084	−0.785
Professional	0.472	−0.398	−0.473	0.311	0.547
Intermediate	0.381	0.028	0.819	0.389	0.179
Novice	0.281	0.896	−0.271	0.201	0.062
No label	0.476	0.062	0.126	−0.839	0.222
Fraction of variation	27.6%	19.5%	19%	17.9%	16%
	(0.079)	(0.027)	(0.031)	(0.043)	(0.060)

Note: This table reports the correlations and principal component analyses of social signals across different user types on StockTwits. Panel A reports the bivariate correlations of attention and sentiment between StockTwits signals from each user group and their complements. Panels B and C use *residualized* attention and sentiment signals, respectively, i.e., residuals from regressing each signal on DJNW sentiment (lagged 0 through 7 days), DJNW attention (lagged 0 through 7 days), dummies for earnings announcements (lagged 0 through 7 days), dummies for 8-k filings (lagged 0 through 7 days), and firm fixed effects. PCA of non-residualized social signals from StockTwits user subgroups are reported in Appendix Table A1. Standard errors in parentheses are double clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

4.1. Does the social signal predict future returns?

To examine whether the social signal predicts returns, we estimate the following specification:

$$Abnormal\,Returns_{i,t+\tau} = \beta_1 Attention_{i,t} + \beta_2 Sentiment_{i,t} + \mathbf{X_{i,t}} \times \Gamma + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{3}$$

where the dependent variable *Abnormal Returns*$_{i,t+\tau}$ is in percentage points, and $\tau = 0, \ldots, 20$. $Attention_{i,t}$ and $Sentiment_{i,t}$ are firm-day measures from a particular platform or the principal components constructed in the previous section. In addition, the controls ($X_{i,t}$) include DJNW sentiment and attention, indicators for 8-K filing or earnings announcement days, lagged volatility ($t-1$ to $t-5$), lagged market returns (CAR $t-1$ to $t-5$ and $t-6$ to $t-30$), and firm and date fixed effects. We also control for log Google ASVI as an alternative measure of retail investor attention.[13] We further control for lagged $Attention_{i,\eta}$ and $Sentiment_{i,\eta}$ (where $\eta = t-1, t-2, \ldots, t-10$) to account for the autocorrelation documented in the preceding section. Table 6 presents the results from estimating Eq. (3) for next day ($t+1$) returns, with each column employing a different source of social signal.

The first column of Table 6 examines the informativeness for next-day returns of the common component in the social media signal captured by the first principal components (PC1s). We find that common social media sentiment is *positively* related to next day returns (a standard deviation increase predicts a 6.1 bps higher return), while attention is *negatively* related (−13 bps); note that these estimates of attention's relation to return are conditional on sentiment (and vice versa).[14] Column 2 includes all six signals, so estimates reflect the platform-specific contributions of each platform's sentiment and attention to informativeness. We see that the informativeness of StockTwits' idiosyncratic component largely aligns with the common component, while those of the other two platforms do not. In particular, Twitter's idiosyncratic sentiment coefficient is near zero, while the attention coefficient is positive and large (+11 bps), making it substantially different from the negative common attention coefficient.[15]

Columns 3–5 reproduce this analysis using the signals from one platform at a time; these single-platform regressions make use of a mix of idiosyncratic and common information. We see that coefficient estimates on StockTwits attention and sentiment in column 3 are well-aligned with the common component coefficients in column 1, making them a good reflection of the overall social signal for next-day returns. By contrast, while Twitter and Seeking Alpha's sentiment coefficients are directionally aligned with the common component, their attention coefficients are not. Comparing columns 1 and 2, we see Twitter's idiosyncratic and common attention components offset each other, leading to a near-zero combined attention effect in column 4. For Seeking Alpha attention, we see that the platform-specific coefficient in column 5 matches the idiosyncratic one from column 2, which suggests that the platform's attention does not load on the common component.

[13] Abnormal Google search volume, is calculated following Niessner (2015): we take the daily Google SVI data for each ticker and divide by its median SVI between days *t-56* and *t-35*. We then take the natural logarithm and replace missing values (caused by a missing median) with zero. The SVI data come from 200-day downloads with a day of overlap that we concatenate to ensure consistency across time.

[14] In Appendix Table A5, we include PC2 and PC3 of sentiment and find that the informativeness of PC1 sentiment is unchanged.

[15] We find that a reversal effect helps explain this positive relation between day t idiosyncratic Twitter attention and next-day returns. Specifically, we find that day t idiosyncratic Twitter attention has a *negative* relation to both day t returns (Appendix Table A9) and to day t retail order imbalance (Appendix Table A10), making the positive relation to next day returns a partial reversal of the day t effect. A plausible alternative mechanism is that day t idiosyncratic Twitter attention predicts *more* retail buying pressure on day t+1, driving up returns. However, we instead find that idiosyncratic Twitter attention on day t predicts slightly *lower* retail buying pressure on day t+1 (Appendix Table A11).

Table 6
How do next-day returns relate to social signals?

	Dependent var.: $AR_{i,t+1}$ (%)				
	(1)	(2)	(3)	(4)	(5)
Sentiment $PC1_{i,t}(z)$	0.061***				
	(0.009)				
Attention $PC1_{i,t}(z)$	−0.131***				
	(0.050)				
StockTwits $sentiment_{i,t}(z)$		0.049***	0.053***		
		(0.008)	(0.008)		
StockTwits $attention_{i,t}(z)$		−0.206***	−0.151***		
		(0.056)	(0.051)		
Twitter $sentiment_{i,t}(z)$		0.011		0.022***	
		(0.007)		(0.007)	
Twitter $attention_{i,t}(z)$		0.112***		−0.010	
		(0.031)		(0.020)	
Seeking Alpha $sentiment_{i,t}(z)$		0.079***			0.081***
		(0.010)			(0.010)
Seeking Alpha $attention_{i,t}(z)$		−0.010			−0.015
		(0.010)			(0.010)
DJNW $sentiment_{i,t}(z)$	0.078***	0.067***	0.079***	0.082***	0.071***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
DJNW $attention_{i,t}(z)$	0.012	−0.019*	0.008	−0.008	−0.012
	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)
8-K report $day_{i,t}$	0.070	0.014	0.061	0.044	0.037
	(0.044)	(0.044)	(0.043)	(0.044)	(0.042)
EA $day_{i,t}$	−0.547***	−0.539***	−0.547***	−0.538***	−0.566***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
$Volatility_{i,(t-5)\to(t-1)}$	−0.045	0.022	−0.009	−0.099	−0.114
	(0.375)	(0.378)	(0.377)	(0.375)	(0.373)
$CAR_{i,(t-5)\to(t-1)}$	−0.007***	−0.007***	−0.007***	−0.008***	−0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$CAR_{i,(t-30)\to(t-6)}$	−0.001*	−0.001*	−0.001*	−0.001*	−0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Google $ASVI_{i,t}$ (z)	−0.053***	−0.054***	−0.050***	−0.064***	−0.065***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Sentiment & $Attention_{i,(t-1),\ldots,(t-10)}$	Y	Y	Y	Y	Y
Firm (i) FE	Y	Y	Y	Y	Y
Date (t) FE	Y	Y	Y	Y	Y
Outcome mean	−0.048	−0.048	−0.048	−0.048	−0.048
Outcome SD	7.124	7.124	7.124	7.124	7.124
Observations	819,210	819,210	819,210	819,210	819,210
R^2	0.0320	0.0323	0.0321	0.0318	0.0319

Note: This table reports how next-day abnormal returns relate to social signals. The outcome is each security's abnormal return (AR) on day t + 1 in percentage points. We control for DJNW standardized sentiment and attention, 8-K report date indicators, earnings announcement indicators, lagged return volatility (previous five trading days), lagged cumulative abnormal returns (previous five trading days and the 25 days before that), and Log Google ASVI. All regressions include ten lags (t − 1 to t − 10) of sentiment, and ten lags of attention. (z) denotes a standardized variable (mean 0, standard deviation 1 using the estimation sample statistics). PC1 is the first principal component of StockTwits subsignals (top 1%, self labeled, professional, intermediate, novice, no experience), Twitter, and Seeking Alpha. Standard errors in parentheses are double clustered by firm and by date. *** 1%, ** 5%, * 10% significance level.

