Predicting stock prices with ChatGPT-annotated Reddit sentiment: Hype or reality?

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Abstract. The surge of retail investor activity on social media, exemplified by the 2021 GameStop short squeeze, raised questions about the influence of online sentiment on stock prices. This paper explores whether sentiment derived from social media discussions can meaningfully predict stock market movements. We focus on Reddit's r/wallstreetbets and analyze sentiment related to two companies: GameStop (GME) and AMC Entertainment (AMC). To assess sentiment's role, we employ two existing text-based sentiment analysis methods and introduce a third, a ChatGPT-annotated and fine-tuned RoBERTa-based model designed to better interpret the informal language and emojis prevalent in social media discussions. We use correlation and causality metrics to determine these models' predictive power. Surprisingly, our findings suggest that social media sentiment has only a weak correlation with stock prices. At the same time, simpler metrics, such as the volume of comments and Google search trends, exhibit stronger predictive signals. These results highlight the complexity of retail investor behavior and suggest that traditional sentiment analysis may not fully capture the nuances of market-moving online discussions.

Keywords: ChatGPT · Stock market · Social media · Sentiment

1 Introduction

The stock market is usually assumed to be largely controlled by large investment funds. Historically, small retail investors did not have enough funds to have a measurable impact on the price of stocks individually. However, the recent rise of social media allows for large-scale cooperation between previously unconnected individuals. This resulted in the situation at the beginning of 2021 when a financial analyst named Keith Gill (usually known under the nickname of "DeepFuckingValue") created a post on Reddit,in which he outlined his arguments for investing in Gamestop.

At the time, investing in Gamestop was largely assumed to be unprofitable, as the company's stock was at an all-time low, and some funds were trying to

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decrease the price further. Despite that, Keith Gill's arguments were accepted by a large amount of Reddit users. The stock started being bought by many of the platform's users, and the price started to increase. The movement began to spiral out of control, mainstream news platforms started covering it, and the whole situation eventually resulted in a $\sim 7900\%$ price increase of the stock.

