The Social Signal*

J. Anthony Cookson — *CU Boulder*
Runjing Lu — *Alberta*
William Mullins — *UC San Diego*
Marina Niessner — *Wharton*

May 10, 2023

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 vs. 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 distinguishing between social media sentiment and attention across different investor social media platforms.

Keywords: Social media, Retail trading, Social finance

JEL Codes: G14, G41, G12

*J. Anthony Cookson: University of Colorado at Boulder (tony.cookson@colorado.edu); Runjing Lu: University of Alberta (runjing1@ualberta.ca); William Mullins: UC San Diego (wmullins@ucsd.edu); Marina Niessner: University of Pennsylvania (marina.niessner@gmail.com). This draft has benefited from comments by Zhi Da, Yao Deng, Joey Engelberg, Lukasz Pomorski, Brian Waters, as well as from seminar and conference presentations at University of Colorado at Boulder, University of Texas-El Paso, University of Toronto, Washington University of St. Louis, University of Notre Dame, George Washington University, University of Florida, University of Miami, Arizona State University, University of Washington, Iowa State University, University of Iowa, National University of Singapore, Singapore Management University, Nanyang Technical University, 8th annual Conference on Network Science and Economics, the Michigan State FCU Conference, the USC Conference on Behavioral and Social Economics, MFA, Kepos Capital, and Citigroup Global Insights.

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 what 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 a myriad of ways.[2] Communication theory implies that social media platforms are not interchangeable, because the characteristics of a communication medium affects both the content and impact of the messages it carries (e.g., McLuhan, 1975). 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.

To examine whether and how these platforms generate differing market-relevant information – the social media *signal* – this paper examines 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* (in our setting, the number of messages about a firm) and *sentiment*

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

[2]For example, Seeking Alpha articles are long-form and are lightly moderated; Twitter posts are limited to 160 characters but multiple posts can be threaded together for longer arguments; while StockTwits posts cannot be threaded, but since 2019 have a 1,000 character limit. These platforms also differ in their user base, recommendation algorithms, how individuals interact on the platform through messages and tagging, and many other characteristics. Figure 1 presents an example post for each platform in our study.

(here: bullish vs. bearish views about a firm), and compare these across platforms. 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 orthogonal. Further, we show that the informativeness of both sentiment and attention in predicting next day returns varies across platforms. Exploiting two events – a change in message character limits on StockTwits and the GameStop (GME) short squeeze – we find that differences in platform *features* (the character-limit event) and differences across *users* (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 a joint principal component analyses (PCA) for attention and sentiment signals. The first principal component loads mostly on attention signals, while the second loads mostly on sentiment signals, indicating that sentiment and attention signals can be analyzed separately. When we perform cross-platform PCA analysis independently for attention and sentiment, the first principal component (PC1) explains 67% of the variation in attention, but the PC1 of sentiment only explains 39% of its variation across platforms. However, the co-variation we capture with the PCAs may be driven by news, firm disclosures, stock returns, or persistent firm components. We first show that attention and sentiment from traditional financial news (Dow Jones News Wire and the Wall Street Journal) are nearly uncorrelated with their social media counterparts. To test this more formally, we perform a conditional PCA in which we first residualize the signals by regressing them on traditional news variables, firm announcements, firm fixed effects, lagged returns and lagged volatility before performing the PCA with these residualized signals. This analysis, which removes covariation from news, yields very similar patterns, indicating that the information in investor social media differs from that in traditional media.

An alternative explanation for the finding that attention is more common than sentiment across platforms is that differences in natural language processing algorithms (NLPs) used to classify sentiment for different platforms affect sentiment more than attention. We provide evidence that NLPs do not fully explain the differences we observe by looking at different *user* types within StockTwits. Consistent with our cross-platform results, we find that attention is highly correlated for influencers, professionals, and novices, (i.e., the PC1 explains 84% of the variation), while sentiment signals have a weak correlation across investor subgroups, despite the fact that these different user groups face the same platform features and their sentiment signal is processed with the same NLP algorithm. While this suggests that differences in NLP are not the main driver of our results, this is also direct evidence that differences in user types matters for our central finding.

When we compare social investor platforms the most salient difference is in the size of the firms they cover. StockTwits focuses more on small-cap firms, while 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 large-cap firms display stronger commonality in attention and sentiment than small cap firms. Similar to the overall sample, attention displays more commonality than sentiment across all firm sizes.

In the second part of our paper, we explore whether the *informativeness* of their sentiment and attention signals are different. As a measure of informativeness we regress next-day abnormal returns on sentiment and attention signals from the three different platforms, controlling for traditional news, firm announcements, lagged returns and volatility, and Google search volume. We find that sentiment *positively* predicts next day abnormal returns, and the extent to which it differs across platforms. By contrast, StockTwits attention *negatively* predicts next day returns; there is no predictability from the other platforms' attention. Because the platforms focus on different-sized firms, we examine heterogeneity in informativeness by firm size. For sentiment, there does not appear to be a size-based difference in informativeness, either across or within platforms. However, StockTwits attention for small and medium-sized firms is more informative than it is for large firms. We next examine two information events to provide insight into whether platform-specific features and user groups contribute the differences in the informativeness of sentiment and attention for next day returns. 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 extracted from longer messages; the informativeness of shorter messages and attention were unchanged. We find that professionals' messages are more informative on average, and that after the limit change they write longer messages, suggesting a possible mechanism. Consistent with the fact that Twitter and Seeking Alpha were unaffected by StockTwits' 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. 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 stay-at-home orders coupled with the introduction of no-fee trading at many brokerages. Bradley et al. (2021) shows that Reddit retail trading based on "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.

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 a plethora of 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).[3] Divergent findings may stem from examining different parts of

[3]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

the investor social media space. In this paper, we show that this concern is particularly important for sentiment, while cross-platform differences are less important for attention.

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 taken connections on a single social media platform as a proxy for social connections in general (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 what 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 sufficiently large changes in the social media space.

Our results also contribute to the literature on retail attention and sentiment (e.g., Da et al., 2011a, 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., 2022a, 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., 2011b) 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.

experience.

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., 2021). 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 trading, and market outcomes, and we show that new entrants lead to much of the decline in informativeness following the GME phenomenon.This finding highlights how the content of previously informative signals can change upon the arrival of new participants, and this is a general phenomenon that is not just confined to one social network. More generally, we illustrate how features of different social media platforms (e.g., character limits and different user-bases) matter for retail trading informativeness.

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 a daily 4pm snapshot 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, 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. (2022a), 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.[4]

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 between 4:00 pm on date $t-1$ and 4:00 pm on date t, in order to match the timing of our Twitter tweet volume data. We then define a firm-day measure of attention, $Attention_{i,t}$, for each platform by dividing the firm-day number of messages by the total number of messages in a day:[5]

$$\text{Attention}_{i,t} = \frac{Messages_{i,t}}{\sum_i Messages_{i,t}} \tag{1}$$

StockTwits users can voluntarily declare their level of experience using the options pro-

[4]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.

[5]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 A8.

vided by StockTwits 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/bearish declarations), as opposed to StockTwits' own 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 by averaging firm-specific sentiment across articles each 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 I/B/E/S.

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 news media information and market data for return reactions, we obtain a final sample of roughly 815,000 firm-day observations.

Summary statistics of our analysis sample 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, for example, the greater volume of messages could contribute to 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 among each subgroup (the average number of posts ranges from 5.87 to 13.37 across the categories with experience).

Panel C illustrates how platforms differ in terms of the size of firms they pay attention to. The first three columns show the size 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 show that 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 share of messages and firms in each bin, suggesting StockTwits has more consistent coverage of firms than the other platforms.

Panel D shows how restricting our sample to firm-days with at least 10 StockTwits messages affects the observation count in our final sample. Our original firm-day sample falls from nearly 2.8 million to roughly 821,000 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. Figure 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 Figure 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 social media investing platforms and across StockTwits investor types. In this discussion we distinguish between two key dimensions of the social signal: sentiment and attention.

3.1 Are social signals common across platforms?

We begin by examining how much overlap there is in the social signal across StockTwits, Twitter, and Seeking Alpha. First, Figure 2 and Panel A of Table 2 present the bivariate correlations between StockTwits attention and sentiment, and the corresponding measures from 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 0.595 between StockTwits and Twitter attention, and 0.398 between StockTwits and Seeking Alpha. By comparison, the correlations with coverage by traditional news media are much weaker: 0.163 for the WSJ and 0.144 for the DJNW. These correlations indicate 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 of StockTwits with Seeking Alpha sentiment is 0.038. The correlation with news sentiment is also weak at 0.010 for the WSJ and 0.069 for the DJNW. This suggests that sentiment is more idiosyncratic across social investing platforms, and as Figure 2 highlights, the difference in the magnitudes of correlations for attention and sentiment is striking.

A priori, there are various reasonable hypotheses about how the six signals we analyze could be cross-correlated. For example, sentiment signals 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 cross-correlations that are strongest are attention across platforms and sentiment across platforms, not within-platform clustering or some mix between attention and sentiment signals.

To systematically describe the cross-correlation of the six signals (attention and sentiment by 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 from a PCA yields the linear combination of the signals that explain the most variation across the six signals. After this, the second principal component is the linear combination that explains the most of the remaining variation, and so on. Thus, to the extent that the loadings on the underlying signal are large within the same principal component, these series are mutually correlated with one another. The loadings tell us what are the important clusters 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. Finally, we compute standard errors for the loadings and the fraction of variation explained by each principal component by conducting a block bootstrap procedure that clusters standard errors by firm and date. To do this, we separately conduct a block bootstrap by firm and date, drawing 1,000 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.

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). The first principal component explains 35% of the variation across the six signals, which is nearly twice the variation explained in the second principal component. Moreover, the first PC 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, which comprises much of the analysis in the first part of the paper.

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 most attention is common across investors on various social media platforms, the first principal component (PC) of attention explains 67% of the variation across platforms. Further, all three attention signals are given similar positive weights in this first PC, suggesting a natural interpretation as the common component of attention manifested in all three social media platforms. The second PC 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.

Interpreting the sentiment PCA, the first PC of sentiment only explains 38.8% of the variation across platforms. This is a weak common component, because purely idiosyncratic variation in three series would result in a first PC explaining 33.3%. Like the attention PCA, the second PC of sentiment mostly highlights 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.

3.2 Conditional PCAs to account for the confounding effects of news and time invariant 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. You might think that we would control for this in a regression of a signal on the other signals, news, controls, and firm fixed effects. However, the problem with that is that we do not isolate the correlations across platforms that are of interest to us (i.e., in a regression of

Stocktwits sentiment on Twitter sentiment 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 adapt the PCA approach to one that includes covariates in a *conditional* PCA. In a conditional PCA, the input signals are first regressed on controls and fixed effects to orthogonalize the signal from confounding variation. We run separate regressions of the form:

$$Signal_{i,t}^{P} = \Gamma^{P} X_{i,t} + \gamma_i^{P} + \epsilon_{it} \tag{2}$$

Where $Signal_{i,t}^{P}$ 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, and γ_i^{P} are firm fixed effects. Then, we extract the residual from each series, and perform the PCA on the 6 residualized signals (3 attention separately from 3 sentiment). This approach removes confounding variation from traditional news coverage and time invariant firm characteristics while still allowing mutual cross-correlations in the series that are of interest to us.