Examining the control variables in the table is also informative. These specifications hold constant the attention and sentiment of traditional media via the DJNW attention and sentiment controls. The coefficient estimates on these controls provide an alternative benchmark: a one standard deviation increase in DJNW sentiment predicts 8 bps higher next-day returns, while there is not a significant relationship between DJNW attention and returns. Log Google ASVI negatively predicts next-day returns and is largely uncorrelated with the social signal measures: coefficients are essentially unchanged when log ASVI is omitted in untabulated results.

4.1.1. Mechanisms for return predictability

To better understand the mechanisms behind the informativeness of attention and sentiment for next-day returns, we estimate a specification using the PC1 of attention and sentiment as of day t to predict cumulative abnormal returns for days $t+1$, $t+2$, …, $t+20$. Fig. 3 Panel (a) presents the estimated cumulative return coefficient on the sentiment PC1; the coefficients for the middle and top terciles of attention are in Panel (b). These figures show that the positive cumulative return coefficients on sentiment are stable out to day t+20 and do not decline. Similarly, the coefficients on middle and high attention increase in magnitude for several days before flattening out by around day t+15. To provide context for these estimates, we run the same specification for day t returns, and find a clear *positive* relation between both sentiment and attention and day t returns (see columns 1–2 of Table 7).[16] Putting these findings together, the negative attention estimates out to day $t+20$ reflect a gradual reversal of the positive return that occurs on day t that is especially pronounced for high-attention days. Moreover, this reversal is only partial, adding up to about 1.5 percentage points relative to the day t estimate of around 4 percentage points on high-attention days.

The above evidence also rules out some alternative interpretations. For example, the sentiment estimates exhibit no reversal, which is inconsistent with uninformed short-term buying pressure driving the positive day t and $t+1$ returns. Instead, this is consistent with the interpretation that social media sentiment contains market-relevant information. Turning to attention, one hypothesis about the negative day $t+1$ coefficient is that attention on day t reflects negative information that is not fully captured by sentiment. However, that is inconsistent with the positive relation between high attention and day t returns. A

[16] Appendix Figure A3 presents the estimates for sentiment and attention by platform for same day return and retail trading imbalance.

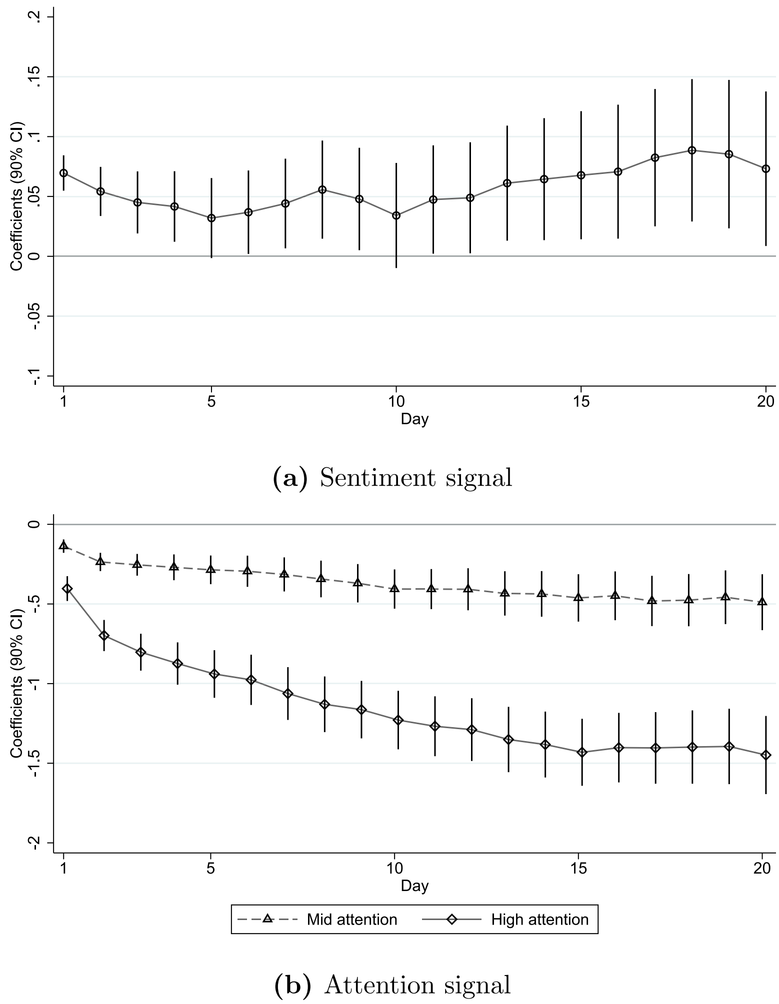


Fig. 3. Informativeness of social signals for cumulative abnormal returns. *Note:* This figure plots the estimated coefficients (and 90% confidence intervals) on the first principal components (PC1s) of sentiment signal (z) in Panel (a) and on high-level and mid-level attention in Panel (b). High-level (or mid-level) attention equals 1 if the firm-day attention PC1 is above the 67th percentile (or between percentiles 33 and 67) within a year, and zero otherwise. The outcome is the cumulative abnormal return as of day t+1, t+2, ..., t+20, starting on day t+1. We estimate separate regressions for each horizon, and sentiment and attention coefficients are estimated in the same regression. (z) denotes a standardized variable (mean 0, standard deviation 1 using estimation sample statistics). Everything else follows Table 6 column 1.

natural way to interpret these dynamic results is that high attention days correspond to an over-reaction.[17]

In Table 7 columns 3–6, we present results on how day t *retail trading* relates to the PC1s of sentiment and attention. Because retail trading reflects the actions of investors, these results illustrate the *impact* of the social signal, in addition to its content. We consider two measures of net retail buying: retail trade imbalance as in Boehmer et al. (2021) and the Robinhood user ratio as in Barber et al. (2022). For both we find that net buying on day t is positively related to sentiment and attention. Coefficient estimates are especially large and statistically significant for attention, consistent with the interpretation that returns overshoot on high-attention days due to net buying by retail investors, and then gradually reverse. Further, in Appendix Figure A5, we present how day t sentiment and attention relate to retail trading imbalance on days t, $t+1$, ..., $t+20$. Retail trading is only significantly related to day t sentiment contemporaneously and for one or two days afterwards; the coefficient estimates on attention fall rapidly after day t.[18] Thus, the dynamic relation between returns and the social signal is unlikely to be driven by retail buying or selling pressure that persists beyond day $t+1$.[19]