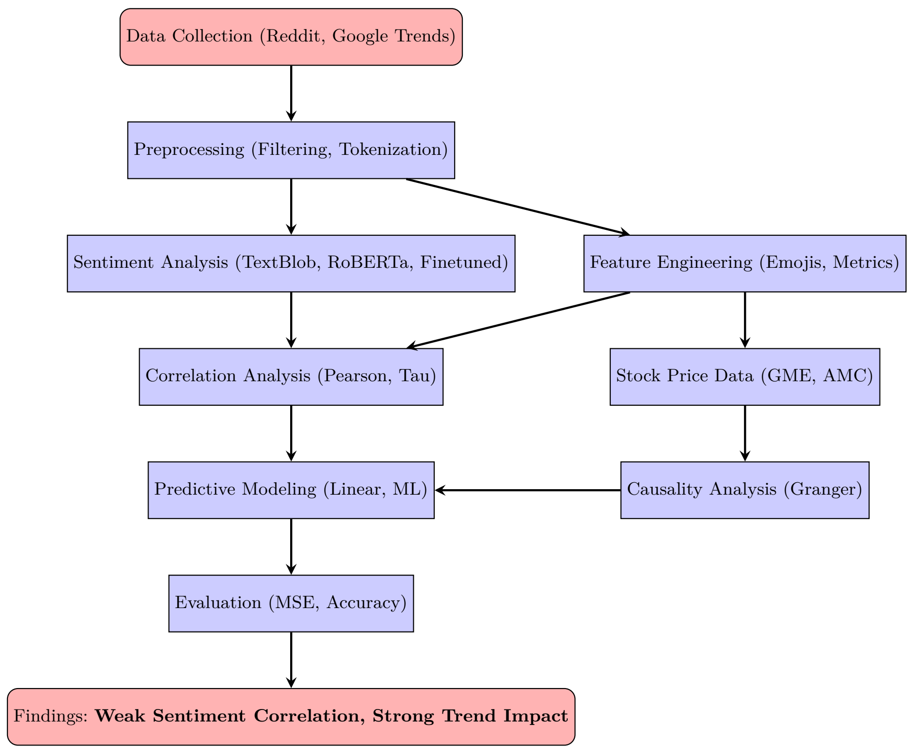

Fig. 1: System overview of sentiment and stock market analysis

This case inspired us to verify if there are other cases where one can attribute the change in stock price to social media. We have identified two companies for which we tested this theory. These companies are Gamestop (GME) and AMC Entertainment Holdings Inc (AMC). For each company, we have gathered a dataset of Reddit posts/comments mentioning it and measured if the sentiment and volume of these posts impact the company's price. The metrics used are:

1. Pearson correlation coefficient [22] – denoted as r, is a statistical measure that evaluates the linear relationship between two variables. It ranges from -1 to 1, where 1 indicates a perfect positive linear correlation, -1 indicates a perfect negative linear correlation, and 0 signifies no linear correlation.
2. Kendall Tau correlation [17] – denoted as τ, is a non-parametric measure used to assess the ordinal association between two measured quantities. It

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evaluates the strength and direction of a relationship between two variables by comparing the ranks of their data points. A value of 1 indicates a perfect agreement, -1 indicates a perfect disagreement, and 0 suggests no association.
3. Granger causality [4] – a statistical hypothesis test for determining if one time series can predict another. It does not test for true causality but rather whether one variable's past values can help predict another's future values. The p-value in Granger causality tests indicates the probability of observing the test statistics if the null hypothesis (that one time series does not help predict the other) is true. A small p-value (typically ≤ 0.05) indicates strong evidence against the null hypothesis, suggesting that the predictor time series has predictive power on the target series.

As an additional input, we checked these metrics for the number of Google searches (interest value from Google Trends) of the company to see if it also impacts the stock price, see Figure 1.

While two out-of-the-box models for classifying the sentiment of text were used, a new one was also created by finetuning an existing model based on RoBERTa. The fine-tuning (similar to [15, 19, 21, 20, 9, 13, 18]) was done to classify better the sentiment of posts, which used phrases very specific to the Reddit platform and a substantial amount of emojis. We provided the training data for finetuning by labeling the collected Reddit posts automatically with the help of ChatGPT, similar to [16, 14, 27, 12].

2 Related work

Since the GameStop black swan event, there has been a tremendous amount of work on this topic. There is a lot of insight into the social behaviors that drove people into doing so [3, 5, 8, 1], which offer explanations as to why the search for correlation and especially causality makes sense. Many researchers were trying to see if there were differences between before the GME short squeeze happened and afterward [26], and there certainly has been a change in how seriously social media is seen in affecting the stock market [6]. Although, it seems impossible to predict stock prices with Reddit [24, 10, 2] or any other social media outlets[11][7][23]. Some research has gone into analyzing the correlation between stock prices and various social indicators[25]. This has led us to explore, refine, and hopefully improve upon these approaches by comparing various stocks with each other in terms of their correlation and causality scores.

3 Datasets

As part of our work, we have prepared a dataset of Reddit posts from the */r/wallstreetbets* subreddit, which had a significant role in the Gamestop situation. The creation dates of the posts range between 2021.01.04 and 2021.03.31. In total, about 7 million posts were collected.

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3.1 Emoji-driven Nature of Dataset

Emojis were segmented as one of the biggest differences between the dataset of Reddit posts and the original financial jargon the base model was trained on. From the new dataset, 561563 posts contained at least one emoji, with 1349 unique emojis overall. The most frequent usages of emojis were:

- 🚀: Associated with the phrase *To the moon*, meaning the stock price will skyrocket. Appeared in the dataset 1445364 times in 253700 posts.
- 💎: Associated with the phrase *Diamond hands*, meaning the investor refrains from selling an investment despite downturns or losses, believing in the long-term gains. Appeared in the dataset 451634 times in 162433 posts.
- 🙌: Associated with the phrase *Diamond hands*, as above. Appeared in the dataset 188311 times in 67247 posts.
- 🦍: Associated with users of the subreddit *r/wallstreetbets* calling themselves apes, meaning social-media traders battling against powerful institutional investors. Appeared in the dataset 113211 times in 41395 posts.