We do this in Table 3 Panels A and B by first residualizing by news. What do we mean by news? This is traditional media coverage of the firm i on date t, drawn from RavenPack. RavenPack provides both the number of articles about the 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 and earnings announcements: including an indicator for whether there is an 8-K disclosure or an earnings announceemnt by firm i on date t, as well as 7 lags. Our intention is to flexibly control for news in the residualization step. What is left over is not a mere reflection of traditional media. We next residualize by news and also add firm fixed effects, to control for any unobserved, time-invariant firm characteristics. Finally, in the last three columns of both panels, we also residualized by lagged return volatility and cumulative abnormal returns.

As our results in Table 3 show, our aggressive approach to controlling for news, time-invariant firm characteristics, and lagged returns does not change the qualitative picture that attention is highly correlated across social media platforms, while sentiment has a more modest correlation. Instead of the first principal component of attention explaining 70% of the variation across attention signals, news-residualized attention explains 64 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, both conditional PCAs have a first principal component that explains 38 to 38.2% of the variation in sentiment signals. 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 there irrespective of news. That is, the information on social media is not a mere reflection of traditional news, firm disclosures, and recent market conditions.

One concern is that these results are driven by the way we define social media attention in Equation eq:attention equation. Appendix Table A2 reproduces the analysis in Tables 2 and 3 using an alternate firm-day attention measure: the deviation from its median number of messages over the preceding 10 days. 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 explore this concern, we construct the extensive margin of attention: whether a stock is mentioned on a platform ("coverage"). Table A4 shows 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.

3.3 Heterogeneity by Firm Size

There are notable differences in coverage across platforms by firm size. Notably, StockTwits over-represents small stocks relative to Twitter and Seeking Alpha. Thus, it is natural to consider heterogeneity by firm size. To do this, we perform 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). Our heterogeneity analysis reports the information from *only* the first principal component because our main interest is in evaluating this component's strength and loadings, as well as how it varies by firm size.

Table 4 reports the results from this heterogeneity analysis. 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 principal component. Panel A and B present the unconditional PCA results. For attention, the first principal component explains 49.5% of variation in small firms, but this increases to 72.5% for large firms. Sentiment's first principal component is stronger for large firms (42.4%) than for small firms (36.3%). Panels C and D present the results conditional PCA. Similar to our main findings, the residualization from the conditional PCA attenuates the strength of the first principal component slightly, but does not change the character of our findings. Notably, differences in news and time-invariant firm characteristics do not explain the heterogeneity across the size distribution, which remains pronounced in the conditional PCAs.

3.4 Similarities and differences in the social signal across user types

One explanation for weak correlation of sentiment across different platforms is that different natural language processing (NLP) algorithms produce different measures for the same underlying text. We test whether that is the main driver of the low correlation in sentiment signals, by focusing on messages by StockTwits users. In addition to allowing us to construct attention and sentiment signals at the firm-day level, the StockTwits data allow us to track these signals separately for difference 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"). This analysis allows us to hold constant the NLP algorithm.

Panel A of Table 5 presents the correlation of each user subset of the StockTwits data with its complement at the firm-day level, i.e., 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 0.819 (top 1%) to 0.987 ("no label" users). In contrast to the high correlations for attention, those for sentiment are quite weak: correlations range from 0.166 (no label) to 0.088 (novices). These weak correlations in sentiment across user subgroups suggest that idiosyncratic differences across user *types* are an important driver of differences in social media sentiment, rather than differences in natural language processing algorithm.

In panels B and C, we extend the PCA from the cross-platform table to include each of these alternative signals from StockTwits subgroups. For brevity, these panels only report the first five PCs. Consistent with our cross-platform evidence, we see that attention contains a strong common component (84.3% of the variation captured by PC1) while sentiment's common component is weaker at 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, components 3 onward explain very little variation. In contrast, these components explain a non-trivial share of variation for sentiment.

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 Figure A2, we compute the PACF for each series out to 20 lags (days). Attention (dashed lines) tends to have high autocorrelations (around 0.8 at lag 1) that decay to near zero after lag 5. By contrast, sentiment has low autocorrelations (between 0.1 and 0.25) and decays more rapidly to zero.

This pattern 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 our paper, we explore whether there is a difference in the *informativeness* of the sentiment and attention signals. As a measure of informativeness we regress next-day abnormal returns on sentiment and attention signals from the three different platforms.

4.1 Does the social signal predict next-day returns?

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

$$\begin{aligned} \textit{Abnormal Returns}_{i,t+1} &= \beta_1 \textit{Attention}_{i,t} + \beta_2 \textit{Sentiment}_{i,t} \\ &\quad + \beta_3 \textit{Sentiment}_{i,t} \times \textit{Attention}_{i,t} + \mathbf{X_{i,t}} \times \mathbf{\Gamma} + \alpha_{\mathbf{t}} + \epsilon_{\mathbf{it}} \end{aligned} \tag{3}$$

where the dependent variable $\textit{Abnormal Returns}_{i,t+1}$ is in percentage points. $\textit{Attention}_{i,t}$ and $\textit{Sentiment}_{i,t}$ are firm-day measures from one of the platforms or the principal components constructed in the previous section. In addition, the controls ($X_{i,t}$) include DJNW sentiment and attention, whether the day is an 8-K filing date or earnings announcement date, lagged volatility ($t-1$ to $t-5$), lagged market returns (CAR $t-1$ to $t-5$ and $t-6$ to $t-30$), and a date fixed effect. We also control for log Google ASVI as an alternative measure of retail investor attention.[6] We furthermore control for lagged $\textit{Attention}_{i,\tau}$ and $\textit{Sentiment}_{i,\tau}$ (where $\tau = t-1,\ t-2,\ ...,\ t-10$) to account for the autocorrelation documented in the preceding section. Table 6 presents the results from estimating Equation (3), with each column employing a different source of social signal.

Columns 1 through 3 of Table 6 present how sentiment and attention from StockTwits, Twitter, and Seeking Alpha predict next-day returns. The differences across columns 1 through 3 illustrate the differing information generated by each platform. All three platforms' sentiment signals have a positive relationship to next day returns, with the magnitude ranging from 2.2 bps (Twitter) to 7.8 bps (Seeking Alpha). In contrast, the point estimates for attention are *negative*, but only StockTwits' attention signal is both large (14 bps for a standard deviation change) and statistically significant. Column 4 shows that the first principal component inherits a sentiment loading in the middle of the platforms' range, while mostly reflecting StockTwits' attention loading.

Our specification holds constant the attention and sentiment of traditional media via

[6] 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.

the DJNW attention and sentiment controls. These coefficients also provide a benchmark of around 8 bps for sentiment, and a non-significant relationship for attention. Log Google ASVI negatively predicts next-day returns, similar to social media attention, and is largely uncorrelated with the social signal measures: coefficients are essentially unchanged when log ASVI is omitted. In Table A5 we examine results found in Table 6 further, by including sentiment and attention from all three platforms in one regression in column 4 and looking at the informativeness of the PCs of sentiment and attention in columns 5 and 6. Results are similar, with sentiment predicting next-day's abnormal returns positively, and attention predicting it negatively, mostly driven by StockTwits. The results in column 3 also suggest that the differences in informativeness of the sentiment and attention signals across platforms found in Table 6 are statistically significant.

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. Figure 3 plots the coefficients of sentiment and attention from regressions similar to the ones in Table 6, except run separately for small, mid-, and large-cap firms. Given that the distribution of returns is different for the three size subgroups, we normalize next days' abnormal returns within each size bin before estimation. 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. Adjusted for the difference in average returns across the size bins, the informativeness of the signal does not appear to vary with firm size. In Panel (b) we show that, consistent with the results in Table 6, attention predicts lower next day returns, mostly driven by StockTwits for small- and mid-cap firms. To sum up, the informativeness of sentiment does not appear to vary across firm size, whereas the that of of attention is concentrated mostly in small-cap and somewhat in mid-cap firms.

One downside to using the PC1 in column (4) of Table 6 is that the PCA is conducted over the entire sample period. Thus it would be impossible to take advantage of this information on date t, since it uses data future data to create the signal (look-ahead bias). Therefore, in Table A7 we use a 1-year rolling PCA. For a given year, we use the PCs constructed using the data from the previous calendar year. In column (1) we examine PC1 from sentiment and attention PCAs, 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 Table A7 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 Equation 1. Therefore, in Table A8 we replicate the analysis using our 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 effect on 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 to understand 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 new social platforms, we collected data on Reddit WSB attention and sentiment from Pushshift.io. We find that Reddit is quite different from the major platforms in its relation to next day returns. WSB attention is positively related and WSB sentiment is unrelated to next-day returns. Although the sample is more limited (from 2018), the signals for the other three platforms reflect the main message we have seen throughout the paper: sentiment is positively related to next-day returns, but attention is negatively related. These contrasting effects may reflect differences in platform features or in user populations. We examine these mechanisms in the next section with evidence from the three main platforms.

4.2 Information from market events

To deeper understand what could be driving the differences in informativeness of the sentiment and attention across different platforms, we study two market events that affected platform-specific features or user bases, thereby potentially changing the information impounded in the social signal. First, we study 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. 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 limits on its posts from 140 characters to 1,000 characters. 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. To focus on the StockTwits format change, we analyze the period from one year before to one year after May 8, 2019.

Figure 4 Panel (a) shows how the distribution of the number of characters per message changes across this event window, while Panel (b) does the same after taking firm-day averages of the number of characters per message, to ensure the figure is not dominated by messages about the most popular firms. Consistent with this message-length change only affecting the content of longer messages, where the 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 format change. Similarly, the impact of the character limit expansion is also larger at the top of the distribution for the firm-day version of the figure (Panel b).