4.1.2. Heterogeneity by size

In Table 1 Panel C, we show that the platforms focus on different parts of the firm size distribution, with StockTwits weighted towards small-cap firms, and Seeking Alpha and Twitter focusing on large-cap firms. Therefore, we examine whether the informativeness of the signal in columns 1–3 of Table 6 varies by firm size. Fig. 4 plots the coefficients of sentiment and attention from regressions similar to the ones in Table 6, except run separately for small, mid-, and

[17] We further examine the role of *news* as a mediator for our social media sentiment and attention estimates in Appendix Figure A4. To do this, we split days into "news days" (days the firm is covered by Dow Jones Newswire, days with an Earnings Announcement, or days with an 8K filing) and "no-news" days (days outside a ±7 day window of any news day). We find that sentiment is informative in the presence of news, but not in its absence. By contrast, attention's over-reaction is greatest on no-news days, suggesting that the presence of news disciplines return overshooting.

[18] In addition, the attention estimates are the wrong sign to explain the negative returns from day $t+1$ through $t+20$ via a buying pressure channel.

[19] Appendix Table A10 presents how the same-day retail trading results differ by platform. Intriguingly, StockTwits sentiment and attention are more robustly related to retail trading imbalance than Twitter or Seeking Alpha. Idiosyncratic Twitter attention (conditional on the other signals) even *negatively* relates to retail buying pressure.

Table 7
How do same-day returns and retail trading relate to social signals?

	Dependent var.:					
	$AR_{i,t}$ (%)		RT imbalance$_{i,t}$ (%)		RH user ratio$_{i,t}$ (%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Sentiment $PC1_{i,t}(z)$	1.591***	1.498***	0.781***	0.655***	1.373	1.182
	(0.036)	(0.033)	(0.046)	(0.043)	(1.025)	(1.055)
Attention $PC1_{i,t}(z)$	3.630***		1.084***		7.033***	
	(0.734)		(0.214)		(1.701)	
Mid attention$_{i,t}$		1.496***		2.000***		1.897***
		(0.058)		(0.089)		(0.531)
High attention$_{i,t}$		4.049***		3.969***		5.976***
		(0.155)		(0.143)		(1.337)
DJNW sentiment$_{i,t}(z)$	0.425***	0.380***	0.135***	0.073***	0.031	−0.029
	(0.023)	(0.021)	(0.025)	(0.024)	(0.073)	(0.074)
DJNW attention$_{i,t}(z)$	−0.272***	0.019	−0.134***	−0.107**	−0.303	0.303
	(0.046)	(0.036)	(0.044)	(0.042)	(0.358)	(0.260)
Sentiment & Attention$_{i,(t-1),\ldots,(t-10)}$	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Firm (i) FE	Y	Y	Y	Y	Y	Y
Date (t) FE	Y	Y	Y	Y	Y	Y
Outcome mean	0.358	0.358	−0.327	−0.327	3.705	3.705
Outcome SD	9.190	9.190	23.173	23.173	178.715	178.715
Observations	819,706	819,706	810,652	810,652	171,479	171,479
R^2	0.0917	0.0779	0.0279	0.0300	0.1988	0.1989

Note: This table reports how same-day abnormal returns and retail trading relate to social signals. The outcome in columns 1–2, 3–4, and 5–6 is abnormal returns (AR) on day t in percentage points, retail trading (RT) imbalance on day t in percentage points, and Robinhood (RH) user ratio on day t in percentage points, respectively. RH user ratio on day t is calculated as (user number around 4 pm on t/number around 4 pm on t − 1) - 1 following Barber et al. (2022). High (or mid) attention equals 1 if the firm-day attention PC1 is above 67 percentile (or between 33 and 67 percentile) within a year, and zero otherwise. We control for DJNW standardized sentiment and attention, 8-K report date indicators, earnings announcement indicators, lagged return volatility (previous five trading days), lagged cumulative abnormal returns (previous five trading days and the 25 days before that), and Log Google ASVI. We additionally control for lagged RT imbalance (previous five trading days and the 25 days before that) in columns 3–4 and lagged RH user ratio (previous five trading days and the 25 days before that) in columns 5–6. All regressions include ten lags (t − 1 to t − 10) of sentiment, and ten lags of high and mid attention indicators. (z) denotes a standardized variable (mean 0, standard deviation 1 using the estimation sample statistics). PC1 is the first principal component of StockTwits subsignals (top 1%, self labeled, professional, intermediate, novice, no experience), Twitter, and Seeking Alpha. Standard errors in parentheses are double clustered by firm and by date. *** 1%, ** 5%, * 10% significance level.

large-cap firms. In Panel (a) we find that sentiment for all three platforms positively predicts next-day abnormal returns, with sentiment on Twitter having the least predictive power across all firm size bins. The informativeness and the differences between platforms are larger for small-cap firms than for large-caps. In Panel (b) we show that, consistent with the results in Table 6, attention predicts lower next day returns, most evident for StockTwits for small- and mid-cap firms. To sum up, the informativeness of sentiment is higher for small-cap and mid-cap firms, whereas that of attention is concentrated mostly in small-cap and somewhat in mid-cap firms.[20]

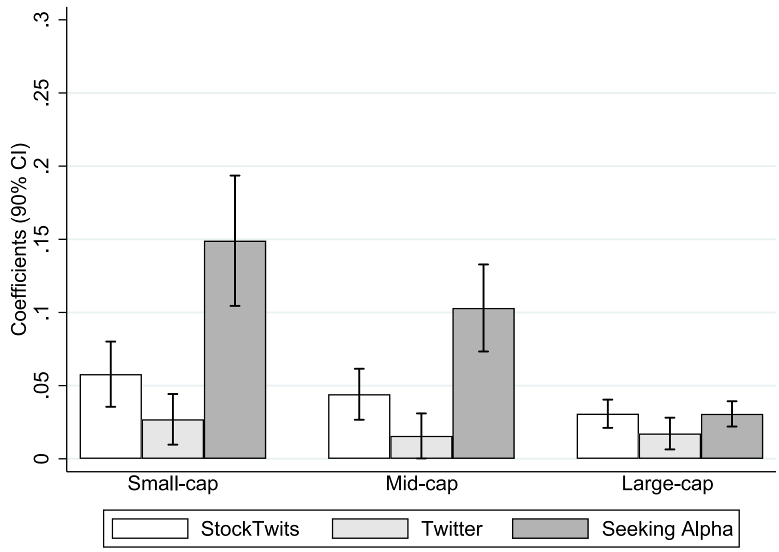
4.1.3. Robustness

One downside to using the PC1 in column 4 of Table 6 is that the PCA is conducted over the entire sample period. This means that it would be impossible to take advantage of this information on date t, since it uses future data to create the signal. Therefore, in Appendix Table A6 we use a 1-year rolling PCA: for each year, we use the PCs constructed using the data from the previous calendar year. In column 1 we examine the PC1s of sentiment and attention, and the results are strikingly similar in magnitude and statistical significance to the corresponding coefficients in column 4 of Table 6. This implies that using data from the future to calculate PCs does not predict next-day returns any better than using data from the prior calendar year. In column 2, we add the second and the third sentiment PCs. Both positively predict next day returns with a smaller coefficient than PC1. Overall, the results in Appendix Table A6 suggest that our results in the main tables are not driven by a look-ahead bias.