3.2 ChatGPT Annotation

Reddit posts containing emojis were fed in batches of 100 into ChatGPT. Below is an example classification prompt and the system's response.

Task: Data annotation using ChatGPT

Prompt

For each line of text below, separated by —, specify sentiment towards the stock as positive, neutral, or negative.
The context is meme stocks.
Respond with sentiment for each text in a separate line, with corresponding id.
Don't add any decorators, just lowercase response in one word.
Make sure to give the response for each id.
Here are the texts:
—
1: To the Muricans 🇺🇸 getting their stimmys today. Don't do the usual Murican thing and shit the bed. Pls and thank you. From a UK Ape 🦍 ✌️
—
2: 🙌🙌🙌
—
3: THIS IS A VOLATILE FUCKING STOCK RIGHT NOW YOU GOTTA HAVE 💎✋
—
4. 😭😭😭😭😭😭😭😭😭😭😭😭😭 —
...
—
99: Fun game GME today! buy 🕤market 📈20 mins later.....💃💰💰....🛌💤
—
100: just got a fraction. im broke but it's what i can do 💎🙌
—

ChatGPT answer

1: positive
2: positive
3: positive
4: negative
...
99: positive
100: positive

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3.3 ChatGPT Augumentation

As negative labels were very sparse in the collected dataset, ChatGPT was used again to generate negative examples based on negative samples from the dataset. Negative Reddit posts were fed in batches of 50 into ChatGPT, expecting to get 50 new samples generated in response. Below is an example generation prompt and the system's response.

Task: Data generation using ChatGPT

Prompt

Here are comments about Gamestock squeeze and meme stocks (stonks).
All of them were marked as negative.
Each one is divided with —.
Learn the style of these comments. Look at emojis.
Respond with 50 new comments, also negative, in the same style. Separate each generated comment with — and give it an index number starting from 1.
Here are the texts:
—
1: Access denied 🙅‍♂️
—
2: GME IS DONE THE STOCK MARKET IS NEVER THAT EASY 🤣 AT LEAST YOU GUYS KNOW NOW💥
—
3: Lol GME are losing enough money as it is without taking on another money losing operation 🤣🤣🤣
—
...
—
100: What an idiot we have here
—

ChatGPT answer

1: Classic move, blame everyone else for your failed predictions and cry foul. 🤷‍♂️😂
2: Technical analysis skills as impressive as a toddler drawing with crayons. Get a grip, OP! 🤦‍♂️
3: Denied access to sanity and logic, just like your stock predictions. 🙅‍♂️📉
4: The only thing dropping faster than the price is the IQ of those defending the plunge. 📉🤣
...
50: Another stonk expert realizing the market isn't a playground for easy gains. 🤣💥💤

Considering the sizes of each class and time and resource constraints, 10525 samples were used for training: 7010 positive, 2219 neutral, and 1296 negative.

4 Models

4.1 TextBlob

TextBlob stands out in the field of natural language processing (NLP) as a versatile and user-friendly Python library. It is built upon the foundations of other well-established Python libraries like NLTK and Pattern and provides a comprehensive toolkit for textual data analysis.

The sentiment analysis feature of TextBlob is particularly noteworthy. It analyzes the emotional undertone of textual data, categorizing it as positive, negative, or neutral. The value we analyze is *polarity*, which is a measure on a scale of -1 to 1, where -1 denotes a highly negative sentiment and 1 represents a highly positive sentiment. A score of 0 indicates neutrality.

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4.2 Financial-RoBERTa

Financial-RoBERTa represents a significant advancement in Natural Language Processing (NLP) applied to financial texts. This model adapts the RoBERTa Large language model, pre-trained and fine-tuned to specialize in the sentiment analysis of various financial documents. The domains of documents it can analyze include, but are not limited to, Financial Statements, Earnings Announcements, Earnings Call Transcripts, Corporate Social Responsibility (CSR) Reports, Environmental, Social, Governance (ESG) News, and other pertinent Financial News.