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

$$\begin{aligned} \textit{Abnormal Returns}_{i,t+1} = {} & \beta_1 \textit{Attention}_{i,t} + \beta_2 \textit{Sentiment}_{i,t} + \beta_3 \textit{Sentiment}_{i,t} \times \textit{Post}_t \\ & + \beta_4 \textit{Attention}_{i,t} \times \textit{Post}_t + \mathbf{X_{i,t}} \times \mathbf{\Gamma} + \alpha_{\mathbf{t}} + \alpha_{\mathbf{i}} + \epsilon_{\mathbf{it}} \end{aligned} \tag{4}$$

This specification includes controls and fixed effects as in Equation 3 for next-day returns while adding firm fixed effects. Relative to Equation 3, the novel terms are sentiment and attention interacted with a $Post_t$ indicator for whether the date is 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 7 presents 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). Although this estimate is only statistically significant at the 5% level, its magnitude is nearly twice the main effect of sentiment (3 bps, row 3 of the table). In column 2 we use the StockTwits sentiment signal extracted exclusively from posts in the top quartile of StockTwits messages by length, and find an even stronger increase in informativeness of 13.8 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 are more informative after the character limit increase is a change in the composition of the messages. Specifically, it could be the case that mainly more sophisticated investors that take advantage of the change to write longer messages. This is indeed what we find in Table A9: Professional and Intermediate investors write longer messages before the change, and increase their message length after it. In Table A10 we find that Professional and Intermediate investors' sentiment has a stronger predictive power for next day's returns than Novices and Influencers. Interestingly, Professional and Intermediate investors' attention predicts next day's returns with a negative sign, similar to Novice's attention. Taken together, the increased informativeness of sentiment from longer messages after the character-limit change, seems to be driven by Professional and Intermediate 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 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 Equation 4 to one that also contains interactions with the *Treated* indicator. When we estimate such a specification, the triple interaction term $Post \times Treated \times Sentiment(z)$ is 0.178 when the dependent variable is next-day return (see Appendix Table A11). This estimate implies that, after the character limit increase, sentiment becomes more informative for next-day returns, especially for long messages affected by the increase. Specifically, a standard deviation increase in sentiment predicts an 17.8 bps greater return for long versus short messages on StockTwits. Attention's informativeness seems to have decreased even further after the character limit change, although the coefficient is only significant at the 10% level.

Figure 5 presents the quarterly estimates of the triple interaction in leads and lags around the character limit increase. These plots indicate that the effect is not driven by any obvious trends in informativeness of sentiment over time.

An alternative explanation for the increased informativeness of the sentiment signal is that once messages become longer, the natural language processing (NLP) algorithms are better able to classify sentiment. In Table A13 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 7. Reassuringly, the coefficients are very similar in sign and magnitude. However, because the standard errors increase due to the reduced sample size, they are not statistically significant. This supports the view that the increase in informativeness after the character limit change is not driven solely by a better NLP classification of longer messages.

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. Bradley et al. (2021) study a class of posts on Reddit's forum Wall Street Bets (WSB) called "due diligence reports" around this event, and find that these reports were informative for future returns before the event, but fell markedly afterwards. We perform a similar analysis for the informativeness of sentiment and attention of StockTwits, Twitter, and Seeking Alpha around the GME event using the first principal components of attention and sentiment constructed of the three platforms in Section 3.1.

We look at 11 months prior and post the GME event since we have data until the end of 2021 (only 11 months). We also exclude January 2021 to have a cleaner pre/post comparison.

The specification is exactly analogous to Equation (4).

Table 8 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, and the informativeness of retail trading imbalance for future returns declines. Specifically, a standard deviation in sentiment (the first PC) is associated with a 12.5 bps lower return after the GME event (column 1). This completely offsets 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 are essentially unchanged.

Similar as with the StockTwits character-limit experiment, we perform analysis akin to a difference-in-differences design in which we define "treated" observations as posts by the new users, and "control" as those made by the existing (old) users. Using this definition, we extend the specification in Equation 4 to one that also contains interactions with the $Treated$ indicator.When we estimate such a specification, the triple interaction term $Post \times Treated \times Sentiment(z)$ is -0.096 when the dependent variable is next-day return (see Appendix Table A12). This estimate implies that, after the GME event, sentiment becomes less informative for next-day returns for users that joined StockTwits after January 2020, although the coefficient is only significant at the 10% level.

To better understand the mechanism behind this decline in informativeness, we use message-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 coupled with the introduction of no-fee trading at many brokerages in late 2019. Using dates on which users joined StockTwits, we split the sample into tweets by those who joined prior to January 2020 (*established users*) and tweets by users who joined more recently (*new users*). From each subsample of tweets, we construct separate measures of attention and sentiment.

We find that new users displayed a stronger interest in "short squeeze" strategies after the GME event. In Figure 6, we document 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 (who registered on StockTwits after January 1, 2020) 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 8 column 3, consistent with new users' stronger interest in "short squeeze," we find that the informativeness of the new users' signal declines significantly by 10.3 bps for a standard deviation increase in sentiment after the GME event, whereas the informativeness of the established users' signal does not change (column 4). In summary, this evidence shows how differences in user bases on an investor social media platform can have first-order effects on the informativeness of the signal it generates. [7]

To explore the "short squeeze" mechanism further, we split the sample of stocks based on exposure to short squeeze strategies – either by mentions of short squeeze-related terms in their StockTwits posts, or by their short sale utilization, which we measure using daily short selling data from Markit.[8] Specifically, we define stocks as highly exposed to the post-GME "short squeeze" phenomenon if their past month's mentions of "short squeeze" terms (or short selling utilization) are above-median (H) and little exposed if below-median (L).[9]

Based on these indicators for high vs. low short selling exposure, we estimate the $Post \times SentimentPC1(z)$ and $Post \times AttentionPC1(z)$ terms separately for above- vs. below-median subsamples. Table 9 presents these results. Consistent with the finding that the social signal became less informative, we find that the decline in the informativeness of sentiment is concentrated in stocks with more short-selling mentions and in heavily-shorted stocks – with estimated coefficients on $Post \times SentimentPC1(z)$ of -0.180 and -0.275 respectively. Outside of these highly-shorted stocks, in columns 2 and 4 we see very little impact of the GME event on the informativeness of the social signal.

An alternative explanation for the deceased informativeness is that new users might be

[7] As a complement to the sample split evidence in the main text, Appendix Tables A12 present evidence from specifications that contrast the informativeness of the social signal for new users vs. established users, pre vs. post the event. These tests reveal that the difference between the change in signal informativeness for new and established users is statistically significant.

[8] Utilization is defined as the value of a given equity on loan from lenders divided by the total lendable value. Higher utilization is generally associated with more-shorted stocks.

[9] Our "short squeeze" dictionary contains the words "squeeze," "short interest," "short seller," and "short volume," similar to Bradley et al. (2021)'s price pressure list.

using characters, like emojis, in a way that could reduce the effectiveness of NLP sentiment classification. In Table A13 columns 3 and 4 we repeat the analysis using only self-labeled sentiment. Reassuringly, the coefficients are very similar in magnitude and statistical significance.

Overall, these findings from the GME event highlight how new users and emergent retail investor coordination (i.e., retail "short squeeze" strategies) can influence the informativeness of the social media signal. This evidence specifically shows how different user bases contribute to the information in 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 (like StockTwits, Twitter, and Seeking Alpha) attract hundreds of thousands of daily users who engage in intense debate about individual securities. 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 (Chang and Peng, 2021, 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.

References

Akçay, E. and Hirshleifer, D. (2021). Social finance as cultural evolution, transmission bias, and market dynamics. *Proceedings of the National Academy of Sciences*, 118(26):e2015568118.

Antweiler, W. and Frank, M. Z. (2004). Is all that talk just noise? the information content of internet stock message boards. *The Journal of finance*, 59(3):1259–1294.

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

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018b). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, 32(3):259–80.

Barber, B. M., Huang, X., Odean, T., and Schwarz, C. (2022). Attention induced trading and returns: Evidence from robinhood users. *Journal of Finance, forthcoming.*

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

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

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

Boehmer, E., Jones, C. M., Zhang, X., and Zhang, X. (2021). Tracking retail investor activity. *Journal of Finance*, 76(5):2249–2305.

Bradley, D., Hanousek Jr, J., Jame, R., and Xiao, Z. (2021). Place your bets? the market consequences of investment research on reddit's wallstreetbets. *Working paper.*

Chang, R. and Peng, L. (2021). Tiktok sentiment, emotional contagion, and global stock returns. *Working paper.*

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

Chen, H. and Hwang, B.-H. (2022). Listening in on investors' thoughts and conversations. *Journal of Financial Economics*, 145(2):426–444.

Chen, H., Hwang, B.-H., and Liu, B. (2019). The emergence of'social executives' and its consequences for financial markets. *Working paper.*

Cookson, J. A., Engelberg, J., and Mullins, W. (2022a). Echo chambers. *Review of Financial Studies, Forthcoming.*

Cookson, J. A., Engelberg, J. E., and Mullins, W. (2020). Does partisanship shape investor beliefs? Evidence from the covid-19 pandemic. *Review of Asset Pricing Studies*, 10(4):863–893.

Cookson, J. A., Fox, C., Gil-Bazo, J., Imbet, J. F., and Schiller, C. (2023). Social media as a bank run catalyst. *SSRN Electronic Journal*.

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

Cookson, J. A., Niessner, M., and Schiller, C. (2022b). Can social media inform corporate decisions? evidence from merger withdrawals. *Working paper*.

Da, Z., Engelberg, J., and Gao, P. (2011a). In search of attention. *The journal of finance*, 66(5):1461–1499.

Da, Z., Engelberg, J., and Gao, P. (2011b). In search of attention. *Journal of finance*, 66(5):1461–1499.

Da, Z., Hua, J., Hung, C.-C., and Peng, L. (2022). Market returns and a tale of two types of attention. *Available at SSRN 3551662*.

Da, Z. and Huang, X. (2020). Harnessing the wisdom of crowds. *Management Science*, 66(5):1847–1867.

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

Dim, C. (2020). Should retail investors listen to social media analysts? evidence from text-implied beliefs. *Working paper*.

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

Farrell, M., Green, T. C., Jame, R., and Markov, S. (2022). The democratization of investment research and the informativeness of retail investor trading. *Journal of Financial Economics*, 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 August 29, 2022).

Garcia, D. (2013). Sentiment during recessions. *Journal of Finance*, 68(3):1267–1300.

Gargano, A. and Rossi, A. G. (2018). Does it pay to pay attention? *The Review of Financial Studies*, 31(12):4595–4649.

Giannini, R., Irvine, P., and Shu, T. (2018). Nonlocal disadvantage: An examination of social media sentiment. *The Review of Asset Pricing Studies*, 8(2):293–336.

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

Gu, C. and Kurov, A. (2020). Informational role of social media: Evidence from twitter sentiment. *Journal of Banking & Finance*, 121:105969.

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

Hirshleifer, D., Peng, L., and Wang, Q. (2023). News diffusion in social networks and stock market reactions. Technical report, National Bureau of Economic Research.

Irvine, P. J., Shen, S., and Shu, T. (2021). Aggregate attention. *Working paper*.

Jame, R., Johnston, R., Markov, S., and Wolfe, M. C. (2016). The value of crowdsourced earnings forecasts. *Journal of Accounting Research*, 54(4):1077–1110.

Kuchler, T. and Stroebel, J. (2021). Social finance. *Annual Review of Financial Economics*, 13:37–55.

Levy, R. (2021). Social media, news consumption, and polarization: Evidence from a field experiment. *American Economic Review*, 111(3):831–870.

Lu, R. and Sheng, S. Y. (2022). How racial animus forms and spreads: Evidence from the Coronavirus pandemic. *Journal of Economic Behavior & Organization*, 200:82–98.

McLuhan, M. (1975). *Understanding media: The extensions of man*. Routledge & Kegan Paul.

Müller, K. and Schwarz, C. (2022). From hashtag to hate crime: Twitter and anti-minority sentiment. *American Economic Journal, Applied Economics*.