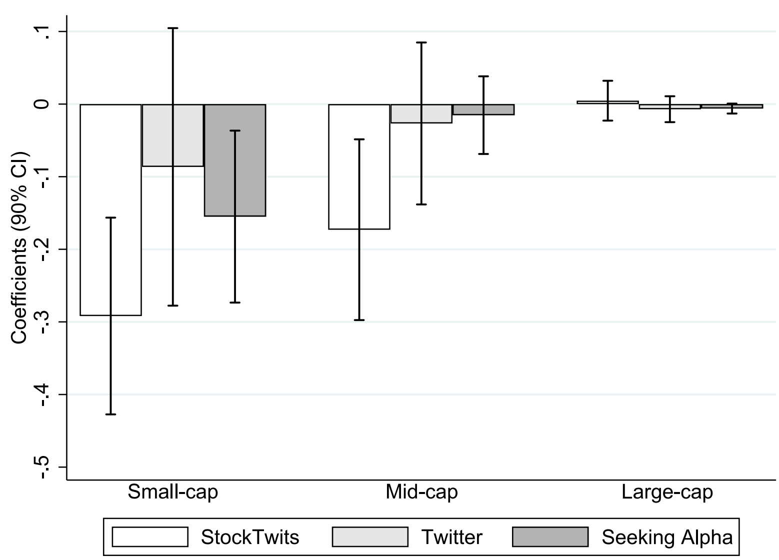
The attention results in Table 6 may be influenced by our definition of social media attention in Eq. (1). Therefore, in Appendix Table A7 we replicate the analysis using an alternate firm-day attention measure: the deviation from its median number of messages over the preceding 10 days. The loading on attention for StockTwits stays negative, albeit with slightly lower magnitude and statistical significance. Further, the table shows that attention from Seeking Alpha has a negative relation to next day's returns, especially when sentiment is negative. Overall, this table further supports the finding that attention is negatively related to next day returns.

A natural question in light of the GameStop short squeeze of January 2021 is how social media attention and sentiment from Reddit's WallStreetBets (WSB) relate to the signals we have examined so far. Our focus has been on the three platforms that have the longest time series of data, going back to 2012 (StockTwits, Twitter and Seeking Alpha). However, to understand the contribution of a new social platform, we collected all messages from Reddit WSB from Pushshift.io starting in 2018, when there is enough data to make this analysis meaningful, and using VADER (Hutto and Gilbert, 2014) to classify sentiment. We find that Reddit appears to be different from the major platforms in its relation to next day returns (see Appendix Table A8). WSB attention is positively related to next-day returns, while WSB sentiment is unrelated. Although the sample time window is more limited (2018–2021), the signals for the other three platforms reflect the same pattern we have seen throughout the paper: sentiment is positively related to next-day returns, but attention is negatively related. These contrasting results between WSB and other platforms may reflect differences in platform features or in user populations. We examine these mechanisms in the next section focusing on the three main platforms.

[20] Given that the distribution of returns is different for the three size subgroups, we normalize next-day returns within each size bin before estimation in Appendix Figure A6. Our conclusions are similar to the analysis in the main text. In addition, Appendix Figure A7 repeats the dynamic plot in Fig. 3 in small-, mid-, and large-cap firm subsamples. These dynamics are similar to the overall results, with larger coefficient estimates for small-cap firms than for larger firms.



(a) Informativeness of sentiment signal



(b) Informativeness of attention signal

Fig. 4. How do next-day returns relate to platform-specific social signals *by Firm Size*? *Note:* This figure plots the estimated coefficients (and 90% confidence intervals) on sentiment and attention signals (z) for StockTwits, Twitter, and Seeking Alpha for small-cap, mid-cap, and large-cap firms, separately. Firm size categories follow those in Table 1. The outcome is the abnormal return on day t+1. (z) denotes a standardized variable (mean 0, standard deviation 1 using estimation sample statistics by firm size). Everything else follows Table 6 columns 3–5.

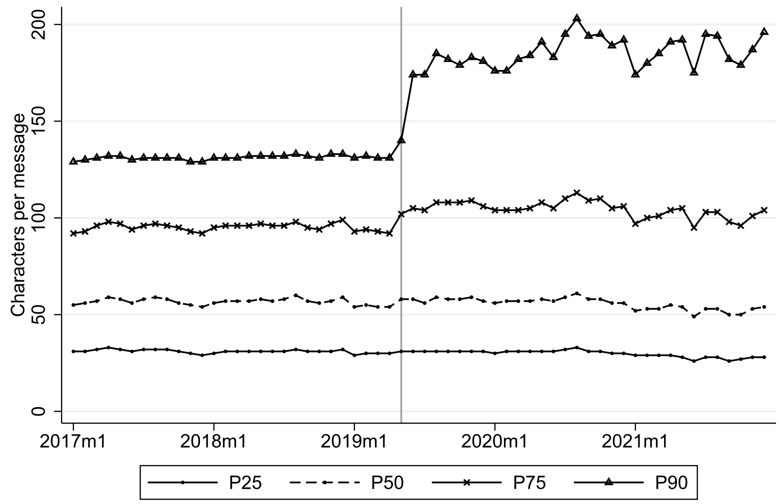
4.2. Information from market events

To understand what could be driving the cross-platform differences in the informativeness of sentiment and attention, we study two market events that affected platform-specific features or user populations, thereby potentially changing the information impounded in the social signal. First, we study changes in the informativeness of the social signal when StockTwits substantially increased its character limit per message. Second, we examine how the informativeness of sentiment and attention changed around the January 2021 GME phenomenon.

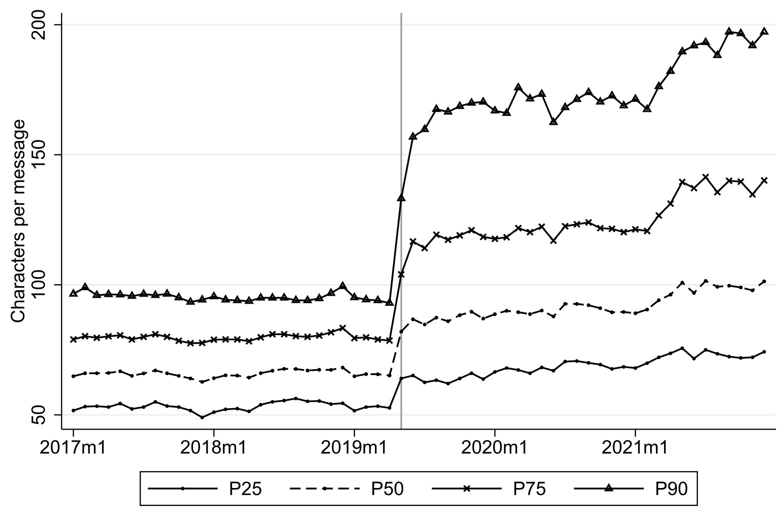
4.2.1. StockTwits character limit change

On May 8, 2019, StockTwits changed the character limit on its posts from 140 characters to 1,000. We explore whether this change affected the informativeness of the signal from StockTwits, in comparison to the plausibly unaffected signals from Twitter and Seeking Alpha. Communication theory suggests that changes to a medium's features may have large effects on the information it communicates (McLuhan, 1975). To focus on the StockTwits format change, we analyze the period from one year before to one year after May 8, 2019.

