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"I just like the stock": The role of Reddit sentiment in the GameStop share rally

Suwan (Cheng) Long[1,2] | Brian Lucey[1,3,4,5] | Ying Xie[6] | Larisa Yarovaya[7]

[1]Trinity Business School, Trinity College Dublin, Dublin 2, Ireland

[2]Judge Business School, University of Cambridge, Cambridge, UK

[3]Institute of Business Research, University of Economics Ho Chi Minh City, Ho Chi Minh, Vietnam

[4]Institute for Industrial Economics, Jiangxi University of Economics and Finance, Jiangxi, China

[5]Abu Dhabi University, Abu Dhabi, United Arab Emirates

[6]Cranfield School of Management, Cranfield University, Cranfield, UK

[7]Southampton Business School, University of Southampton, Highfield Campus, Southampton, UK

Correspondence
Brian Lucey, Trinity Business School, Trinity College Dublin, Dublin 2, Ireland.
Email: blucey@tcd.ie

Abstract

This paper investigates the role played by the social media platform Reddit in the events around the GameStop (GME) share rally in early 2021. In particular, we analyze the impact of discussions on the r/WallStreetBets subreddit on the price dynamics of the American online retailer GameStop. We customize a sentiment analysis dictionary for Reddit platform users based on the Valence Aware Dictionary and Sentiment Reasoner (VADER) sentiment analysis package and perform textual analysis on 10.8 million comments. The analysis of the relationships between Reddit sentiments and 1-, 5-, 10-, and 30-min GameStop returns contribute to the growing body of literature on "meme stocks" and the impact of discussions on investment forums on intraday stock price movements.

KEYWORDS
GameStop, herding, media sentiments, meme stocks, Reddit, Robinhood, sentiment analysis, textual analysis

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D91, G41

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1 | INTRODUCTION

In early 2021, shares in the American video game retailer GameStop surged more than 700% in 1 week following the speculative involvement of individual investors, a move touted as investors piling in to buy stock they like. The *"to the moon"* movement coordinated on the r/WallStreetBets subreddit during the GameStop share rally provides an opportunity to add to the literature on the market impact of online discussion on investment forums (Cookson & Niessner, 2019; Corbet et al., 2021; Renault, 2017). The impact of investment sentiments extracted from Reddit on stock prices is a particularly interesting topic for textual analysis since investors create the content of the forums and influence each other rather than reacting to any published news. In this paper, we aim to add to the media-sentiment literature by designing a Reddit-specific investment lexicon and testing it using GameStop intraday data.

The GameStop and related social media moderated investment "pile-on" was extensively discussed in broadcast and print media, perhaps both reporting on and fueling the perception of small investors. Media sentiments have previously been analyzed using news-aggregation databases (e.g., Chahine et al. (2015); Ahmad et al. (2016); An et al. (2020)), printed newspapers (Bajo & Raimondo, 2017), Yahoo Finance and Raging Bull message boards (Antweiler & Frank, 2004), and social media platforms, such as Twitter (Al Guindy, 2021; Behrendt & Schmidt, 2018), Facebook (Danbolt et al., 2015), Weibo (Feng & Johansson, 2019), Stock Twits, (Cookson and Niessner, 2019), amongst others. In our research, we extract investment discussion-related sentiments from Reddit, and analyze how the tone and timing of the r/WallStreetBets subreddit's posts affected the share price movements. We collect 10.8 million comments from the Reddit platform and analyze the impact of the message board sentiment on intraday GameStop stock prices for the period from January 1st to February 28th, 2021.

The results of previous studies show diverse effects of tone and timing of media coverage on corporate performance and stock market returns. The impact of media has been found to be especially pronounced during periods of stock price explosivity, that is, an asset prices bubble (Campbell et al., 2012), and during the stressed market conditions of a recession (Garcia, 2013), while the impact of positive and negative sentiments can be time varying and asymmetric. Furthermore, it is evident that media coverage affects the performance of highly speculative assets, such as cryptocurrencies (e.g., Corbet et al. (2020); Guegan and Renault (2021)). Cioroianu et al. (2021) considered the impact of social media "hype" on short-term profitability of the firm around blockchain-related announcements. Their results showed that investors were subject to a very sophisticated form of asymmetric information, which in turn led to market euphoria, contributing to the findings of Akyildirim et al. (2020). Danbolt et al. (2015) analyzed the impact of sentiments extracted from Facebook on bidder announcement returns and showed that uninformed traders were the most susceptible of all investors to social media sentiments. This is in line with the behavioral finance literature on investment overconfidence and other cognitive biases in capital markets (Daniel et al., 2002).

There have already been some analyses of the Robinhood/GameStop experience that are related to ours. Corbet et al. (2021) examined Reddit posts around the GameStop situation to examine possible stock price manipulation. Umar et al. (2021b) examined fundamentals sentiment for GameStop but used Twitter data as a proxy for sentiment. In our paper, we directly measure sentiment on the (widely agreed) main social media platform influencing the GameStop price. While Eaton et al. (2021) considered the causal effects of the Robinhood trading platform on financial markets, in this paper, we focus on the impact of meme-driven culture and extract investors' sentiments from r/WallStreetBets subreddit posts. Hu et al. (2021) analyzed the impact of Reddit on the "Robinhood 50" stocks, including GameStop, and demonstrated strong and significant impacts of positive comments on daily stock returns. In our paper, we focus on GameStop stock performance only, considering evidence from high-frequency data.

The GameStop share rally has attracted significant academic attention in terms of analysis of investors' behavior on online trading forums, such as those found on Reddit. However, there is no paper available to date that offers a specific lexicon for Reddit forums that sufficiently explains the underlying mechanism behind the observed impacts on stock markets. The novelty of this paper is twofold. First, we introduce a unique Reddit lexicon that can be used by scholars to extract the investment sentiments from this platform. Before the GameStop share rally, Reddit was not widely consid-

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ered as a platform that could influence the stock markets. In meme culture, emotions are often expressed with images, videos, and emojis, while the text messages on Reddit often contain offensive terms, slang, as well as a significant larger volume of data that would be highly challenging to analyze using standard academic software (e.g., Das and Chen (2007)) or using existing lexicons employed by popular textual analysis packages. In order to extract sentiments from Reddit messages, we designed a unique lexicon containing specific terms frequently used on the r/WallStreetBets subreddit. This offers a better tool for sentiment analysis on Reddit than any existing approaches. Thus, in this paper, we provide a first attempt to capture these sentiments using a unique Reddit lexicon, establishing a foundation for future research in this area. Second, this paper contributes to the literature on the impact of social media on high-frequency intraday stock prices. Our results indicate that Reddit sentiments affected GME intraday returns, and demonstrate the relationships between specific tone and number of comments and 1-min GME returns, confirming the (limited but real) role of r/WallStreetBet's discussion in GameStop's price rally.