Niessner, M. (2015). Strategic disclosure timing and insider trading. *Working paper*.

Pedersen, L. H. (2022). Game on: Social networks and markets. *Journal of Financial Economics*.

Pew (2021). News use across social media platforms in 2020. *Pew Research Center*.

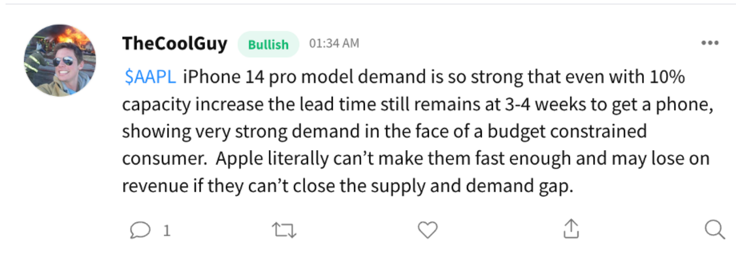
Pyun, C. (2021). Social media group investing. *Working paper*.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the us stock market. *Journal of Banking & Finance*, 84:25–40.

Sicherman, N., Loewenstein, G., Seppi, D. J., and Utkus, S. P. (2016). Financial attention. *The Review of Financial Studies*, 29(4):863–897.

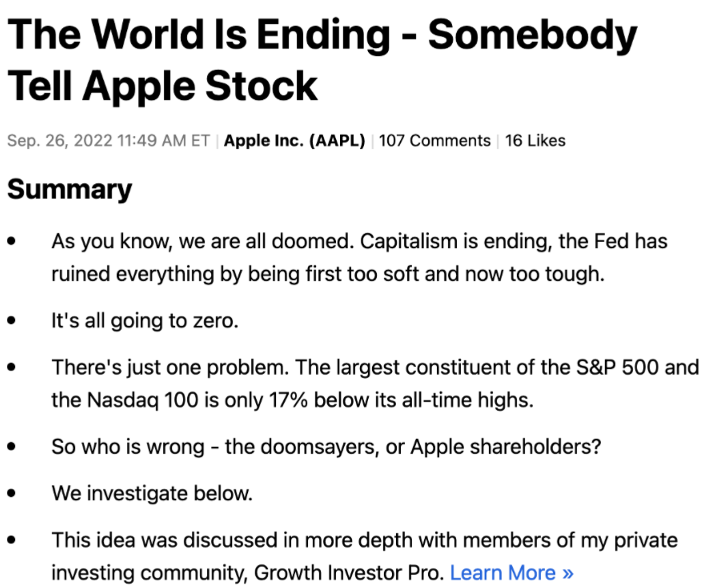
Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, 62(3):1139–1168.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of financial Economics*, 99(1):1–10.



(a) StockTwits

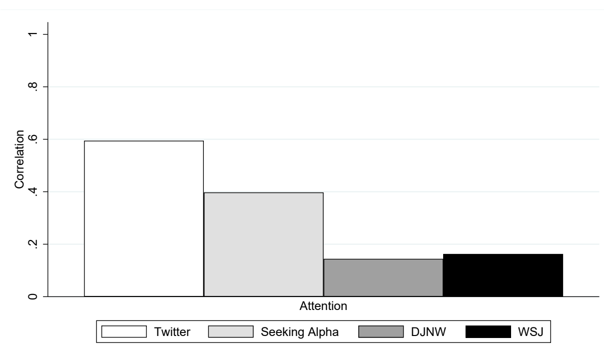
(b) Twitter



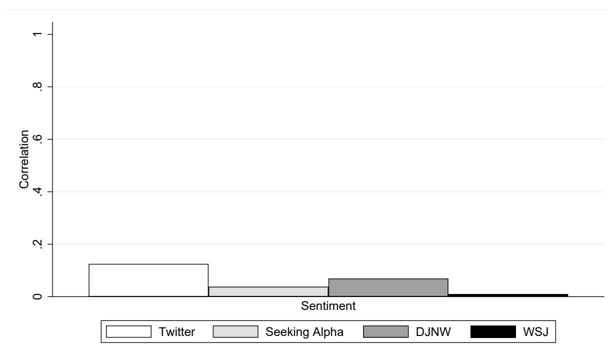
(c) Seeking Alpha

Figure 1: Examples of Posts Across Three Social Media Platforms

Note: This figure presents example posts and tweets separately by social media platform for StockTwits, Twitter, and Seeking Alpha. For ease of direct comparison, all three example posts are about Apple stock (AAPL) on the same day (September 28, 2022).



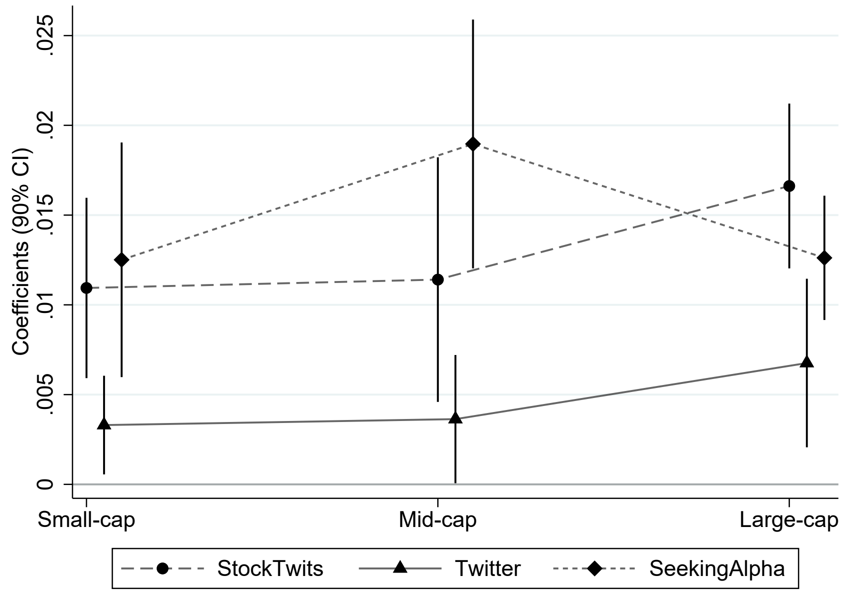
(a) Attention



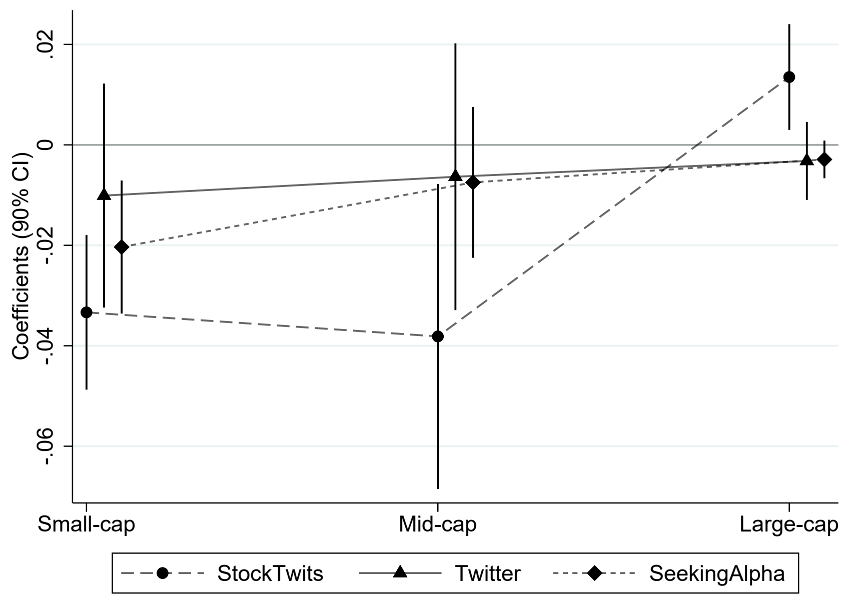
(b) Sentiment

Figure 2: Cross-platform Correlation for Social Signals

Note: This figure reports the bivariate correlations of attention and sentiment between StockTwits and another platform at the firm-day level. Attention is measured by the fraction of messages, reports, or articles about a firm across all firms on a platform in a day. Sentiment is measured by the average sentiment of all messages about a firm on a platform in a day. Sample consists of firm-day observations with at least 10 messages on StockTwits.



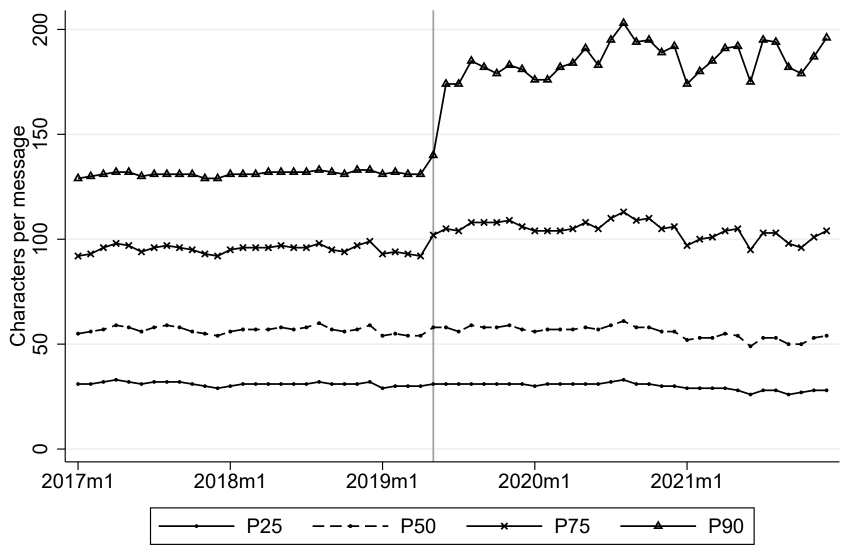
(a) Informativeness of sentiment signal



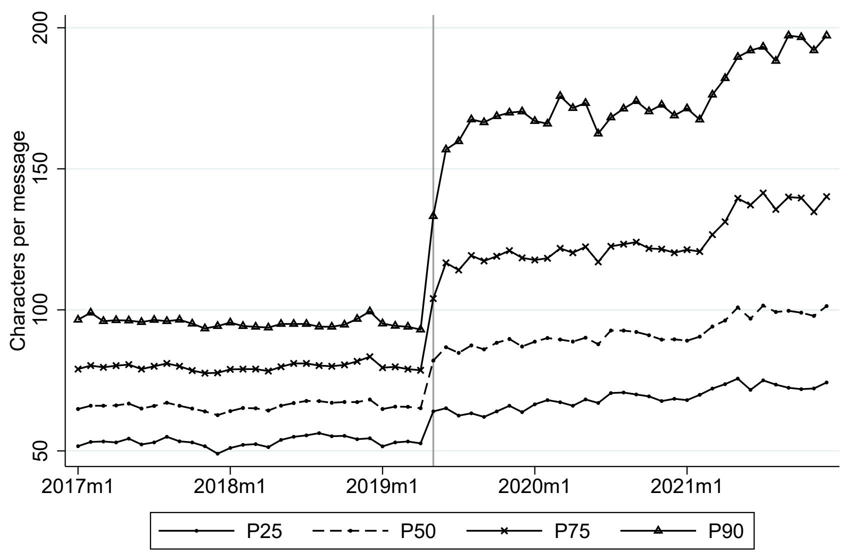
(b) Informativeness of attention signal

Figure 3: How Do Next-Day Returns Relate to Social Signals *by Firm Size*?