The development of Financial-RoBERTa involved an extensive training process using a diverse and comprehensive corpus. This corpus comprises various financial documents, such as 10-K, 10-Q, and 8-K filings, Earnings Call Transcripts, CSR Reports, ESG News, and Financial News texts. By utilizing such a varied and relevant dataset, the model is finely attuned to the nuances and specificities of financial language and terminology.

4.3 Finetuned version of Financial-RoBERTa

The Financial-RoBERTa model, while robust in analyzing formal financial texts, initially faced challenges in interpreting colloquial language, particularly prevalent in social media contexts. To address this, a specialized version of Financial-RoBERTa has been developed and fine-tuned using a unique dataset of Reddit posts. These posts, characterized by informal language, abundant use of emojis, and community-specific jargon, provide a rich resource for adapting the model to a more diverse linguistic environment.

The fine-tuning process involved the integration of a large corpus of Reddit posts, each labeled with sentiment tags generated by ChatGPT. This approach leveraged ChatGPT's advanced understanding of colloquial expressions and emoji usage to accurately tag each post with a corresponding sentiment label: Positive, Negative, or Neutral. The inclusion of this colloquially-rich and emoji-laden dataset aimed to enhance the Financial-RoBERTa model's proficiency in handling non-traditional financial texts, which are becoming increasingly relevant in today's digital and social-media-driven financial landscape.

Originally, Financial-RoBERTa's training on formal financial documents limited its effectiveness in contexts where informal language prevailed. This gap was particularly noticeable when analyzing texts from platforms like Reddit, where users frequently employ a casual tone, slang, and visual elements like emojis to express sentiments. By incorporating this informal, emoji-rich dataset into the fine-tuning process, the enhanced Financial-RoBERTa model now demonstrates improved accuracy and adaptability in analyzing texts that deviate from conventional financial language.

The fine-tuned version of the Financial-RoBERTa model retains its original proficiency in analyzing formal financial texts while extending its capabilities to comprehend and accurately classify sentiments in less formal, emoji-enriched

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texts. This advancement makes the model an even more versatile tool for financial analysts who seek to harness insights from a broader range of sources, including social media platforms where investors and consumers frequently express opinions and reactions colloquially.

5 Experiments

For every previously mentioned company, we have performed the following experiments:

1. Calculating stock price correlation and causality metrics for the daily number of comments and Google Trends values (0-100).
2. Calculating stock price correlation and causality metrics for the sentiment produced by TextBlob, Financial-RoBERTa, and the finetuned version of Financial-RoBERTa. Furthermore, as the finetuned version was supposed to handle emojis better, we also provided a baseline model, which counts the number of emojis in a text. We shall refer to this model as the Emoji Counter.

When we calculate correlation and causality metrics, we also provide them for two modifications of the original stock price data:

1. *SHIFTED* - we shift the stock price data by one day to the past. That way, we calculate the metrics as if we're trying to predict the price of the current day, not the next day.
2. *STATIONARY* - we operate not on absolute stock price values but on the daily price change. We believe this type of information is more suited for the Granger causality test, as it works best for stationary data.
3. *SHIFTED STATIONARY* - both STATIONARY and SHIFTED modifications are applied.

6 Results

6.1 Gamestop

In Table 1, a significant correlation is observed between stock price and the number of comments, indicating that social media discussions align closely with market movements, Fig. 2. The correlation with Google Trends values is slightly weaker, suggesting that while public interest follows price changes, it may not be as immediate as social media reactions. This difference implies that active trader discussions have a stronger short-term impact on stock fluctuations, whereas search trends may reflect broader, less engaged curiosity. Future research could further explore how different online activities influence stock behavior across various market conditions.