The remainder of this paper is organized as follows. Section 2 specifies the research hypotheses. Section 3 explains the data and methodology. Section 4 discusses the empirical results, while Section 5 concludes and provides directions for future research.

2 | WHY MIGHT SENTIMENT MATTER?

Analysis of the behavior of subgroups of investors and their speculative activity on financial markets has a long history. Since Shiller (1990) and Shiller (2014), many scholars have focused on this research question. For example, the impact of retail traders on stock price formation has been explored by Barber and Odean (2002), Kumar and Lee (2006), and Dorn et al. (2008), among others. Barber and Odean (2002) explained the overconfidence and higher trading activity of online investors by self-attribution bias and illusions of knowledge and control, while Kumar and Lee (2006) further highlighted the key role of investor sentiment. Dorn et al. (2008) distinguished between two different types of retail traders: speculative and other traders, and showed that retail speculators as a group behave as positive feedback traders. The impacts of feedback trading and herding behavior have been further considered by Nofsinger and Sias (1999), who reported that institutional investors play a more influential role in financial markets. These papers are in line with early ideas expressed by Shleifer and Summers (1990) on the irrational behavior of noise traders and the limits of arbitrage being superior to the efficient market hypothesis (Fama, 1970). These effects can be persistent, even in liquid markets (Han et al., 2022)

The role of social media in stock price formation is increasingly of interest to researchers. Rantala (2019) examined how investment ideas transmit among retail investors via social interactions considering the inviter–invitee relationships as a Ponzi scheme, showing the power of word-of-mouth. Eliaz and Spiegler (2020), using Bayesian networks, empirically showed that people are drawn to hopeful narratives. Cookson and Niessner (2019) explored an investment disagreement using more than 18 million messages from the StockTwits website, and demonstrated that more than half of investor disagreements were driven by differences in investment philosophies. In contrast to the above mentioned studies, the large body of literature on investment sentiments considers social media platforms as a channel of dissemination of corporate information, which might be especially beneficial for small firms that have relatively less analyst coverage (e.g., Feng and Johansson (2019), Al Guindy (2021)). Therefore, the majority of empirical papers on investment sentiments do not distinguish between different groups of investors publishing their posts on social media, and consider the impact of sentiments extracted from social media as any other variable or factor affecting share prices. This approach is closely related to increasingly popular news-based indices that have been constructed using big data collected from various news aggregated platforms (e.g., Lucey et al. (2021)), and are then used as predictors of financial market performances.

Social media sentiment analysis has been found to be a powerful tool in forecasting stock market returns. For example, Gu and Kurov (2020) reported that Twitter contains information that is not fully reflected in the share price, showing the ability of the Twitter sentiment index constructed by Bloomberg to predict Russell 3000 returns. Liang

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et al. (2020) compared the predictive ability of three sentiment indexes using positive and negative social media posts, newspaper news, and Internet media news, and showed that while traditional newspapers have no impact on Chinese stock markets, both social media and Internet news have strong predictive power. Furthermore, the findings of Dong and Gil-Bazo (2020), who constructed media sentiment measures using more than 58 million social media messages in China, suggest that stock returns are mainly driven by positive sentiment and amateur investors. The impact of social media sentiments on intraday stock returns has been examined by Broadstock and Zhang (2019) using Twitter data, Sun et al. (2016) using Thomson Reuters MarkPsych sentiment data, and Renault (2017) using the StockTwits microblogging platform, among others. It was found that investor sentiment can predict intraday market returns throughout the day and especially during the last two trading hours (Sun et al., 2016), where this predictive power cannot be explained by lagged macroeconomic fundamentals and news. Renault (2017) constructed a lexicon of words used by online investors on StockTwits, and showed that the first half-hour change in investor sentiment can be used to forecast the last half-hour market returns. Finally, sentiment-based trading biases are found in comodity markets such as described by Liu et al. (2021)

Considering the nature and main features of the Reddit platform, we have limited opportunity to split investors into specific groups, therefore, we utilize an alternative approach to Dorn et al. (2008), Rantala (2019), or Cookson and Niessner (2019), and make an assumption that all r/WallStreetBets participants are speculative retail traders. Some existing evidence suggests the importance of both *timing* and *tone* of media-extracted investment sentiments (e.g., Ahmad et al. (2016); You et al. (2017); Liu and Han (2020)). For example, Ahmad et al. (2016) examined the relationships between media-expressed firm-specific tone and firm-level returns, showing that the effect of negative media tone varies from significant effect to no effect at all. Therefore, there are strong reasons to believe that the tone of the Reddit sentiments will be time-varying as will be any predictive power of the sentiment. Umar et al. (2021a) used Twitter publication count as a proxy of media sentiments in analysis of the GameStop share rally and the role of Reddit amateurs in it. However, Twitter Count would not be an accurate proxy to capture Reddit's sentiments. Therefore, in this paper, we consider comments published specifically on the r/WallStreetBets subreddit.

Reddit's comments are organized into *Threads* with titles and some of those threads become more popular and receive more up-votes and higher numbers of comments from the forum's participants. Thus, the number of comments in a thread can be used as a determinant of the popularity of this discussion among Redditors, while comments' scores can indicate the popularity of the specific comment. Reddit has a unique design that allows for a better understanding of the mechanism of "hype" creation on investment forums. Thus, our empirical investigation will help to shed light on the role of Reddit sentiments in asset price dynamics (Campbell et al., 2012). While Garcia (2013) reported an effect of negative media tone during recession, Sun et al. (2016) reported stronger predictive power of high-frequency investment sentiment during economic expansion, which is consistent with several studies, which have highlighted the role of investment mania during periods of stock market explosivity.

3 | DATA AND METHODOLOGY

3.1 | Data

This paper utilizes high-frequency stock price data for GameStop (GME) from January 1st, 2021 to February 28th, 2021. The GME data and Russell 2000 index (of which GME is a constituent) were collected at 1-min intervals from Bloomberg.