Note: This figure plots the estimated coefficients on sentiment and attention signals for StockTwits, Twitter, and Seeking Alpha for small-cap, mid-cap, and large-cap firms, separately. Firm size categories follow those in Table 1. Outcome is abnormal return on day t+1 scaled by 100 normalized within each firm-size sub-sample. Other variable definitions and specifications mirror those in Table 6 columns 2-4.



(a) Number of characters per message



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

Figure 4: Monthly Quartile of Number of Characters per Message

Note: This figure plots the monthly quartile of number of characters per message (panel A) and the monthly quartile of the firm-day level average number of characters per message (panel B). The vertical line represents May 8, 2019, the date when StockTwits increased its character limit from 140 to 1,000.

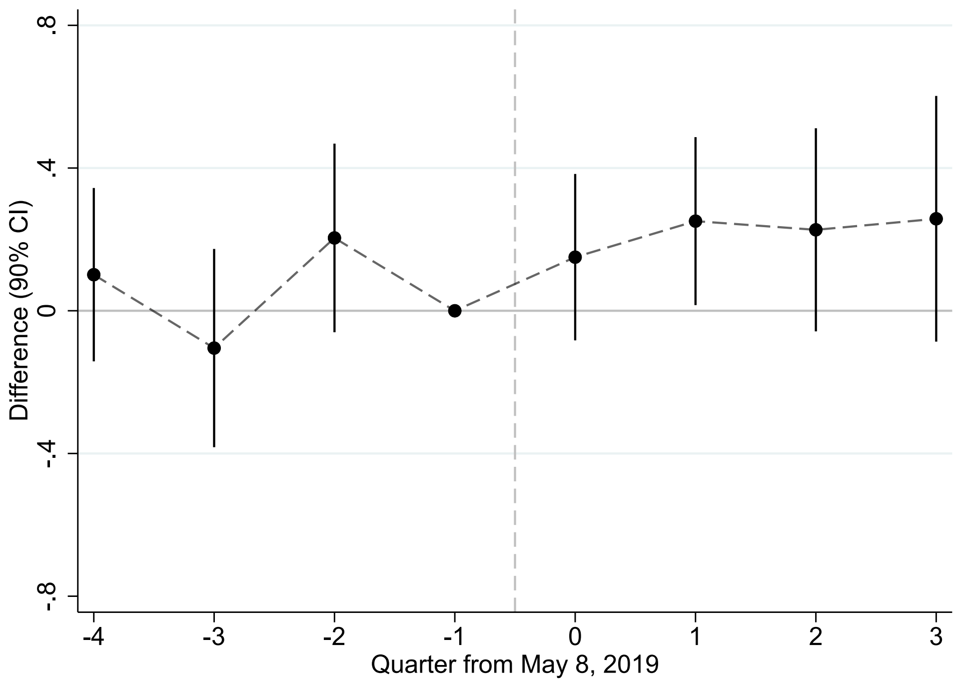


Figure 5: How Did the Informativeness of Sentiment Signal on Next-day Returns Change Around StockTwits Character Limit Increase?

Note: This figure compares the change in how StockTwits sentiment signal relates to AR t+1 in the quarters around StockTwits character limit increase on May 8, 2019. The treated group is stocks whose daily average number of characters per message is in the top quartile; the comparison group is the stocks whose daily average number of characters per message is in the bottom quartile. Sample consists of firm-day observations with at least 10 messages on StockTwits between May 8, 2018 and May 8, 2020. Event time 0 represents the three months following May 8, 2019. The omitted period is -1. Coefficients and 90 percent confidence intervals are plotted. Specifications and variable definitions mirror those in Tables A11 column (1).

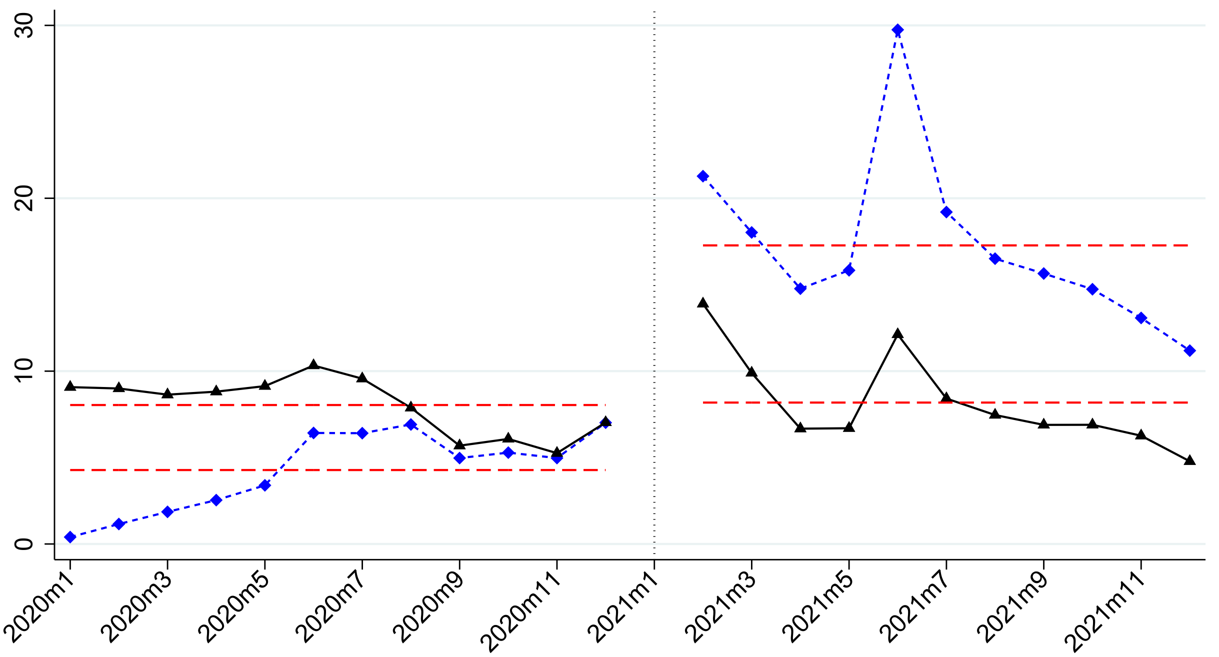


Figure 6: StockTwits Mentions of "Short Squeeze" Around the GameStop Event
Old versus New Users

Note: This figure presents evidence on the changing user composition of StockTwits in the months around the GME short squeeze event. Specifically, the figure plots mentions of "short squeeze" from new users (blue diamonds) and old users (black triangles) by month in the GME event window. Old users are those who joined StockTwits before January 2020 and new users are those joined in or after January 2020.

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	DS.	Min	Max	Mean	DS.	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 bn., between 2 and 10 bn., and above 10 bn. Panel D shows how sample restrictions reduce the # of firm-day observations to arrive at our analysis sample.

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 for attention and sentiment 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 clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

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%	32.8%	29.1%	38.2%	32.8%	29%	38%	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 *residualized* social signal. 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 4-6, 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). Sample consists of firm-day observations with at least 10 messages on StockTwits. Standard errors in parentheses are clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

Table 4: How Common is the Social Signal across Platforms?
Heterogeneity by Firm Size in First Principal Component (PC1)

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 for the principal component analysis in Table 2 panel C and Table 3 columns 1-6. 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. Sample consists of firm-day observations with at least 10 messages on StockTwits. Standard errors in parentheses are clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

Table 5: How Common is the Social Signal across User Types?
Commonality across Groups of Users on StockTwits

Panel A: Correlations within StockTwits

	Top 1%	Professional	Intermediate	Novice	No label
StockTwits attention	0.819	0.884	0.966	0.929	0.987
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 and other platforms. 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 raw social signals are reported in Table A1. Sample consists of firm-day observations with at least 10 messages on StockTwits. Standard errors in parentheses are clustered by firm and by date via a block bootstrap procedure following Thompson (2011).

Table 6: How Do Next-Day Returns Relate to Social Signals?

	Dependent var.: AR_{t+1}(%)			
	(1) StockTwits	(2) Twitter	(3) Seeking Alpha	(4) PC1 signal
Sentiment (z)	0.058***	0.022***	0.078***	0.060***
	(0.012)	(0.007)	(0.010)	(0.009)
Attention (z)	-0.143***	-0.010	-0.018	-0.135***
	(0.052)	(0.021)	(0.012)	(0.050)
Sentiment (z) × Attention (z)	0.035	-0.001	0.003	-0.013
	(0.053)	(0.008)	(0.005)	(0.022)
DJNW sentiment (z)	0.079***	0.082***	0.071***	0.079***
	(0.008)	(0.008)	(0.008)	(0.008)
DJNW attention (z)	0.009	-0.008	-0.011	0.011
	(0.010)	(0.010)	(0.009)	(0.011)
8-K report date	0.061	0.045	0.038	0.070
	(0.043)	(0.043)	(0.042)	(0.044)
EA date	-0.549***	-0.538***	-0.566***	-0.546***
	(0.091)	(0.091)	(0.091)	(0.091)
$\text{Volatility}_{(t-5)\rightarrow(t-1)}$	-0.016	-0.099	-0.114	-0.043
	(0.378)	(0.375)	(0.373)	(0.376)
$\text{CAR}_{(t-5)\rightarrow(t-1)}$	-0.008***	-0.008***	-0.008***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
$\text{CAR}_{(t-30)\rightarrow(t-6)}$	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Log Google ASVI (z)	-0.051***	-0.064***	-0.065***	-0.053***
	(0.017)	(0.017)	(0.017)	(0.017)
Sentiment & attention (t-1), ..., (t-10)	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Outcome Mean	-0.048	-0.048	-0.048	-0.048
Outcome SD	7.124	7.124	7.124	7.124
Observations	819,210	819,210	819,210	819,210
R^2	0.0321	0.0318	0.0319	0.0320

Note: This table reports how next-day returns relate to social signals. Sample consists of firm-day observations with at least 10 messages on StockTwits. The outcome is abnormal return on day t+1 in percentage units. 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 control for firm fixed effects, date fixed effects, ten lags (t-1 to t-10) of sentiment, and similarly for attention. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table 7: How Did the Informativeness of Social Signals Change around the StockTwits Character Limit Increase?