Fig. 5 Panel (a) plots the distribution of the number of characters per message across this event window, and Panel (b) firm-day averages of the number of characters per message, which ensures the figure is not dominated by messages about the most popular firms. Consistent with the character limit increase only affecting the content of longer messages, whose authors most likely were writing at the character limit, we see that only messages in the top quartile of characters per message become longer after the change. Similarly, the impact of the character



(a) Number of characters per message



(b) Firm-day level average number of characters per message

Fig. 5. Monthly quartiles of number of message length. *Note:* This figure plots monthly quartiles of number of characters per message (panel a) and monthly quartiles of the firm-day level average number of characters per message (panel b). The vertical line denotes May 8, 2019, the date when StockTwits increased its character limit from 140 characters to 1,000.

limit expansion is also larger at the top of the distribution for the firm-day averages (Panel b).

To focus more cleanly on the impact of the StockTwits character limit increase, we present a set of platform-specific regressions of the form:

$$\begin{aligned} Abnormal\,Returns_{i,t+1} = {} & \beta_1 Attention_{i,t} + \beta_2 Sentiment_{i,t} \\ & + \beta_3 Sentiment_{i,t} \times Post_t \\ & + \beta_4 Attention_{i,t} \times Post_t + \mathbf{X_{i,t}} \times \Gamma + \alpha_t + \alpha_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

This specification includes controls and fixed effects as in Eq. (3) for next-day returns. Relative to Eq. (3), the novel terms are sentiment and attention interacted with a $Post_t$ indicator for the date being after May 8, 2019. The coefficients of interest are these interactions with $Post_t$, which capture changes in the informativeness of the social signal around the character limit increase.

Table 8 reports the results from estimating this specification separately for StockTwits, Twitter, and Seeking Alpha. Consistent with StockTwits sentiment becoming more informative after the character limit increase, we find that the coefficient on sentiment for next-day returns increases by 7 bps (column 1). This estimate is nearly twice the size of the main effect of sentiment (3 bps, row 3 of the table). In column 2 we focus on StockTwits signals for stocks with an average character length in the top quartile on a day, and find an even stronger increase in informativeness of nearly 14 bps. By contrast, we see no change for Twitter or Seeking Alpha in columns 3 and 4, indicating that the change in informativeness is specific to StockTwits.

A potential mechanism through which posts become more informative after the character limit increase is a change in the composition of the messages. Specifically, it could be the case that more sophisticated investors take advantage of the change to write longer messages, either because the salience of the feature change induces some of them to modify their influence strategy, or because longer posts are more persuasive than shorter ones. This is indeed what we find in Appendix Table A12: Professional investors write longer messages before the change, and increase their message length by more after it. In Appendix Table 13 we find that Professional investors' sentiment has a stronger predictive power for next day's returns than Novices and Influencers, while the attention of each user type predicts next day returns with a

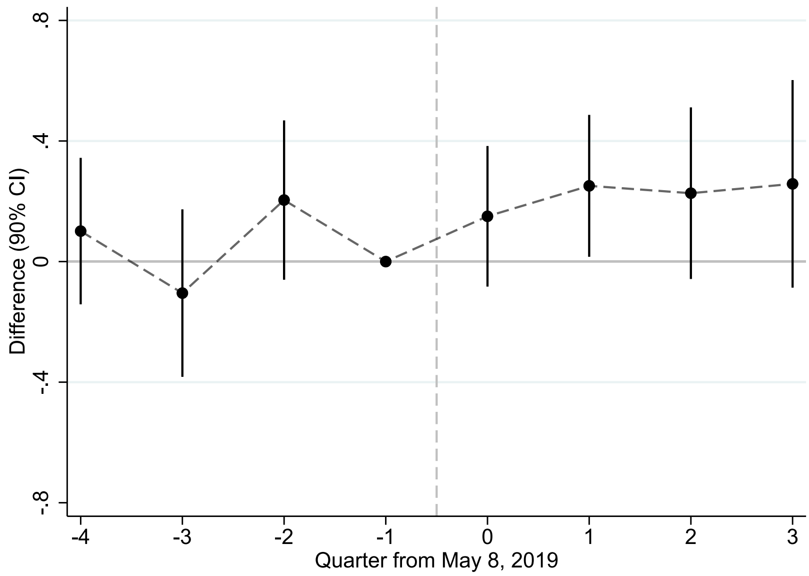


Fig. 6. How did the informativeness of the sentiment signal for next-day returns change around the StockTwits character limit increase? *Note:* This figure provides event study estimates (and 90% confidence intervals) of how the StockTwits sentiment signal relates to next day abnormal returns around the StockTwits character limit increase. The treated group is stocks whose daily average number of characters per message is in the top quartile; the comparison group is stocks in the bottom quartile. Event time 0 represents the three months following May 8, 2019 — the date of the character limit change. The omitted period is quarter −1. The sample consists of firm-day observations with at least 10 messages on StockTwits between May 8, 2018 and May 8, 2020. Everything else follows Appendix Table A14.

Table 8
How did the informativeness of social signals change around the StockTwits character limit increase?

	Dependent var.: $AR_{i,t+1}$ (%)			
	(1) StockTwits	(2) StockTwits top quartile	(3) Twitter	(4) Seeking Alpha
$Post_t \times Sentiment_{i,t}(z)$	0.070**	0.138**	−0.010	−0.007
	(0.034)	(0.055)	(0.043)	(0.034)
$Post_t \times Attention_{i,t}(z)$	0.165*	−0.269	−0.005	−0.016
	(0.088)	(0.226)	(0.026)	(0.031)
$Sentiment_{i,t}(z)$	0.031	0.004	0.000	0.078***
	(0.024)	(0.037)	(0.019)	(0.024)
$Attention_{i,t}(z)$	−0.382***	−0.290	−0.032	−0.016
	(0.117)	(0.200)	(0.025)	(0.022)
DJNW $sentiment_{i,t}(z)$	0.098***	0.091***	0.101***	0.087***
	(0.016)	(0.026)	(0.016)	(0.016)
DJNW $attention_{i,t}(z)$	0.019	−0.008	−0.005	−0.011
	(0.025)	(0.053)	(0.025)	(0.022)
Controls	Y	Y	Y	Y
Firm (i) FE	Y	Y	Y	Y
Date (t) FE	Y	Y	Y	Y
Outcome mean	−0.093	0.004	−0.093	−0.093
Outcome SD	7.819	6.455	7.819	7.819
Observations	215,319	53,659	215,319	215,319
R^2	0.027	0.065	0.026	0.026

Note: This table compares how social signals from different platforms changed their predictive power for next-day returns around the character limit increase on StockTwits. The outcome is abnormal returns (AR) on day t + 1 in percentage points. $Post_t$ is one if a day is on or after May 8, 2019. Social signals in columns 1–4 are StockTwits signals, StockTwits signals for stocks with top quartile daily average character length per message, Twitter signals, and Seeking Alpha signals, respectively. Controls are 8-K report date indicators, earnings announcement indicators, lagged return volatility (previous five trading days), lagged cumulative abnormal returns (previous five trading days and the 25 days before that), and Log Google ASVI. The sample consists of firm-day observations with at least 10 messages on StockTwits between May 8,2018 and May 7, 2020. (z) denotes a standardized variable (mean 0, standard deviation 1 using the estimation sample statistics). Standard errors in parentheses are double clustered by firm and by date. *** 1%, ** 5%, * 10% significance level.

negative sign. Taken together, the increased informativeness of sentiment from longer messages after the character-limit change seems to be driven by Professional investors taking disproportionate advantage of the new feature.