Shown in Figure 1 are the price dynamics of GameStop and the R2000 index over the 2 months of the analysis.

For sentiment analysis, we collected 10.8 million comments from the r/WallStreetBets subreddit for the same observation period, that is, the first two calendar months of 2021.

Table 1 shows the number of comments collected for each group out of the 10.8 million comments.

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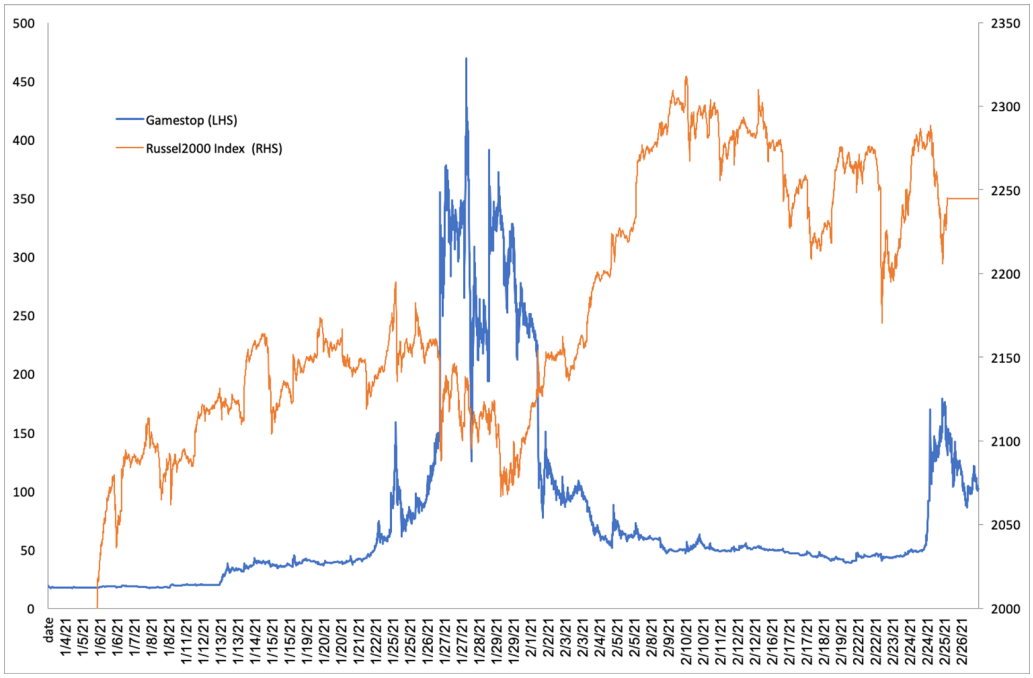


FIGURE 1 GME and Russell 2000 index, 1-min frequency

TABLE 1 Number of r/WallStreetBets threads and comments

Total threads	**846,628**
Total comments	**10,024,617**
Total	**10,871,245**

3.2 | Methods

We began our analysis by extracting sentiments from texts scraped from the r/WallStreetBets subreddit. Text Sentiment Analysis is a trending field with a substantial amount of academic research behind it. There are two main approaches employed in the existing literature: the lexical approach and the machine learning approach. Lexical approaches aim to map words to sentiments by building a lexicon or a "dictionary of sentiment." We can use this dictionary to assess the sentiment of phrases and sentences, without the need to look at anything else. Lexical approaches look at the sentiment category or score of each word in the sentence and decide what the sentiment category or score of the whole sentence is. This approach has been utilized by Loughran and McDonald (2011) and Renault (2017), among others. Machine learning approaches, on the other hand, look at previously labeled data in order to determine the sentiment of never-before-seen sentences. The machine learning approach involves training a model using previously seen text to predict/classify the sentiment of some new input text.

Valence Aware Dictionary and Sentiment Reasoner (VADER) is a sentiment package that is explicitly sensitive to feelings expressed in social media text. VADER relies on a lexicon and five general rules to map lexical features to sentiment scores (Hutto and Gilbert, 2014). When compared with feature-based machine learning methods, VADER has a few advantages: (1) VADER was designed with a focus on social media data, with an emphasis on the rules that captured the essential meaning of social media texts. The lexicon and rules used by VADER are directly accessible and can be easily inspected and updated in discipline context. (2) VADER does not require any training data, and it utilizes a

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human-validated sentiment lexicon and general rules that are related to grammar and syntax. Threads and comments posted on Reddit are usually short sentences with emojis and rich use of punctuation, hence, VADER was selected to conduct the sentiment analysis. However, the lexicon developed by Hutto and Gilbert (2014) for VADER is not specific for the finance field, thus some key financial words are excluded, such as "Bear" and "Bull." Key phrases and hashtags unique to financial social media platforms are also missing from the VADER lexicon, such as "Diamond Hands." Directly applying VADER to analysis of sentiment of the r/WallStreetBets subreddit may mis-classify words when gauging tone in financial applications.

Using LDA modeling, first we classified the threads and comments into 49 topics, then we created a list of the 130 most common words used on r/WallStreetBets by analyzing the content and key information in the 49 topics. The number of LDA modeling topics was determined in such a way that the topic coherence score was maximized. To construct and validate the new VADER lexicon, a human-centered approach was adopted and 10 annotators were hired to manually estimate the sentiment valence (intensity) of each keyword. This approach is consistent with the methods used by Hutto and Gilbert (2014) in developing the original VADER lexicon. We updated the lexicon in VADER by (1) adding new r/WallStreetBets subreddit words and corresponding valence scores to the original lexicon and (2) replacing the original valence scores with new valence scores if some words already exist in VADER. The updated valence scores are in the range of [−4, +4], with [−4] being Extremely Negative, [0] being Neutral, and [+4] being Extremely Positive. The results of this are shown in Tables 2 and 3.