	Dependent var.: AR_{t+1}(%)			
	(1) StockTwits	(2) StockTwits top quartile	(3) Twitter	(4) Seeking Alpha
Post × Sentiment (z)	0.070**	0.138**	-0.010	-0.007
	(0.034)	(0.055)	(0.043)	(0.034)
Post × Attention (z)	0.165*	-0.269	-0.005	-0.016
	(0.088)	(0.226)	(0.026)	(0.031)
Sentiment (z)	0.031	0.004	0.000	0.078***
	(0.024)	(0.037)	(0.019)	(0.024)
Attention (z)	-0.382***	-0.290	-0.032	-0.016
	(0.117)	(0.200)	(0.025)	(0.022)
DJNW sentiment (z)	0.098***	0.091***	0.101***	0.087***
	(0.016)	(0.026)	(0.016)	(0.016)
DJNW attention (z)	0.019	-0.008	-0.005	-0.011
	(0.025)	(0.053)	(0.025)	(0.022)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date 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 StockTwits character limit increase n May 8, 2019. Sample consists of firm-day observations with at least 10 messages on StockTwits between May 8,2018 and May 7, 2020. The outcome is AR t+1 scaled by 100. *Post* 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. All regressions control for firm fixed effects and date fixed effects. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table 8: How Did the Informativeness of Social Signals Change around the GameStop Event?

	Dependent var.: $AR_{t+1}(\%)$			
	(1) PC signal	(2) PC signal	(3) StockTwits new	(4) StockTwits old
Post × Sentiment (z)	-0.125***	-0.124***	-0.103**	0.002
	(0.048)	(0.048)	(0.043)	(0.034)
Post × Attention (z)	0.001	-0.001	0.015	-0.019
	(0.093)	(0.094)	(0.107)	(0.090)
Sentiment (z)	0.111***	0.111***	0.101**	0.038
	(0.042)	(0.042)	(0.039)	(0.028)
Attention (z)	-0.071	-0.070	-0.065	-0.065
	(0.056)	(0.057)	(0.065)	(0.054)
Post × Sentiment PC2 (z)		0.028		
		(0.033)		
Post × Sentiment PC3 (z)		0.014		
		(0.030)		
Sentiment PC2 (z)		-0.004		
		(0.026)		
Sentiment PC3 (z)		0.022		
		(0.026)		
DJNW sentiment (z)	0.086***	0.081***	0.088***	0.087***
	(0.016)	(0.016)	(0.017)	(0.016)
DJNW attention (z)	-0.058**	-0.060**	-0.064**	-0.060**
	(0.029)	(0.029)	(0.029)	(0.029)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date 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 returns around the GameStop event on January 28, 2021. Sample consists of firm-day observations with at least 10 messages on StockTwits between February 1, 2020 and December 31, 2021, excluding January 2021. The outcome is AR t+1 scaled by 100. *Post* is one if a day is on or after February 1, 2021. Social signals in columns 1-4 are based on the first PC (standardized) of attention or sentiment signals (from all StockTwits subgroups, StockTwits self-labelled messages, Twitter, and Seeking Alpha), messages from users who joined StockTwits in or after 2020 (StockTwits new), and messages from users who joined StockTwits before 2020 (StockTwits old), respectively. Controls are 8-K report date indicators, earnings announcement 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. All regressions control for firm fixed effects and date fixed effects. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table 9: How Did the Informativeness of Social Signals Change around the GameStop Event?

Heterogeneity by Short Mentions and Short Utilization

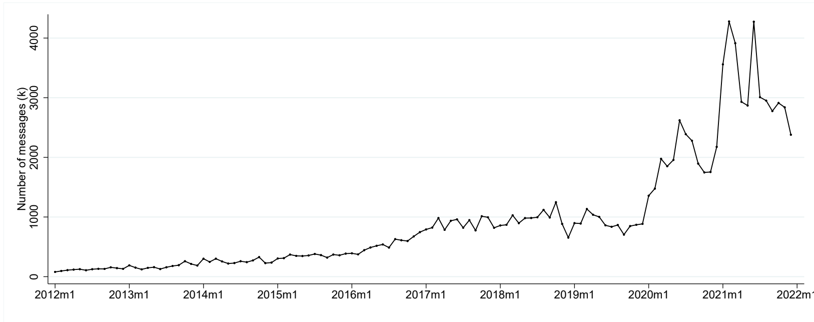
	Dependent var.: $AR_{t+1}(\%)$			
	(1)	(2)	(3)	(4)
	H mentions	L mentions	H utilization	L utilization
Post × Sentiment PC1 (z)	-0.180**	-0.057*	-0.275***	0.035
	(0.072)	(0.032)	(0.064)	(0.046)
Post × Attention PC1 (z)	0.026	0.958***	-0.035	-0.155**
	(0.092)	(0.331)	(0.140)	(0.064)
Sentiment PC1 (z)	0.146**	0.060**	0.200***	-0.007
	(0.063)	(0.028)	(0.056)	(0.038)
Attention PC1 (z)	-0.078	-1.242***	0.011	-0.173*
	(0.058)	(0.269)	(0.109)	(0.091)
DJNW sentiment (z)	0.102***	0.065***	0.135***	0.045***
	(0.028)	(0.014)	(0.028)	(0.013)
DJNW attention (z)	-0.113**	0.008	-0.346***	0.039
	(0.054)	(0.017)	(0.067)	(0.033)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Outcome Mean	0.074	-0.132	0.016	-0.030
Outcome SD	9.351	4.557	8.850	6.503
Observations	178,100	110,992	156,897	132,195
R^2	0.056	0.081	0.064	0.045

Note: This table compares how social signals among stocks with high vs. low interest from short sellers changed their predictive power for next-day returns around the GameStop event on January 28, 2021. Social signals are the first PC (standardized) of attention or sentiment signals from all StockTwits subgroups, StockTwits self-labelled messages, Twitter, and Seeking Alpha. Samples in column 1 (or 2) consist of stocks with an above-median (or below-median) mentions of "squeeze," "short interest," "short seller" or "short volume" on StockTwits in a month. Samples in columns 3 (or 4) consist of stocks with an above-median (or below-median) utilization in a month. All other specifications and variable definitions mirror those in Table 8 column 1. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

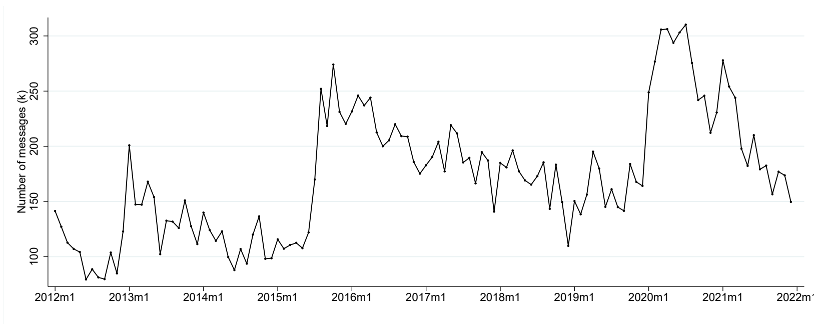
Online Appendix

The Social Signal

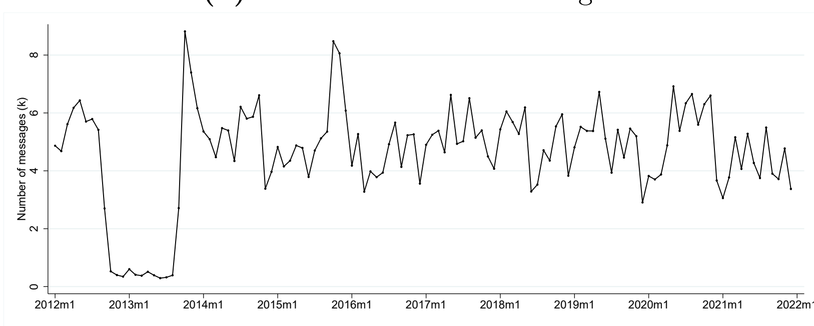
J. Anthony Cookson, Runjing Lu, William Mullins, and Marina Niessner



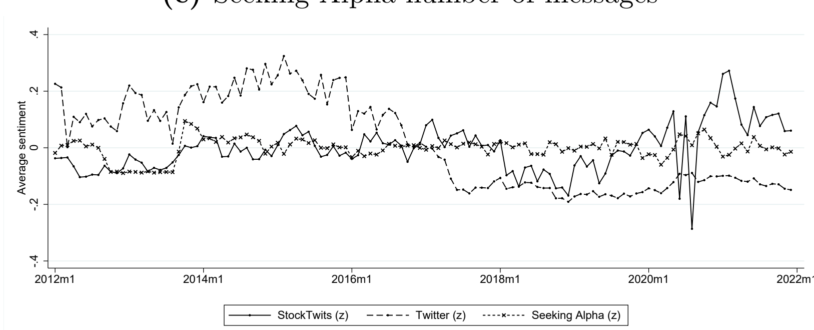
(a) StockTwits number of messages



(b) Twitter number of messages



(c) Seeking Alpha number of messages



(d) Sentiment by platform

Figure A1: Monthly Number of Messages and Sentiment Across Platforms

Note: This figure plots the monthly number of messages on StockTwits in panel A, Twitter in panel B, and Seeking Alpha in panel C, as well as monthly average standardized sentiment on each of the three platforms in panel D. Units are in thousands of messages in panels A-C and of one in panel D.

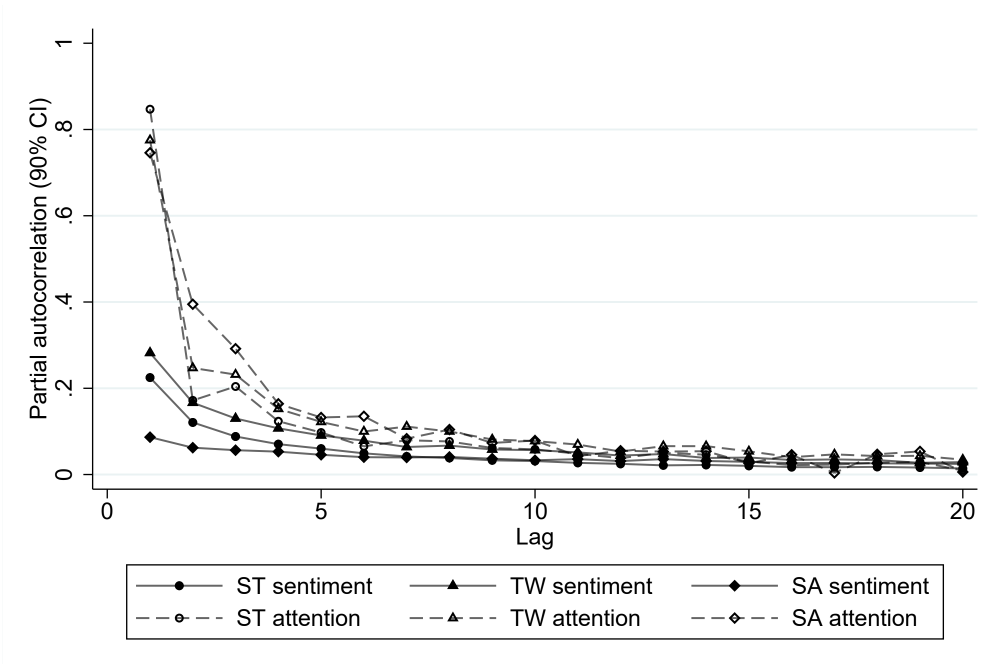


Figure A2: Partial Auto-correlation Function for Social Signals

Note: This figure reports the partial auto-correlation for attention and sentiment on StockTwits (ST), Twitter (TW), and Seeking Alpha (SA). Sample consists of firm-day observations with at least 10 messages on StockTwits.