To more formally estimate the impact of the character limit increase, we perform analysis akin to a difference-in-differences design in which we define "treated" observations as firms with an average character length in the top quartile on any given day, and "control" as those in the bottom quartile. Using this definition, we extend the specification in Eq. (4) to one that also contains interactions with the $Treated_i$ indicator and report estimates in Appendix Table A14. The estimate on the triple interaction term $Post_t \times Treated_i \times Sentiment_{it}(z)$ shows that, after the character limit increase, sentiment becomes more informative for next-day returns, especially for stocks most affected by the increase. Specifically, a standard deviation increase in sentiment predicts an 17.8 bps greater return for stocks most discussed by long vs. short messages on StockTwits. By contrast, attention's informativeness falls after the character limit change, although the coefficient on the triple interaction is only weakly statistically significant.

Fig. 6 presents quarterly estimates of the triple interaction around the character limit increase. This plot indicates that the effect is not driven by any obvious trends in informativeness of sentiment over time.[21]

An alternative explanation for the increased informativeness of the sentiment signal is that once messages become longer, natural language processing (NLP) algorithms are better able to classify sentiment. In Appendix Table A15 columns 1 and 2 we focus only on the subset of StockTwits messages that have user-labeled sentiment (as described in Section 2), and reproduce the analysis in Table 8. Reassuringly, the coefficients are similar in sign and magnitude, supporting the view that the increased informativeness after the character limit change is not driven solely by a better NLP classification of longer messages. However, because the standard errors increase due to the reduced sample size, the coefficients are not statistically significant.

[21] Appendix Figure A8 extends the sample window relative to Fig. 6 and plots coefficient estimates on sentiment for stocks most discussed by long messages on StockTwits at the semester level. We see no pre-trend in the informativeness over this extended period, and the heightened informativeness persists until the beginning of the pandemic (first semester of 2020).

Table 9
How did the informativeness of social signals change around the GameStop event?

	Dependent var.: $AR_{i,t+1}$ (%)			
	(1) PC signal	(2) PC signal	(3) StockTwits new	(4) StockTwits old
$Post_t$ × $Sentiment_{i,t}(z)$	−0.125***	−0.124***	−0.103**	0.002
	(0.048)	(0.048)	(0.043)	(0.034)
$Post_t$ × $Attention_{i,t}(z)$	0.001	−0.001	0.015	−0.019
	(0.093)	(0.094)	(0.107)	(0.090)
$Sentiment_{i,t}(z)$	0.111***	0.111***	0.101**	0.038
	(0.042)	(0.042)	(0.039)	(0.028)
$Attention_{i,t}(z)$	−0.071	−0.070	−0.065	−0.065
	(0.056)	(0.057)	(0.065)	(0.054)
$Post_t$ × Sentiment $PC2_{i,t}(z)$		0.028		
		(0.033)		
$Post_t$ × Sentiment $PC3_{i,t}(z)$		0.014		
		(0.030)		
Sentiment $PC2_{i,t}(z)$		−0.004		
		(0.026)		
Sentiment $PC3_{i,t}(z)$		0.022		
		(0.026)		
DJNW $sentiment_{i,t}(z)$	0.086***	0.081***	0.088***	0.087***
	(0.016)	(0.016)	(0.017)	(0.016)
DJNW $attention_{i,t}(z)$	−0.058**	−0.060**	−0.064**	−0.060**
	(0.029)	(0.029)	(0.029)	(0.029)
Controls	Y	Y	Y	Y
Firm (i) FE	Y	Y	Y	Y
Date (t) FE	Y	Y	Y	Y
Outcome mean	−0.005	−0.005	−0.005	−0.005
Outcome SD	7.864	7.864	7.864	7.864
Observations	289,092	289,092	289,092	289,092
R^2	0.049	0.049	0.049	0.049

Note: This table compares how social signals from different platforms and/or user types changed their predictive power for next-day abnormal returns (AR) around the GameStop event on January 28, 2021. The outcome is abnormal returns (AR) on day t + 1 in percentage points. $Post_t$ is one for days on or after February 1, 2021. Social signals in columns 1–2 are based on principal components (z) of attention or sentiment signals from all StockTwits subgroups, StockTwits self-labeled messages, Twitter, and Seeking Alpha (*PC signal*); column 3 messages from users who joined StockTwits in or after 2020 (*StockTwits new*); and column 4 messages from users who joined StockTwits before 2020 (*StockTwits old*), respectively. Controls are 8-K report day indicators, earnings announcement day indicators, lagged return volatility (previous five trading days), lagged return volatility (previous five trading days), lagged cumulative abnormal returns (previous five trading days and the 25 days before that), and Log Google ASVI. The sample consists of firm-day observations with at least 10 messages on StockTwits between February 1, 2020 and December 31, 2021, excluding January 2021. (z) denotes a standardized variable (mean 0, standard deviation 1 using the estimation sample statistics). PC1 is the first principal component of StockTwits subsignals (top 1%, self labeled, professional, intermediate, novice, no experience), Twitter, and Seeking Alpha. Standard errors are double clustered by firm and by date. *** 1%, ** 5%, * 10% significance level.