In Table 2, the stock price shows symmetrical causal relationships with the number of comments and Google Trends values, particularly after applying the

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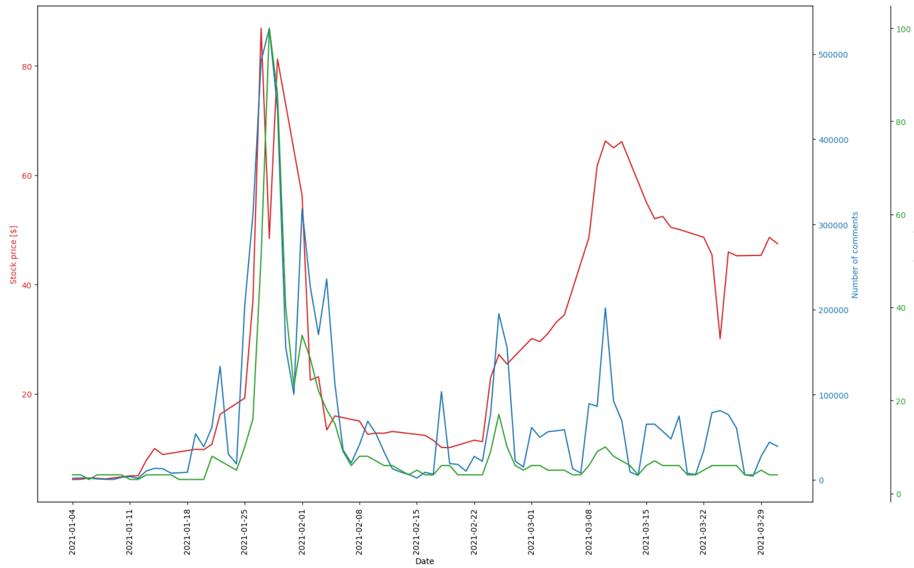

Fig. 2: Stock price, number of comments, and Google Trends value for Gamestop

Type	**Shifted**	**Value**	**Correlation**
Pearson	false	Number of comments	**0.521863**
Pearson	true	Number of comments	0.470033
Kendall/Tau	false	Number of comments	0.479781
Kendall/Tau	true	Number of comments	0.442623
Pearson	false	Google Trends	0.426960
Pearson	true	Google Trends	0.434461
Kendall/Tau	false	Google Trends	0.410597
Kendall/Tau	true	Google Trends	0.407103

Table 1: Stock price correlation measurements for Gamestop

Cause	**Effect**	**p**	**Stationary**	**Shifted**
Stock price	Number of comments	0.9116	false	false
Stock price	Number of comments	**0.0408**	true	false
Number of comments	Stock price	0.4686	false	false
Number of comments	Stock price	**0.0180**	true	false
Number of comments	Stock price	**0.0406**	false	true
Number of comments	Stock price	**0.0003**	true	true
Stock price	Google Trends	0.2495	false	false
Stock price	Google Trends	**0.0302**	true	false
Google Trends	Stock price	0.9169	false	false
Google Trends	Stock price	**0.0008**	true	false
Google Trends	Stock price	0.3491	false	true
Google Trends	Stock price	0.0541	true	true

Table 2: Granger Causality measurements (p-value) for Gamestop

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STATIONARY modification, according to the Granger Causality metric. This suggests a feedback loop where increased discussions and search trends can predict stock price movements while price fluctuations also drive online engagement. The bidirectional nature of this relationship supports the idea that modern markets are influenced by social sentiment alongside fundamental financial indicators. Stronger causal effects with stationarity adjustments indicate that investors react more to daily price changes than absolute stock levels, highlighting the role of event-driven volatility and momentum in shaping online discourse. Future research could examine whether specific social media interactions—such as sentiment, engagement, or trading discussions—impact stock movements more than general activity metrics.