Table A1: How Common is the Social Signal across User Types on StockTwits?

Panel A: PCA of Attention Signals

	PC1	PC2	PC3	PC4	PC5
Top 1%	0.426	0.694	0.570	-0.105	-0.034
Professional	0.446	0.359	-0.684	0.413	0.186
Intermediate	0.462	-0.187	-0.234	-0.393	-0.736
Novice	0.443	-0.501	0.391	0.630	-0.055
No label	0.458	-0.322	-0.007	-0.518	0.647
Fraction of variation	87.7%	6.4%	3%	1.8%	1.1%
	(2.757)	(1.368)	(0.882)	(0.386)	(0.276)

Panel B: PCA of Sentiment Signals

	PC1	PC2	PC3	PC4	PC5
Top 1%	0.561	-0.215	-0.129	0.078	-0.785
Professional	0.468	-0.446	-0.432	0.294	0.556
Intermediate	0.387	0.104	0.799	0.419	0.159
Novice	0.287	0.858	-0.369	0.205	0.052
No label	0.484	0.087	0.147	-0.831	0.215
Fraction of variation	28.2%	19.4%	18.9%	17.5%	15.9%
	(0.090)	(0.033)	(0.032)	(0.047)	(0.067)

Note: This table reports PCAs in Table 5 panels B and C using raw social signals. Sample and variable definitions follow those in Table 5. Standard errors in parentheses are clustered by firm and by date.

Table A2: How Common is the Social Signal across Platforms?
Abnormal Attention

Panel A: PCA of Abnormal Attention Signals

	PC1	PC2	PC3
StockTwits StockTwits	0.525	-0.695	0.491
Twitter	0.679	-0.005	-0.734
Seeking Alpha	0.513	0.719	0.469
Fraction of variation	51.7%	30.7%	17.6%
	(1.068)	(0.631)	(0.766)

Panel B: PCA of Residualized Abnormal Attention Signals

	Residualize news			Residualize news & firm FEs		
	PC1	PC2	PC3	PC1	PC2	PC3
StockTwits	0.595	-0.531	0.603	0.610	-0.489	0.623
Twitter	0.685	-0.056	-0.726	0.686	-0.068	-0.725
Seeking Alpha	0.419	0.846	0.330	0.397	0.870	0.294
Fraction of variation	49%	31.6%	19.5%	48.6%	31.7%	19.7%
	(1.073)	(0.483)	(1.034)	(1.004)	(0.428)	(1.073)

Note: This table repeats the principal component analysis in Table 2 and Table 3 using abnormal attention, i.e., the deviation in number of messages for a firm-day observation from its median in the prior 10 days. Sample consists of firm-day observations with at least 10 messages on StockTwits. Standard errors in parentheses are clustered by firm and by date.

Table A3: How Common is the Social Signal across Platforms?
Including Reddit Wall St. Bets Signal

Panel A: PCA of Residualized Attention Signals

	PC1	PC2	PC3	PC4
StockTwits	0.564	0.153	-0.567	0.580
Twitter	0.575	-0.150	-0.249	-0.764
Seeking Alpha	0.428	-0.674	0.532	0.281
Reddit WSB	0.409	0.707	0.577	-0.020
Fraction	51.1%	24.1%	13.3%	11.5%
	(3.794)	(0.512)	(2.041)	(1.716)

Panel B: PCA of Residualized Sentiment Signals

	PC1	PC2	PC3	PC4
StockTwits	0.640	-0.082	-0.338	0.686
Twitter	0.660	-0.127	-0.178	-0.719
Seeking Alpha	0.369	0.001	0.923	0.110
Reddit WSB	0.138	0.988	-0.052	-0.036
Fraction	27.5%	25%	24.6%	22.9%
	(0.090)	(0.014)	(0.035)	(0.085)

Note: This table repeats the principal component analysis in the third set of columns of Table 3 while adding Reddit Wall Street Bets social signal. Sample consists of firm-day observations with at least 10 messages on StockTwits from 2018 January through 2021 December, excluding January and February of 2021 (months surrounding the GME event). Standard errors in parentheses are clustered by firm and by date.

Table A4: How Common is *Stock Coverage* across Platforms?

Panel A: Correlations with Coverage on StockTwits

	Twitter	Seeking Alpha
StockTwits	0.341	0.152

Panel B: PCA of Coverage

	PC1	PC2	PC3
StockTwits	0.598	-0.490	0.635
Twitter	0.640	-0.185	-0.746
Seeking Alpha	0.482	0.852	0.203
Fraction of variation	49.6%	28.8%	21.6%
	(0.354)	(0.178)	(0.260)

Panel B: PCA of Residualized Coverage

	Residualize news			Residualize news & firm FEs		
	PC1	PC2	PC3	PC1	PC2	PC3
StockTwits	0.614	-0.434	0.659	0.685	-0.177	0.707
Twitter	0.651	-0.194	-0.734	0.685	-0.177	-0.707
Seeking Alpha	0.447	0.880	0.164	0.250	0.968	0.000
Fraction of variation	47.9%	30%	22.1%	43.4%	32.7%	23.9%
	(0.354)	(0.188)	(0.264)	(0.198)	(0.044)	(0.197)

Note: This table reports the correlations and principal component analyses of social media coverage across platforms. Panel A reports the bivariate correlations of coverage (equal 1 if a firm is mentioned on a platform in a day) between StockTwits and Twitter (Seeking Alpha). Panels B and C reports the principal components for stock coverage across platforms. Panels B uses raw coverage while panel C uses residualized coverage. Residualization method follows that in Table 3 columns 1-6. Sample consists of firm-day observations on all trading days. Standard errors in parentheses are clustered by firm and by date.

Table A5: How Do Next-Day Returns Relate to Social Signals?

	Dependent var.: AR_{t+1}(%)					
	(1)	(2)	(3)	(4)	(5)	(6)
ST sentiment (z)	0.051***			0.050***		
	(0.012)			(0.014)		
ST attention (z)	-0.151***			-0.198***		
	(0.052)			(0.058)		
ST sentiment (z) × ST attention (z)	0.026			0.047		
	(0.050)			(0.063)		
Twitter sentiment (z)		0.029***		0.017**		
		(0.007)		(0.007)		
Twitter attention (z)		-0.016		0.111***		
		(0.020)		(0.033)		
Twitter sentiment (z) × Twitter attention (z)		-0.006		-0.021		
		(0.008)		(0.013)		
SA sentiment (z)			0.084***	0.080***		
			(0.010)	(0.010)		
SA attention (z)			-0.018	-0.012		
			(0.011)	(0.012)		
SA sentiment (z) × SA attention (z)			0.001	0.002		
			(0.004)	(0.004)		
Sentiment PC1 (z)					0.057***	0.061***
					(0.009)	(0.010)
Sentiment PC2 (z)						0.068***
						(0.009)
Sentiment PC3 (z)						0.021**
						(0.008)
Attention PC1 (z)					-0.142***	-0.154***
					(0.049)	(0.053)
Sentiment PC1 × Attention PC1 (z)					-0.012	0.012
					(0.021)	(0.024)
Sentiment PC2 × Attention PC1 (z)						0.052***
						(0.018)
Sentiment PC3 × Attention PC1 (z)						-0.089***
						(0.030)
DJNW sentiment (z)	0.079***	0.080***	0.068***	0.066***	0.078***	0.068***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.007)
DJNW attention (z)	0.021**	0.002	0.001	-0.010	0.024**	0.015
	(0.009)	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)
Sentiment & attention (t-1), ..., (t-10)	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y
Outcome Mean	-0.048	-0.048	-0.048	-0.048	-0.048	-0.048
Outcome SD	7.124	7.124	7.124	7.124	7.124	7.124
Observations	819,210	819,210	819,210	819,210	819,210	819,210
R^2	0.0293	0.0291	0.0292	0.0295	0.0293	0.0294

Note: This table provides robustness check for Table 6 by (i) dropping firm fixed effects and (ii) including all platform-level social signals in one regression and by including additional sentiment PC's. 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. Everything else follows those in Table 6. Standard errors are clustered by firm and by date. *** 1%, ** 5%, * 10% significance level

Table A6: How Do Next-Day Returns Relate to Social Signals?
Including Reddit Wall St. Bets Signal

	Dependent var.: AR_{t+1}(%)				
	(1)	(2)	(3)	(4)	(5)
WSB sentiment (z)	-0.007				-0.008
	(0.013)				(0.013)
WSB attention (z)	0.059*				0.134***
	(0.031)				(0.033)
WSB sentiment (z) × WSB attention (z)	0.012				0.011
	(0.009)				(0.009)
ST sentiment (z)		0.071**			0.085**
		(0.033)			(0.035)
ST attention (z)		-0.337***			-0.468***
		(0.106)			(0.119)
ST sentiment (z) × ST attention (z)		0.172			0.237
		(0.141)			(0.151)
Twitter sentiment (z)			-0.006		-0.053*
			(0.026)		(0.028)
Twitter attention (z)			-0.104*		0.020
			(0.053)		(0.069)
Twitter sentiment (z) × Twitter attention (z)			-0.045		-0.212***
			(0.058)		(0.074)
SA sentiment (z)				0.022	0.025
				(0.016)	(0.016)
SA attention (z)				-0.119***	-0.112***
				(0.039)	(0.040)
SA sentiment (z) × SA attention (z)				0.092***	0.091***
				(0.022)	(0.022)
DJNW sentiment (z)	0.096***	0.095***	0.098***	0.085***	0.087***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
DJNW attention (z)	-0.055**	-0.011	-0.028	-0.038*	-0.042
	(0.023)	(0.024)	(0.026)	(0.023)	(0.026)
Sentiment & attention t-1 ... t-10	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Outcome Mean	-0.073	-0.073	-0.073	-0.073	-0.073
Outcome SD	7.386	7.386	7.386	7.386	7.386
Observations	491,939	491,939	491,939	491,939	491,939
R^2	0.0344	0.0347	0.0344	0.0344	0.0351

Note: This table reports how next-day returns relate to social signals on Reddit as compared to other social signals. Sample consists of firm-day observations with at least 10 messages on StockTwits from 2018 January through 2021 December, excluding January and February of 2021 (months surrounding the GME event). The outcome is AR t+1 scaled by 100. Everything else follows those in Table A5. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A7: How Do Next-Day Returns Relate to Social Signals?
Annual rolling PCs