The *SentimentIntensityAnalyser* object from the VADER package[1] was used to extract the *polarity_scores*. *polarity_scores* provide the overall sentiment metrics (compound score) for the comments. The compound score was computed by taking the sum of the valence scores of each word in the lexicon, adjusted according to the five general rules defined by Hutto and Gilbert (2014), and then normalized to be between −1 (most negative) and +1 (most positive). When the compound score is greater than 0.05, it denotes a positive sentiment. When the compound score is less than −0.05, it denotes a negative sentiment. A compound score between 0.05 and −0.05 denotes a neutral sentiment. In addition to the compound score, VADER *SentimentIntensityAnalyser* also returns Positive, Negative, and Neutral scores for a text. These scores were calculated as the sum of Positive, Negative, and Neutral valence scores in the lexicon, respectively. Taking the difference between the Positive and Negative measures, we obtained the net sentiment score of a text. A new variable *NET* was defined as the sum of the net sentiment scores of the texts posted in a time period, for example, within a 5-min period. We also introduced the variable *AVERAGE* that is the mean value of the net sentiment scores of all the texts posted in a time period. VADER sentiment analysis package has been employed widely across different disciplines, see Pano and Kashef (2020), Shelar and Huang (2018), Sivasangari et al. (2018), and Oliveira et al. (2016).

After sentiment variables were constructed, we analyzed the impact of *NET* and *AVERAGE* sentiments on the GME intraday prices using the standard Granger Causality approach (Granger, 1969)[2].

4 | RESULTS

4.1 | GameStop overview

Short-selling strategies are commonly used by large institutional investors and hedge funds that have both substantial investment and human capital to affect the market. In anticipation of a stock price decline, a large hedge fund Melvin Capital opened short positions against GameStop shares, a game and gaming retailer that was one of the many suffering during the COVID-19 induced economic disruption. At that time, on average, GameStop shares were

[1] See for details: https://www.nltk.org/api/nltk.sentiment.html

[2] Considering that this approach is well-known and used widely in the finance literature, for space considerations, we do not include detailed specifications of the method, and the details are available upon request.

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TABLE 2 New words dictionary and their valence scores

Word	Score	Word	Score	Word	Score	Word	Score
available	0.8	diamond_hand	3	cash	0.6	advice	1.3
awesome	3.7	dip	−0.4	concern	−1.3	alternative	0.9
baby	1.2	dumb	−1.9	crash	−3.2	amazing	3.2
bad	−2.7	earning	1.8	crazy	0.7	ass	−1.9
ball	0.4	easy	1.6	crypto	0.5	attack	−1.9
bull	2.8	end	−0.8	damn	−1.7	capital	1
bullshit	−2.4	enough	0.1	diamond	2.9	fact	0.3
buy	1.9	hype	1.2	hard	−1.1	fake	−2.3
call	0.9	idiot	−2.6	hedge	0.5	fight	−1.2
future	1.1	illegal	−3.2	hell	−2.5	fine	1.3
gain	2.2	interest	1.1	high	2.4	flair	1.4
gamma	0	issue	−1.1	hodl	2.8	fuck	−2.8
gang	−0.3	joke	−0.5	hold	1.5	fucking	−2.7
gold	2	jump	1.4	holding	1.6	fun	1.9
good	2.5	least	−0.4	hope	1.5	funny	1.9
great	3.1	legal	1.9	limit	−0.4	problem	−2.3
green	2	manipulation	−2.3	lmao	2.6	profit	2.5
hand	0.1	margin	−0.1	lol	1	proud	2.1
party	0.8	moment	0.7	long	1.8	pump	−0.5
penny	−0.2	moon	2.1	loss	−2.5	purchase	1.3
poor	−1.9	movement	0.9	love	2.3	push	0.5
possible	0.8	naked	−1.1	low	−1.7	quick	0.8
potential	1.4	nice	2	luck	2.1	retard	−2.2
power	2.2	order	0.4	revolution	2	share	0.8
pretty	2.3	panic	−3	rich	2.5	shit	−2.6
probably	0.4	straight	1	ride	1	short	−1.8
top	2.4	strong	2.1	rocket	2.8	silver	−0.2
trade	0.6	stupid	−2.1	sale	−0.7	small	−0.3
value	1.3	support	2.2	scare	−2.3	squeeze	−1.6
win	2.7	target	1.3	scared	−2.6	star	2.4
worth	1.9	tendie	1.7	sell	−1.8	stonk	1.5
wrong	−1.8	to_the_moon	3.5	seller	−1.3	stop	−0.8
yolo	2.4			selling	−1.9		

3*Note*: This table shows the list of words used in the new lexicon with their associated valence scores.

trading around $7 per share, however, the company experienced a noticeable increase in share price creating sufficient volatility for the hedge fund to implement a short selling strategy. The prevailing argument then runs that a coordinated movement led by retail investors on the r/WallStreetBets subreddit caused a rapid increase in GME's share price. The outcome was particularly bad for Melvin Capital, which required nearly $3b in additional capital, with

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TABLE 3 Updated VADER keywords and valence scores

New word	New score	Existing word	Original score	New scores
bull	2.8	crazy	−1.4	0.7
buy	1.9	crash	−1.7	−3.2
diamond_hand	3	interest	2	1.1
tendie	1.7	loss	−1.3	−2.5
to_the_moon	3.5	profit	1.9	2.5

3*Note*: This table shows the valence scores assigned to the *new* words and updated scores assigned to the *existing* words in the lexicon.

an overall short squeeze loss nearing $25b[3]. Figure 1 shows the dynamics of GME shares in comparison to Russell 2000 for the period from January 2020 to March 2021, showing the GME roller-coaster ride in January to February 2021.

The GameStop case received enormous public attention and was widely discussed in the media. The gamification of trading and increased ease of access to financial markets to retail investors via online trading platforms such as Robinhood gave rise to extensive debates and was followed by a sequence of congregational hearings and lawsuits. This case showed the growth of the decentralized financial system and technology and their potential to destabilize financial markets, therefore, the GameStop case became significant from a policy perspective.

Apart from GameStop, other *"meme stocks"* and assets were targeted by Reddit's amateurs, which suggests that the GameStop phenomenon uncovered a new channel for potential market manipulation—Reddit. In comparison to Twitter, Reddit is a much more chaotic platform, and extracting sentiments from the subreddits is a challenging semantic problem. As pointed out earlier, the majority of papers on media sentiments use aggregated news or social media platforms, while only a few papers have actually targeted micro-blogging trading platforms, such as StockTwits (Oliveira et al., 2016; Renault, 2017), the content of which, however, is still highly correlated with Twitter due to the high degree of integration between the two platforms. Considering the platform design, Reddit might contain unique sentiments, which are not captured by Twitter. Furthermore, the lexicon of Redditors differs from that of other forums, since Reddit in itself is a manifestation of meme culture where messages are absurd and often offensive, as demonstrated in Figure 2. Therefore, a better understanding of the investors' lexicon used by Redditors can help to improve the quality of sentiment analysis of other social media platforms.