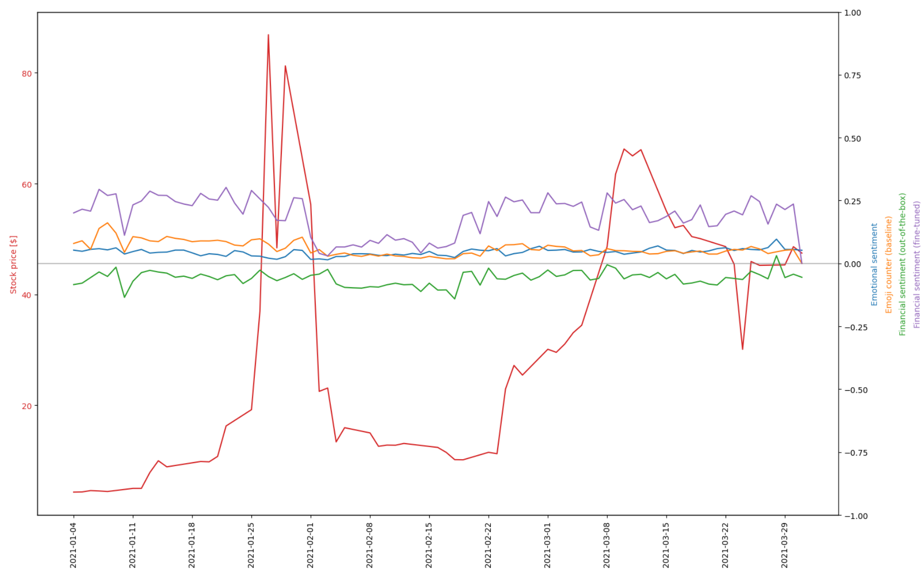

Fig. 3: Stock price and sentiment values for Gamestop

In Table 3, all sentiment values show very weak correlation with the stock price of Gamestop, indicating that traditional sentiment analysis may not effectively capture the factors influencing stock movements in this case, Fig. 3. In Table 4, some causal relationships were identified, suggesting an interaction between stock price movements and social media sentiment. Notably, the stock price can predict the number of emojis in Reddit posts about GME, indicating that price fluctuations influence how users express sentiment, particularly through informal and emotion-driven communication. Furthermore, the stock price has a symmetric causal relationship with the output of the fine-tuned financial model, suggesting that while sentiment analysis can reflect market trends, it may also be shaped by them. This bidirectional effect highlights the complex

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Type	**Shifted**	**Sentiment**	**Correlation**
Pearson	false	Emotional	-0.028362
Pearson	true	Emotional	-0.058245
Kendall/Tau	false	Emotional	-0.060109
Kendall/Tau	true	Emotional	-0.040437
Pearson	false	Financial (out-of-the-box)	0.230485
Pearson	true	Financial (out-of-the-box)	0.135628
Kendall/Tau	false	Financial (out-of-the-box)	0.095082
Kendall/Tau	true	Financial (out-of-the-box)	0.029508
Pearson	false	Emoji counter	-0.290720
Pearson	true	Emoji counter	-0.393952
Kendall/Tau	false	Emoji counter	-0.239344
Kendall/Tau	true	Emoji counter	-0.339891
Pearson	false	Financial (finetuned)	0.053431
Pearson	true	Financial (finetuned)	-0.123969
Kendall/Tau	false	Financial (finetuned)	-0.107104
Kendall/Tau	true	Financial (finetuned)	-0.218579

Table 3: Stock price correlation measurements for Gamestop (sentiment data)

Cause	**Effect**	**p**	**Stationary**	**Shifted**
Stock price	Emotional	0.9259	false	false
Stock price	Emotional	0.1407	true	false
Emotional	Stock price	0.4594	false	false
Emotional	Stock price	0.6635	true	false
Emotional	Stock price	0.7703	false	true
Emotional	Stock price	0.3562	true	true
Stock price	Financial (out-of-the-box)	0.8971	false	false
Stock price	Financial (out-of-the-box)	0.1127	true	false
Financial (out-of-the-box)	Stock price	0.1998	false	false
Financial (out-of-the-box)	Stock price	0.5392	true	false
Financial (out-of-the-box)	Stock price	0.0927	false	true
Financial (out-of-the-box)	Stock price	0.7953	true	true
Stock price	Emoji counter	**0.0267**	false	false
Stock price	Emoji counter	0.1010	true	false
Emoji counter	Stock price	0.5876	false	false
Emoji counter	Stock price	0.6167	true	false
Emoji counter	Stock price	0.4617	false	true
Emoji counter	Stock price	0.8832	true	true
Stock price	Financial (finetuned)	**0.0097**	false	false
Stock price	Financial (finetuned)	0.1816	true	false
Financial (finetuned)	Stock price	0.0550	false	false
Financial (finetuned)	Stock price	0.6349	true	false
Financial (finetuned)	Stock price	**0.0120**	false	true
Financial (finetuned)	Stock price	0.1488	true	true