	Dependent var.: AR_{t+1}(%)	
	(1)	(2)
Sentiment PC1 (z)	0.059***	0.065***
	(0.012)	(0.011)
Sentiment PC2 (z)		0.048***
		(0.011)
Sentiment PC3 (z)		0.027***
		(0.009)
Attention PC1 (z)	-0.160***	-0.164***
	(0.054)	(0.054)
Sentiment PC1 × Attention PC1 (z)	-0.014	0.017
	(0.043)	(0.033)
Sentiment PC2 × Attention PC1 (z)		0.060**
		(0.027)
Sentiment PC3 × Attention PC1 (z)		-0.082*
		(0.049)
DJNW sentiment (z)	0.081***	0.075***
	(0.008)	(0.008)
DJNW attention (z)	0.011	0.005
	(0.012)	(0.012)
Sentiment & attention t-1 ... t-10	Y	Y
Controls	Y	Y
Firm FE	Y	Y
Date FE	Y	Y
Outcome Mean	-0.047	-0.047
Outcome SD	7.180	7.180
Observations	799,169	799,169
R^2	0.0322	0.0323

Note: This table provides robustness check for Table 6 by using annual-rolling principal component of social signals. PCs in a given year are estimated using data in the prior year, so annual-rolling PCs are only available for 2013 through 2021. 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. Everything else follows those in Table 6. Standard errors are clustered by firm and by date.
** 1%, ** 5%, * 10% significance level

Table A8: How Do Next-Day Returns Relate to Social Signals?
Abnormal Attention

	Dependent var.: $AR_{t+1}(\%)$			
	(1) StockTwits	(2) Twitter	(3) Seeking Alpha	(4) PC1 signal
Sentiment (z)	0.060***	0.022***	0.040***	0.061***
	(0.010)	(0.007)	(0.010)	(0.010)
Attention (z)	-0.092*	-0.013	-0.044***	-0.083*
	(0.047)	(0.028)	(0.010)	(0.042)
Sentiment (z) $\times$ Attention (z)	0.077	0.006	0.040***	0.002
	(0.058)	(0.015)	(0.008)	(0.045)
DJNW sentiment (z)	0.077***	0.079***	0.069***	0.076***
	(0.008)	(0.008)	(0.008)	(0.008)
DJNW attention (z)	0.028**	0.020	0.015	0.033**
	(0.013)	(0.014)	(0.014)	(0.013)
8-K report date	0.022	0.021	0.028	0.034
	(0.044)	(0.050)	(0.043)	(0.047)
EA date	-0.628***	-0.619***	-0.630***	-0.633***
	(0.104)	(0.104)	(0.105)	(0.104)
$\text{Volatility}_{(t-5)\to(t-1)}$	-0.038	-0.077	-0.108	-0.044
	(0.368)	(0.369)	(0.375)	(0.370)
$\text{CAR}_{(t-5)\to(t-1)}$	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
$\text{CAR}_{(t-30)\to(t-6)}$	-0.001	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Log ASVI (z)	-0.057***	-0.065***	-0.065***	-0.057***
	(0.017)	(0.017)	(0.017)	(0.017)
Sentiment & attention (t-1), ..., (t-10)	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Outcome Mean	-0.049	-0.049	-0.049	-0.049
Outcome SD	7.127	7.127	7.127	7.127
Observations	818,516	818,516	818,516	818,516
R^2	0.0320	0.0319	0.0320	0.0320

Note: This table provides robustness check for Table 6 by using abnormal attention, i.e., the deviation in number of messages for a firm-day observation from its median in the prior 10 days. Everything else follows those in Table 6. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A9: Relationship between StockTwits Message Length and User Type

	Dependent var.: Message Length	
	(1)	(2)
Post × Top 1%	0.449	
	(1.432)	
Post × Professional		9.806***
		(1.485)
Post × Intermediate		1.894**
		(0.939)
Post × Novice		-1.438
		(1.284)
Top 1%	0.535	
	(0.722)	
Professional		5.270***
		(0.522)
Intermediate		3.697***
		(0.366)
Novice		-1.664**
		(0.644)
Firm FE	Y	Y
Date FE	Y	Y
Outcome Mean	74.793	74.793
Outcome SD	79.773	79.773
Observations	24,575,440	24,575,440
R^2	0.0319	0.0331

Note: This table presents the relationship between message length and user type on StockTwits. The outcome is the number of characters in a message. *Post* is an indicator for messages being posed on or after May 8, 2020, and zero otherwise. $Top1\%$, $Professional$, $Intermediate$, and $Novice$ are indicators for being influencers, professionals, intermediate experienced, and novice, respectively. Sample consists of all messages posted between May 8, 2018 and May 8, 2020 for firm-day with at least 10 messages on StockTwits. All regressions control for firm fixed effects and date fixed effects. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A10: How Do Next-Day Returns Relate to Social Signals?
By StockTwits User Group

	Dependent var.: AR_{t+1}(%)				
	(1) Top 1%	(2) Professional	(3) Intermediate	(4) Novice	(5) No label
Sentiment (z)	0.015*	0.042***	0.027*	0.000	0.035***
	(0.008)	(0.012)	(0.015)	(0.011)	(0.011)
Attention (z)	-0.077**	-0.114**	-0.101**	-0.110***	-0.154***
	(0.035)	(0.044)	(0.045)	(0.038)	(0.050)
Sentiment (z) × Attention (z)	0.018	0.089*	0.089	-0.022	0.008
	(0.025)	(0.050)	(0.067)	(0.047)	(0.051)
DJNW sentiment (z)	0.082***	0.080***	0.082***	0.083***	0.081***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
DJNW attention (z)	0.002	0.008	0.003	0.002	0.006
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
8-K report date	0.052	0.063	0.053	0.051	0.059
	(0.043)	(0.044)	(0.043)	(0.042)	(0.043)
EA date	-0.546***	-0.549***	-0.546***	-0.544***	-0.545***
	(0.091)	(0.091)	(0.091)	(0.091)	(0.091)
$\text{Volatility}_{(t-5)\to(t-1)}$	-0.076	-0.068	-0.088	-0.038	-0.025
	(0.373)	(0.376)	(0.377)	(0.376)	(0.378)
$\text{CAR}_{(t-5)\to(t-1)}$	-0.008***	-0.008***	-0.008***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\text{CAR}_{(t-30)\to(t-6)}$	-0.001*	-0.001*	-0.001*	-0.001*	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log ASVI (z)	-0.058***	-0.055***	-0.056***	-0.053***	-0.051***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Sentiment & attention (t-1), ..., (t-10)	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y
Date 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	0.0319	0.0320	0.0319	0.0320	0.0320

Note: This table repeats Table 6 using social signal from various user groups on StockTwits. Everything else follows those in Table 6. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A11: How Did Informativeness of StockTwits Signals Change around the StockTwits Character Limit Increase?
Firms with Long vs. Short Messages

	(1) AR_{t+1}(%)
Post × Treated × Sentiment (z)	0.178**
	(0.082)
Post × Treated × Attention (z)	-0.533*
	(0.302)
Post × Sentiment (z)	-0.039
	(0.071)
Post × Attention (z)	0.294
	(0.221)
Treated × Sentiment (z)	-0.023
	(0.053)
Treated × Attention (z)	0.255
	(0.220)
Sentiment (z)	0.038
	(0.049)
Attention (z)	-0.642***
	(0.175)
Post × Treated	0.090
	(0.119)
Treated	-0.034
	(0.080)
Controls	Y
Firm FE	Y
Date FE	Y
Outcome Mean	-0.097
Outcome SD	8.335
Observations	107,631
R^2	0.033

Note: This table compares how social signals about firms with long versus short StockTwits messages changed their predictive power for AR t+1 around StockTwits character limit increase on May 8, 2019. Sample consists of firm-day observations with at least 10 messages on StockTwits between May 8, 2018 and May 8, 2020. The outcome is AR t+1 scaled by 100. *Treated* is one if a firm's daily average number of characters per message is in the top quartile; the omitted category is those is in the bottom quartile. *Post* is one if a day is on or after May 8, 2019. 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. All regressions control for firm fixed effects and date fixed effects. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A12: How Did the Informativeness of the Social Signal for Next-Day Returns Change around the GameStop Event?
Difference-in-Differences

	(1) AR_{t+1}(%)
Post × New user × Sentiment (z)	-0.096*
	(0.049)
Post × New user × Attention (z)	0.038
	(0.032)
New user × Sentiment (z)	0.058
	(0.041)
New user × Attention (z)	-0.017
	(0.030)
Post × Sentiment (z)	-0.000
	(0.032)
Post × Attention (z)	-0.021
	(0.092)
Sentiment (z)	0.037
	(0.026)
Attention (z)	-0.052
	(0.046)
Post × New user	-0.027***
	(0.010)
New user	0.025***
	(0.009)
DJNW sentiment (z)	0.088***
	(0.016)
DJNW attention (z)	-0.063**
	(0.029)
Controls	Y
Firm FE	Y
Date FE	Y
Outcome Mean	-0.005
Outcome SD	7.864
Observations	578,184
R^2	0.049

Note: This table compares how social signals from new versus old StockTwits users changed their predictive power for next-day returns around the GameStop event on January 28, 2021. Sample consists of firm-day observations with at least 10 messages on StockTwits between February 1,2020 and December,31,2021, excluding January 2021. The outcome is AR t+1 scaled by 100. *Post* is one if a day is on or after February 1, 2021. *New user* is one if the social signals are from users who joined StockTwits in 2020 or 2021; the comparison group is the social signals from users who joined before 2020. 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. All regressions control for firm fixed effects and date fixed effects. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level

Table A13: How Did the Informativeness of Social Signals for Next-Day Returns Change around Information Experiments?
Robustness Using Self-labeled Sentiment

	StockTwits experiment		GME experiment	
	(1)	(2)	(3)	(4)
	Self-labeled	Self-labeled top quartile	Self-labeled new users	Self-labeled old users
Post × Sentiment (z)	0.073	0.099	-0.134**	-0.063
	(0.050)	(0.065)	(0.062)	(0.056)
Post × Attention (z)	0.146	-0.316	0.025	-0.002
	(0.092)	(0.242)	(0.108)	(0.090)
Sentiment (z)	0.089***	-0.005	0.077	0.179***
	(0.031)	(0.048)	(0.055)	(0.050)
Attention (z)	-0.321***	-0.270	-0.065	-0.045
	(0.098)	(0.194)	(0.068)	(0.059)
DJNW sentiment (z)	0.099***	0.096***	0.079***	0.093***
	(0.019)	(0.031)	(0.022)	(0.021)
DJNW attention (z)	0.013	-0.044	-0.079***	-0.069*
	(0.028)	(0.089)	(0.027)	(0.038)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Outcome Mean	-0.088	0.047	-0.062	0.007
Outcome SD	8.212	6.825	8.263	8.568
Observations	182,539	42,387	189,562	205,047
R^2	0.027	0.073	0.061	0.051

Note: This table presents robustness checks for Table 7 and Table 8 by using signal based on self-labeled messages on StockTwits. Sample consists of firm-day observations with at least 10 messages on StockTwits and at least 5 messages from the corresponding users on StockTwits. Everything else follows those in Table 7 and Table 8. Standard errors are clustered by firm and by date.
*** 1%, ** 5%, * 10% significance level