4.2 | A new lexicon and sentiments in r/WallStreetBets

A unique Reddit-specific lexicon was designed following a three-step process. First, all threads from the r/WallStreetbets subreddit were classified into 49 topics using LDA modeling. Second, a list of the 130 most commonly used words was created, and 10 annotators were asked to manually rank the sentiment valence of each word. Table 2 shows the list of words in the new lexicon and their respective scores. The human-centered approach to sentiment valence ranking was particularly helpful in providing scores for jargon terms; for example, "to the moon" received a [+3.5] score, and "yolo" and "diamond hand" [+2.4] and [+3], respectively. To express negative sentiments, various curse words were often used in addition to standard negative words, such as "loss" [−2.5], "wrong" [−1.8], and "fake" [−2.3].

Third, the existing lexicon in VADER was updated by adding new Reddit-specific words with their corresponding valence scores, as well as updating the scores of the words in the original VADER lexicon. Table 3 shows an example

[3] See https://www.ai-cio.com/news/gamestops-robinhood-boosters-clobbering-hedge-funds/for a comprehensive overview.

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FIGURE 2 Wordcloud of all threads and comments

of the updating process. The new scores not only show the differences in the intensity of the sentiment, but also often display the change in tone of the sentiment from negative to positive, for example, "crazy" from [−1.4] to [0.7]. Figures 3 and 4 show some overall sentiment measures. These plot the frequency and intensity of sentiments over the time-frame of the sample, across different sampling frequencies. We see a major burst of sentiment (net positive as per Figure 4) in the middle and a slightly smaller burst of net positive at the end of the sample period. As can be seen from Figures 5 and 6, a simple overlay of the net sentiment value against GME price suggests a relationship with a weaker against returns.

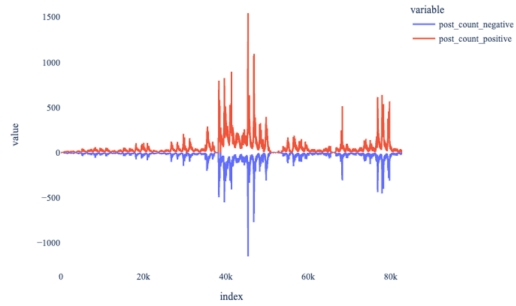
4.3 | The impact of Reddit net sentiment on GME

We begin our analysis of the impact of Reddit sentiments on GameStop by plotting the dynamics of the *NET* Sentiment (Positive–Negative), open and closing GME prices, Open-to-Open and Close-to-Close returns, and trading volume at 1-, 5-, 10-, and 30-min frequencies. Figure 5 displays the results for the 1-min frequency. According to Figure 5a, the relationships between the *NET* Sentiments and Opening and Closing GME prices at 1-min frequency were much stronger during the up market days, that is, from January 20, 2021 to January 27, 2021. The engagement of Redditors with the discussion forum affected opening and closing prices specifically during the bullish market, however, when GME stock turned bearish, we can see that 1-min sentiments and opening and closing prices decoupled from each other and moved in opposite directions. It is particularly visible on Figure 5a during the period after January 31st, 2021, where the spike in *NET* Sentiment occurred (Positive > Negative) but the GME price continued to fall. This implies that positive comments and encouragements to hold GME stocks on Reddit were not able to stop or prevent this downturn of its price. Similar patterns are identified for Open-to-Open and Close-to-Close at the 1-min frequency, as shown in Figure 5b. There is a second period of stronger positive relationships between the *NET* Sentiment and GME returns during the up market movement at the end of February 2021, however, similarly, the linkages are weakened during the down market days. These are in line with the results obtained for 1-min total trading volumes, showing that the discussions on the Reddit forum during the down market movements were only weakly linked to trading volume of GME stocks.

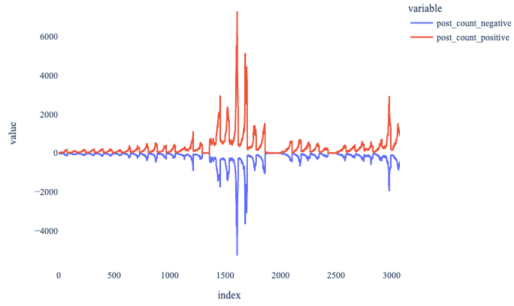
These patterns can be observed more clearly using 5-min data, as shown in Figure 6. There are clear break points in relationships between *NET* Sentiment and GME prices and returns, however, during the bearish market, the positive linkages are weakened. These results shed light on the mechanism of sentiment formation on r/WallStreetBets and

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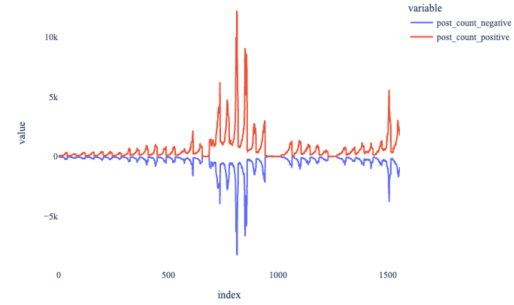
(a) 1 Minute



(b) 5 Minutes



(c) 10 Minutes



(d) 30 Minutes

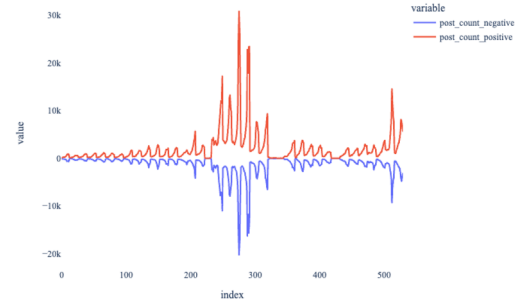
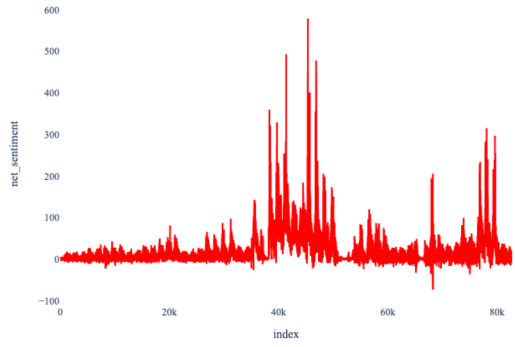