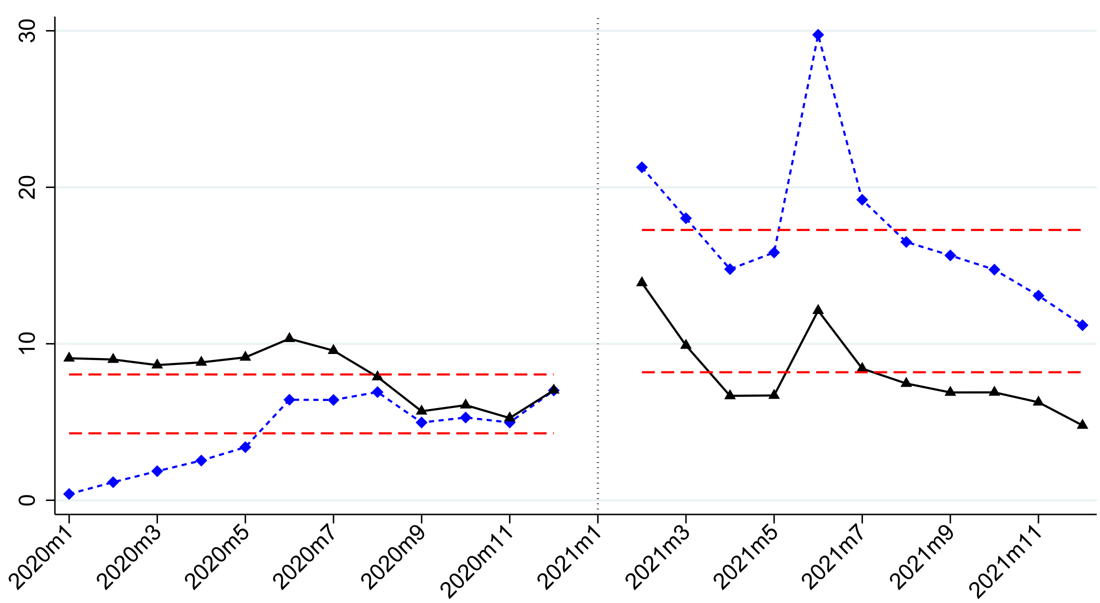


Fig. 7. Mentions of "Short Squeeze" on StockTwits around the GameStop event Old vs. new users. *Note:* This figure presents evidence on the changing narratives of StockTwits users in the months around the GME short squeeze event. Specifically, the figure plots monthly mentions of "short squeeze" from new users (blue diamonds) and old users (black triangles) around the event. Old users are those who joined StockTwits before January 2020 and new users are those joined in or after January 2020. Dashed horizontal lines denote sub-period averages for each user group.

4.2.2. Changes around the GameStop short squeeze

In this section, we analyze a second market event that likely influenced the informativeness of social media signals: the GameStop Short Squeeze event (GME event) in late January 2021, interacted with the large influx of new retail investors in US equity markets that occurred in 2020. Bradley et al. (2024) studies a class of posts on Reddit's WallStreetBets (WSB) called "due diligence reports" around this event, finding that these reports were informative for future returns before the event but were much less informative afterwards. We perform a similar analysis for signals from StockTwits, Twitter, and Seeking Alpha around the GME event using the first PCs of attention and sentiment constructed from the three platforms in Section 3.1.

We look at 11 months before and after the GME event since we have data until the end of 2021 (only 11 months after January 2021). We exclude January 2021 to have a cleaner pre/post comparison. The specification follows Eq. (4). Table 9 presents the findings on the informativeness of the social signal for next-day returns. We find that next-day returns' sensitivity to sentiment drops substantially following the GME event. Specifically, a standard deviation increase in sentiment (the first PC) is associated with a 12.5 bps lower return after the GME event (column 1), completely offsetting the pre-GME informativeness of social media sentiment (11.1 bps). In column 2, we additionally include the second and third PCs of sentiment (capturing cross-platform differences in sentiment), but the coefficients related to sentiment's first PC are virtually identical.

To better understand the mechanism behind this decline in informativeness, we use tweet-level data from StockTwits. Most social media platforms, including StockTwits, saw an influx of new users and increase in posts starting in 2020, likely the result of stay-at-home orders together with the introduction of no-fee trading at many brokerages in late 2019. We split the sample into tweets by those who joined StockTwits prior to January 1, 2020 (*established or old users*) and tweets by users who joined more recently (*new users*). From each subsample of tweets, we construct separate measures of attention and sentiment.

New users display a stronger interest in "short squeeze" strategies after the GME event. Fig. 7 documents a persistent uptick in mentions of short squeezes on StockTwits from an average of roughly 6,200 mentions per month in the year before the GME event to an average of nearly 13,000 afterwards. This spike in posts mentioning "short squeeze" is primarily driven by new users with an increase from around 4,300 to over 17,000 posts per month; in contrast, short squeeze posts from established users only see a moderate uptick (from 8,040 to 8,180 per month).

In Table 9 column 3, consistent with new users' stronger interest in "short squeeze", we find that the informativeness of the new users' signal for next-day returns declines by 10.3 bps for a standard deviation increase in sentiment after the GME event, again fully offsetting the pre-GME effect of sentiment. Importantly, however, the informativeness of the established users' signal does not change (column 4).[22]

An alternative explanation for the deceased informativeness is that new users might be using non-word tokens, like emojis, in a way that could reduce the effectiveness of NLP sentiment classification. In Appendix Table A15 columns 3 and 4, we repeat the analysis using only self-labeled sentiment. Reassuringly, the coefficients are similar in magnitude and statistical significance.

Finally, as a complement to the sample split-based evidence, we perform analysis akin to a difference-in-differences design in which we define "treated" observations as posts by new users, and "control" as those made by existing (old) users. This analysis contrasts the informativeness of the social signal for new users vs. established users, before vs. after the event. We report the results in Appendix Table A16. The estimate on the sentiment triple interaction implies that, after the GME event, sentiment becomes less informative for next-day returns for new users – relative to old users – although the coefficient is only significant at the 10% level.

Overall, these findings from the GME event highlight how the arrival of new users can influence the informativeness of the social media signal.

5. Conclusion

In this paper, we explore the similarities and differences in the social signals generated from StockTwits, Twitter, and Seeking Alpha. Our analysis reveals differences across social investing platforms that are much more pronounced for sentiment than for attention. We attribute these differences to differences in types of investors (e.g., influencers, professionals, and novices) *and* differences across platform features (e.g., character limits on posts).

Investor social media has increased steadily in popularity over the past two decades, and has grown rapidly in recent years. Online investment forums attract hundreds of thousands of daily users who intensively discuss individual securities in real time. Given the differences across platforms, particularly new entrants that rely on other kinds of media (e.g., Discord and TikTok), it is natural to expect the informativeness of future social signals and retail trading to evolve as well (Pyun, 2021). Will these new technologies enhance or weaken the information environment? We expect ample opportunities for future work to examine the consequences of these emerging technologies.

CRediT authorship contribution statement

J. Anthony Cookson: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Runjing Lu:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **William Mullins:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Marina Niessner:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interest with respect to this manuscript.

Data availability

Code and Data from "The Social Signal" (Original data) (Mendeley Data)

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jfineco.2024.103870.

[22] While the coefficient on sentiment in column 4 is not statistically significant, we show in Appendix Figure A9 that it does not represent a meaningful departure from prior years' coefficient estimates, which are positive and statistically significant.

References

Akçay, E., Hirshleifer, D., 2021. Social finance as cultural evolution, transmission bias, and market dynamics. Proc. Natl. Acad. Sci. 118 (26), e2015568118.

Antweiler, W., Frank, M.Z., 2004. Is all that talk just noise? The information content of internet stock message boards. J. Finance 59 (3), 1259–1294.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., 2018a. The economic effects of social networks: Evidence from the housing market. J. Polit. Econ. 126 (6), 2224–2276.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., Wong, A., 2018b. Social connectedness: Measurement, determinants, and effects. J. Econ. Perspect. 32 (3), 259–280.

Barber, B.M., Huang, X., Odean, T., Schwarz, C., 2022. Attention-induced trading and returns: Evidence from robinhood users. J. Finance 77 (6), 3141–3190.

Barber, B.M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. Q. J. Econ. 116 (1), 261–292.

Barber, B.M., Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Rev. Financ. Stud. 21 (2), 785–818.

Ben-Rephael, A., Da, Z., Israelsen, R.D., 2017. It depends on where you search: A comparison of institutional and retail attention. Rev. Financ. Stud. 30 (9), 3009–3047.