Table 4: Granger Causality measurements (p-value) for Gamestop (sentiment data)

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interplay between investor emotions, online discourse, and market dynamics, warranting further exploration into how different sentiment signals contribute to price movements.

6.2 AMC

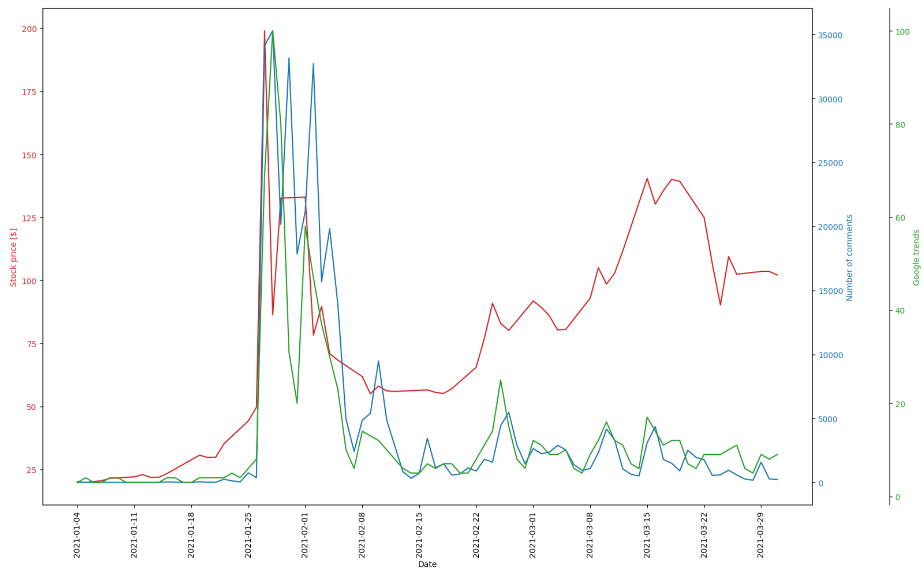

Fig. 4: Stock price, number of comments and Google Trends value for AMC

Type	Shifted	Value	Correlation
Pearson	false	Number of comments	0.377953
Pearson	true	Number of comments	0.387969
Kendall/Tau	false	Number of comments	0.363188
Kendall/Tau	true	Number of comments	0.363188
Pearson	false	Google Trends	0.475918
Pearson	true	Google Trends	0.482916
Kendall/Tau	false	Google Trends	**0.551863**
Kendall/Tau	true	Google Trends	**0.537192**

Table 5: Stock price correlation measurements for AMC

In Table 5, a significant correlation is observed between the stock price and Google Trends values, suggesting that public interest closely follows market

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movements, Fig. 4. The correlation with the number of comments is slightly weaker, indicating that while social media discussions align with price changes, they may not be as immediate or strong as search trends. This difference implies that Google search activity, often driven by broader awareness and media coverage, may serve as a stronger indicator of investor attention compared to direct engagement in online discussions.