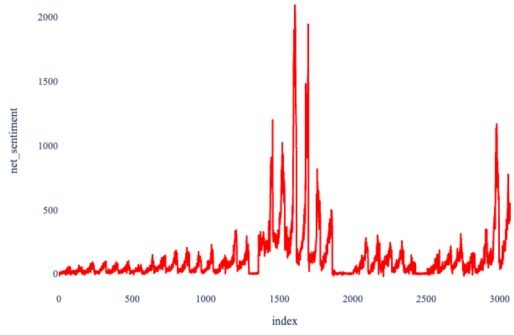
FIGURE 3 Positive and Negative Sentiments at different frequencies

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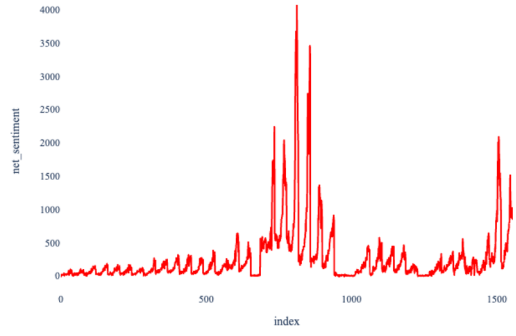
(a) 1 Minute



(b) 5 Minutes



(c) 10 Minutes



(d) 30 Minutes

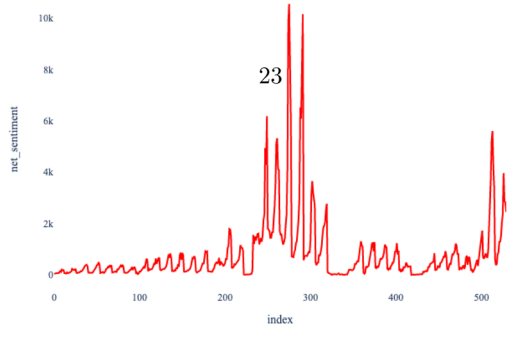
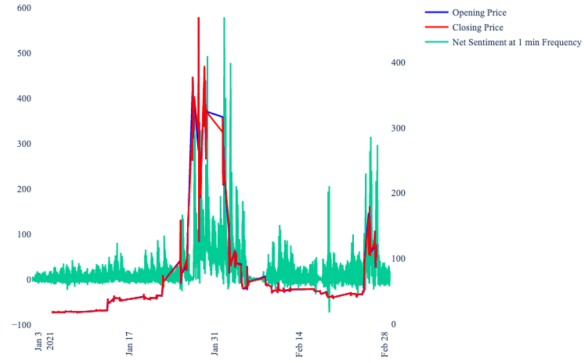


FIGURE 4 Net Sentiments at different frequencies

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(a) 1-minute net sentiment and GME prices



(b) 1-minute net sentiment and GME returns



(c) 1-minute net sentiment and GME trading volume

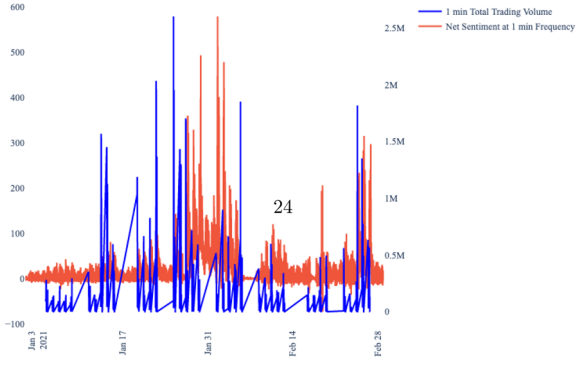


FIGURE 5 1-min frequency

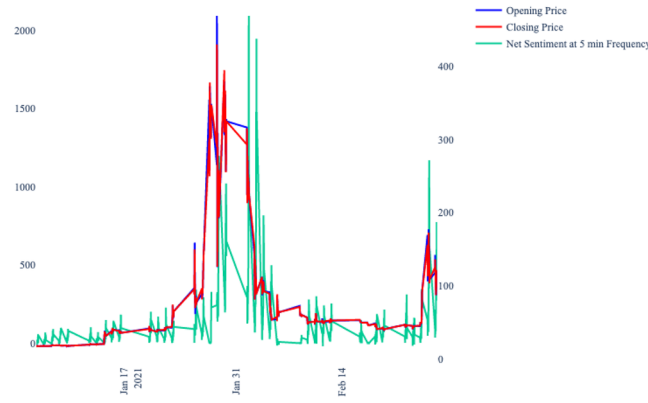
its impact on the GME share rally, and show that Reddit discussions helped to spike interest in buying GME stock, but was incapable of maintaining it when the price returned to a fair value. For example, Figure 5c shows linkages between trading volume and *NET* Sentiment at the beginning of the estimation period, but not in the period around January 31st, when the market had already turned bearish.

These results are consistent even for lower frequencies, and Figures 7 and 8 display similar patterns. At 10- and 30-min frequencies, we can clearly observe how the relationships intensify specifically during two short periods of GME price increase. However, outside of these two periods, the growth in *NET* Sentiment, that is, increase in number of positive comments over negative comments in r/WallStreetBets, the relationships were weaker.

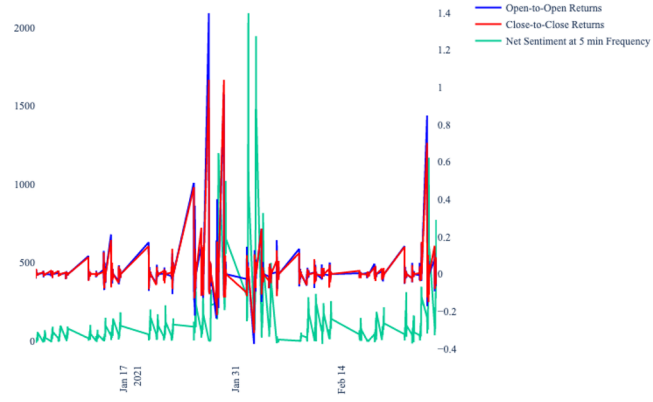
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FIGURE 6 5-min frequency