Bianchi, F., Gómez-Cram, R., Kind, T., Kung, H., 2023. Threats to central bank independence: High-frequency identification with Twitter. J. Monetary Econ. 135, 37–54.

Bianchi, F., Gómez-Cram, R., Kung, H., 2024. Using social media to identify the effects of congressional viewpoints on asset prices. Rev. Financ. Stud..

Blankespoor, E., Miller, G.S., White, H.D., 2014. The role of dissemination in market liquidity: Evidence from firms' use of Twitter. Account. Rev. 89 (1), 79–112.

Boehmer, E., Jones, C.M., Zhang, X., Zhang, X., 2021. Tracking retail investor activity. J. Finance 76 (5), 2249–2305.

Bradley, D., Hanousek, Jr., J., Jame, R., Xiao, Z., 2024. Place your bets? The value of investment research on Reddit's Wallstreetbets. Rev. Financ. Stud. 37 (5), 1409–1459.

Chen, H., De, P., Hu, Y.J., Hwang, B.-H., 2014. Wisdom of crowds: The value of stock opinions transmitted through social media. Rev. Financ. Stud. 27 (5), 1367–1403.

Chen, H., Hwang, B.-H., 2022. Listening in on investors' thoughts and conversations. J. Financ. Econ. 145 (2), 426–444.

Chen, H., Hwang, B.-H., Liu, B., Tang, Y., 2023. Tweeting Away Firm Value: How Investors Evaluate CEOs' Use of Social Media. Working Paper.

Cookson, J.A., Engelberg, J.E., Mullins, W., 2020. Does partisanship shape investor beliefs? Evidence from the COVID-19 pandemic. Rev. Asset Pricing Stud. 10 (4), 863–893.

Cookson, J.A., Engelberg, J., Mullins, W., 2023a. Echo chambers. Rev. Financ. Stud. 36 (2), 450–500.

Cookson, J.A., Fox, C., Gil-Bazo, J., Imbet, J.F., Schiller, C., 2023b. Social Media as a Bank Run Catalyst. Working Paper.

Cookson, J.A., Niessner, M., 2020. Why don't we agree? Evidence from a social network of investors. J. Finance 75 (1), 173–228.

Cookson, J.A., Niessner, M., Schiller, C., 2024. Can social media inform corporate decisions? Evidence from merger withdrawals. J. Finance forthcoming.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Finance 66 (5), 1461–1499.

Da, Z., Hua, J., Hung, C.-C., Peng, L., 2022. Market Returns and a Tale of Two Types of Attention. Working Paper.

Da, Z., Huang, X., 2020. Harnessing the wisdom of crowds. Manage. Sci. 66 (5), 1847–1867.

Da, Z., Huang, X., Jin, L.J., 2021. Extrapolative beliefs in the cross-section: What can we learn from the crowds? J. Financ. Econ. 140 (1), 175–196.

Daniel, K., Hirshleifer, D., 2015. Overconfident investors, predictable returns, and excessive trading. J. Econ. Perspect. 29 (4), 61–88.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. J. Finance 53 (6), 1839–1885.

Dim, C., 2024. Social Media Analysts' Skills: Insights from Text-implied Beliefs. Working Paper.

Eaton, G.W., Green, T.C., Roseman, B.S., Wu, Y., 2022. Retail trader sophistication and stock market quality: Evidence from brokerage outages. J. Financ. Econ. 146 (2), 502–528.

Farrell, M., Green, T.C., Jame, R., Markov, S., 2022. The democratization of investment research and the informativeness of retail investor trading. J. Financ. Econ. 145 (2), 616–641.

Forbes, 2021. Americans spent on average more than 1,300 hours on social media last year. Forbes https://www.forbes.com/sites/petersuciu/2021/06/24/americans-spent-more-than-1300-hours-on-social-media/?sh=352920522547. (Accessed 29 August 2022).

Garcia, D., 2013. Sentiment during recessions. J. Finance 68 (3), 1267–1300.

Gargano, A., Rossi, A.G., 2018. Does it pay to pay attention? Rev. Financ. Stud. 31 (12), 4595–4649.

Giannini, R., Irvine, P., Shu, T., 2018. Nonlocal disadvantage: An examination of social media sentiment. Rev. Asset Pricing Stud. 8 (2), 293–336.

Giannini, R., Irvine, P., Shu, T., 2019. The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. J. Financial Mark. 42, 94–120.

Gu, C., Kurov, A., 2020. Informational role of social media: Evidence from Twitter sentiment. J. Bank. Financ. 121, 105969.

Heimer, R.Z., 2016. Peer pressure: Social interaction and the disposition effect. Rev. Financ. Stud. 29 (11), 3177–3209.

Hirshleifer, D., 2020. Presidential address: Social transmission bias in economics and finance. J. Finance 75 (4), 1779–1831.

Hirshleifer, D., Peng, L., Wang, Q., 2023. News diffusion in social networks and stock market reactions. Rev. Financ. Stud. forthcoming.

Hutto, C., Gilbert, E., 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In: Proceedings of the International AAAI Conference on Web and Social Media. Vol. 8, pp. 216–225.

Irvine, P.J., Shen, S., Shu, T., 2021. Aggregate Attention. Working Paper.

Jame, R., Johnston, R., Markov, S., Wolfe, M.C., 2016. The value of crowdsourced earnings forecasts. J. Account. Res. 54 (4), 1077–1110.

Kogan, S., Moskowitz, T.J., Niessner, M., 2023. Social media and financial news manipulation. Rev. Finance 27 (4), 1229–1268.

Kuchler, T., Stroebel, J., 2021. Social finance. Annu. Rev. Finan. Econ. 13, 37–55.

Levy, R., 2021. Social media, news consumption, and polarization: Evidence from a field experiment. Amer. Econ. Rev. 111 (3), 831–870.

Liu, H., Peng, C., Xiong, W.A., Xiong, W., 2020. Resolving the Excessive Trading Puzzle: An Integrated Approach Based on Surveys and Transactions. NBER Working Paper.

Lu, R., Sheng, S.Y., 2022. How racial animus forms and spreads: Evidence from the coronavirus pandemic. J. Econ. Behav. Organ. 200, 82–98.

McLuhan, M., 1975. Understanding Media: The Extensions of Man. Routledge & Kegan Paul.

Müller, K., Schwarz, C., 2022. From hashtag to hate crime: Twitter and anti-minority sentiment. Am. Econ. J.: Appl. Econom.

Niessner, M., 2015. Strategic Disclosure Timing and Insider Trading. Working Paper.

Pedersen, L.H., 2022. Game on: Social networks and markets. J. Financ. Econ..

Pew, 2021. News use across social media platforms in 2020. Pew Res. Cent..

Pyun, C., 2021. Social Media Group Investing. Working Paper.

Renault, T., 2017. Intraday online investor sentiment and return patterns in the US stock market. J. Bank. Financ. 84, 25–40.

Sicherman, N., Loewenstein, G., Seppi, D.J., Utkus, S.P., 2016. Financial attention. Rev. Financ. Stud. 29 (4), 863–897.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. J. Finance 62 (3), 1139–1168.

Thompson, S.B., 2011. Simple formulas for standard errors that cluster by both firm and time. J. Financ. Econ. 99 (1), 1–10.