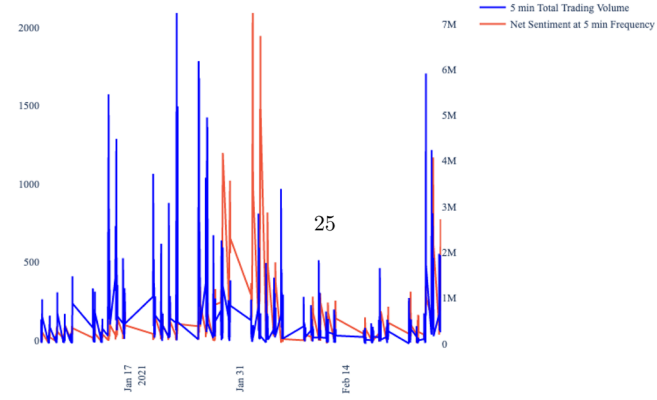
(a) 5-minute net sentiment and GME prices



(b) 5-minute net sentiment and GME returns



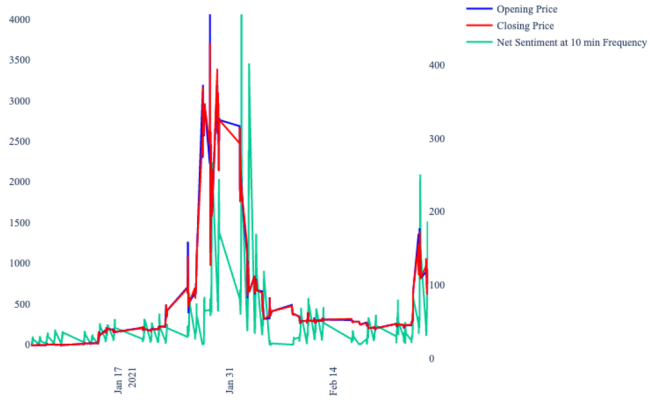
(c) 5-minute net sentiment and GME trading volume



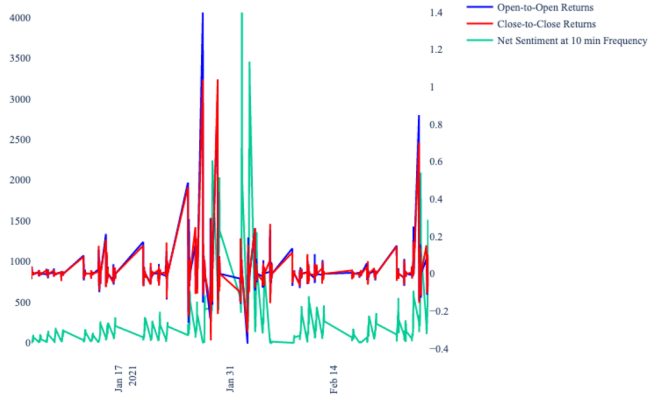
To further examine the causal linkages between NET Sentiments and GME returns, we employ the standard Granger causality test (Granger, 1969), and the results are presented in Table 4. The findings show that at 1-min frequency GME Open-to-Open returns affected *NET* Sentiments and *AVERAGE* Sentiments, but not the other way around. Neither *NET* nor *AVERAGE* Sentiments had any effect on GME 1-min returns. The impact of *NET* sentiments on GME

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(a) 10-minute net sentiment and GME prices



(b) 10-minute net sentiment and GME returns



(c) 10-minute net sentiment and GME trading volume

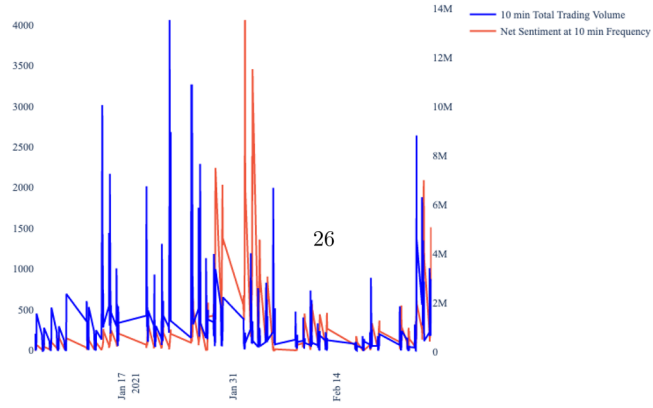


FIGURE 7 10-min frequency

return became significant only at lower frequencies, and we can see clear evidence of a positive impact for 5-, 10-, and 30-min data. However, the causal linkages between *AVERAGE* sentiment and GME returns were not identified at these frequencies.

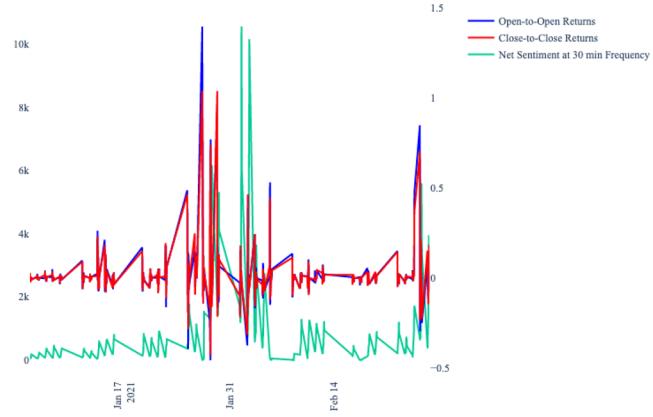
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FIGURE 8 30-min frequency

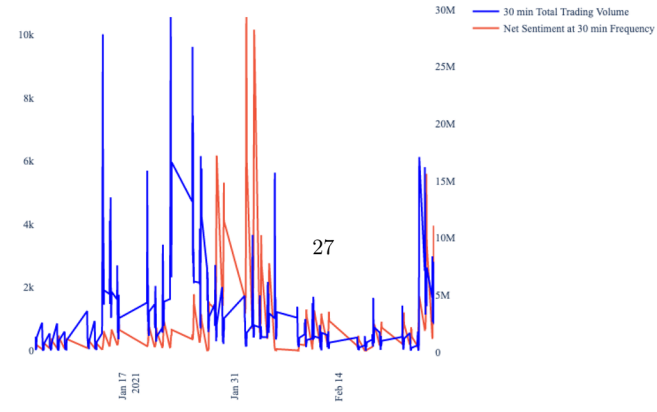
(a) 30-minute net sentiment and GME prices



(b) 30-minute net sentiment and GME returns



(c) 30-minute net sentiment and GME trading volume



5 | CONCLUSIONS

This paper investigates the impact of sentiments extracted from Reddit on GameStop's intraday returns. Using 10.8 million comments from the r/WallStreetBets subreddit for the period from the January 1st to February 28th, 2021, this paper introduces a unique Reddit-specific lexicon with the corresponding senti-

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TABLE 4 Granger causality results at 1-, 5-, 10-, and 30-min frequency

1 min			
GMEO_R does not Granger Cause NET_SENTIMENT	15227	2.39737*	0.09
NET_SENTIMENT does not Granger Cause GMEO_R	15227	1.12244	0.33
AVERAGE_SENTIMENT does not Granger Cause GMEO_R	15227	1.15125	0.32
GMEO_R does not Granger Cause AVERAGE_SENTIMENT	15227	4.02723**	0.02
5 min			
NET_SENTIMENT does not Granger Cause GMEO_R	3074	5.95583*	0.00
GMEO_R does not Granger Cause NET_SENTIMENT	3074	0.43033	0.65
AVERAGE_SENTIMENT does not Granger Cause GMEO_R	3074	0.40559	0.67
GMEO_R does not Granger Cause AVERAGE_SENTIMENT	3074	0.95974	0.38
10 min			
NET_SENTIMENT does not Granger Cause GMEO_R	1554	6.6658***	0.0013
GMEO_R does not Granger Cause NET_SENTIMENT	1554	0.00043	1.00
GMEO_R does not Granger Cause AVERAGE_SENTIMENT	1554	1.43995	0.24
AVERAGE_SENTIMENT does not Granger Cause GMEO_R	1554	0.45851	0.63
30 min			
NET_SENTIMENT does not Granger Cause GMEO_R	528	3.2623**	0.04
GMEO_R does not Granger Cause NET_SENTIMENT	528	0.22412	0.8
AVERAGE_SENTIMENT does not Granger Cause GMEO_R	528	1.8199	0.16
GMEO_R does not Granger Cause AVERAGE_SENTIMENT	528	1.79278	0.17

3*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

ment scores obtained using a human-centered approach. The lexicon's aim is to support researchers conducting textual analyses of investment sentiments derived from Reddit. The power of the lexicon to capture investment sentiments on the social media platform was examined using the GameStop share rally in early 2021.

The impact of *NET* Investment Sentiments on 5-min, 10-min, and 30-min GME open-to-open returns was identified. However, there was no impact of *AVERAGE* Sentiments on GME performance. For 1-min data, our results suggest the opposite direction of causality, GME returns Granger cause both *NET* and *AVERAGE* Sentiments. Analysis of the dynamics of the *NET* Senitments and GME prices, returns and trading volume, further show that linkages tended to be stronger during the bullish market in comparison to the bearish market. This implies the role of Reddit in transmitting positive sentiments during up market movements, however, it also implies a weak power of social media to influence markets during downward market movements and to stop a share's downfall. Hence, this paper has uncovered a limited, but real, role of Reddit in the GameStop share rally.

This paper contributes to the literature on the impact of social media sentiments on stock prices providing novel empirical evidence from Reddit. Our results will be of interest to institutional and retail investors, as well as policy makers, academics, and media, since they shed a light on the "meme stocks" phenomenon. While the impact of Reddit sentiments on the stock market is confirmed, our results represent a warning to individual investors that social media discussions might not be able to protect their investments when the market turns bearish. Even if r/WallStreetBets and other investment forums show the growing power of retail investors to act in an organized manner, the influence is still not strong enough to protect individual investors from losses in highly speculative "meme" stock markets.

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APPENDIX A

In consistence with the human-centered approach adopted by Hutto and Gilbert (2014) to construct and validate a Valence-Aware Sentiment Lexicon, we hired 10 annotators to manually estimate the sentiment valence (intensity) of each context-free keyword collected from Reddit WallStreetBets posts and comments. Hiring a group of 10 annotators follows the wisdom-of-the-crowd approach (Surowiecki, 2004), to acquire a valid point of estimate for the sentiment valence score.

1. Screening, training, and selecting annotators before assigning tasks to the annotators, screening, training, selecting and data quality checking are performed to control the quality of manual annotation, and to make sure meaningful scores are received from annotators (Hutto and Gilbert, 2014). I. Every annotator is prescreened for English language reading of stock market comprehension exercise. Each annotator needs to achieve over 80 II. Every annotator receives an online or in person sentiment rating training session. Annotators are asked to rate each keyword using a score between [−4, +4], with [−4] being Extremely Negative, [0] being Neutral (or Neither, N/A), and [+4] being Extremely Positive. A list of words and prevalidated sentiment scores was extracted from the VADER dictionary, and it was used to run the training session. III. After the training session, every annotator is asked to manually label a list of test lexical items that have prevalidated scores. These items are extracted from the four distinct gold standard ground truth sentiment annotated corpora and the VADER lexicon developed by Hutto and Gilbert (2014), including individual words, emotions, acronyms, and tweets. To be eligible for the appointment, an annotator needs to achieve a score of 90 IV. Every batch of 25 keywords contained five "golden words" that have revalidated sentiment scores and standard deviations. These "golden words" are extracted from the VADER lexicon developed by Hutto and Gilbert (2014). If an annotator's score is more than 1 standard deviation away from the mean of this known distribution on three or more of the five "golden words," we discarded all the ratings given by this annotator, and asked him/her to re-annotate.
2. Instructions of manual annotation: (1) Every appointed annotator has to pass the screening, training, and selecting process outlined in steps I–IV in Section 1. (2) Ratings are obtained using either Amazon Mechanical Turk, Finance academics, or students studying Finance subject. A group of 10 annotators are appointed. (3) Annotators rate each keyword on a scale from "[−4] Extremely Negative" to "[4] Extremely Positive," with "[0] being Neutral (or Neither, N/A)." (4) The aggregate of 10 independent ratings for each keyword is used to calculate mean score and standard deviation for that word. (5) Keywords with a nonzero mean score and a standard deviation $\leq$2.5 are kept. (6) The list of keywords, with associated valence sentiment scores, comprise the EXTRA VADER sentiment lexicon. (7) Update the VADER lexicon using the EXTRA VADER sentiment lexicon. Words and associated valence sentiment scores in the EXTRA VADER replace the corresponding words and scores in the VADER lexicon, and new words in the EXTRA VADER are appended to the end of the VADER lexicon. (8) Calculate new sentiment scores using the updated VADER lexicon.

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[Correction added on 23 November 2022, after first online publication: funding information has been added.]

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