Cause	**Effect**	**p**	**Stationary**	**Shifted**
Stock price	Number of comments	0.2567	false	false
Stock price	Number of comments	**0.0007**	true	false
Number of comments	Stock price	0.2459	false	false
Number of comments	Stock price	0.0823	true	false
Number of comments	Stock price	0.3028	false	true
Number of comments	Stock price	**0.0000**	true	true
Stock price	Google Trends	0.2541	false	false
Stock price	Google Trends	**0.0060**	true	false
Google Trends	Stock price	0.7648	false	false
Google Trends	Stock price	0.5194	true	false
Google Trends	Stock price	0.1554	false	true
Google Trends	Stock price	**0.0000**	true	true

Table 6: Granger Causality measurements (p-value) for AMC

In Table 6, the stock price exhibits strong symmetrical causal relationships with the number of comments and Google Trends values, particularly after applying the *STATIONARY* modification, as indicated by the Granger Causality metric. This suggests a dynamic feedback loop where stock price fluctuations influence both online discussions and search interest, while increased public attention may also contribute to market movements. The stronger causality with stationarity adjustments highlights that investors and social media users react more to daily price changes rather than absolute stock levels, reinforcing the role of short-term volatility in driving online engagement and market sentiment.

In Table 7, all sentiment values show a very weak correlation with the stock price of AMC, suggesting that sentiment analysis alone may not be a strong predictor of price movements. This indicates that while social media discussions reflect investor emotions, they do not necessarily translate into direct market impact. The weak correlation also implies that other factors, such as trading volume, external news, or institutional activity, may play a more dominant role in shaping AMC's stock price than sentiment-driven retail investor behavior.

Interestingly, Table 8 shows that only the number of emojis had a measurable causal effect on the stock price, suggesting that non-textual sentiment indicators may play a unique role in market dynamics. This finding implies that emoji usage, which often conveys strong emotional reactions concisely, could be a more immediate and reliable signal of investor sentiment compared to traditional text-based sentiment analysis. The absence of significant causality for other sentiment

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Type	**Shifted**	**Sentiment**	**Correlation**
Pearson	false	Emotional	-0.203991
Pearson	true	Emotional	-0.215998
Kendall/Tau	false	Emotional	-0.016954
Kendall/Tau	true	Emotional	-0.018048
Pearson	false	Financial (out-of-the-box)	0.075078
Pearson	true	Financial (out-of-the-box)	0.047219
Kendall/Tau	false	Financial (out-of-the-box)	-0.028887
Kendall/Tau	true	Financial (out-of-the-box)	-0.097962
Pearson	false	Emoji counter	0.443890
Pearson	true	Emoji counter	0.308529
Kendall/Tau	false	Emoji counter	0.398197
Kendall/Tau	true	Emoji counter	0.306439
Pearson	false	Financial (finetuned)	0.025702
Pearson	true	Financial (finetuned)	-0.042367
Kendall/Tau	false	Financial (finetuned)	-0.035623
Kendall/Tau	true	Financial (finetuned)	-0.134539

Table 7: Stock price correlation measurements for AMC (sentiment data)

Cause	**Effect**	**p**	**Stationary**	**Shifted**
Stock price	Emotional	0.0676	false	false
Stock price	Emotional	0.9952	true	false
Emotional	Stock price	0.5122	false	false
Emotional	Stock price	0.8800	true	false
Emotional	Stock price	0.6406	false	true
Emotional	Stock price	0.9490	true	true
Stock price	Financial (out-of-the-box)	0.6116	false	false
Stock price	Financial (out-of-the-box)	0.8307	true	false
Financial (out-of-the-box)	Stock price	0.4661	false	false
Financial (out-of-the-box)	Stock price	0.6542	true	false
Financial (out-of-the-box)	Stock price	0.6501	false	true
Financial (out-of-the-box)	Stock price	0.8125	true	true
Stock price	Emoji counter	0.5455	false	false
Stock price	Emoji counter	0.0503	true	false
Emoji counter	Stock price	**0.0073**	false	false
Emoji counter	Stock price	0.1809	true	false
Emoji counter	Stock price	**0.0092**	false	true
Emoji counter	Stock price	0.7610	true	true
Stock price	Financial (finetuned)	0.8773	false	false
Stock price	Financial (finetuned)	0.6278	true	false
Financial (finetuned)	Stock price	0.5053	false	false
Financial (finetuned)	Stock price	0.7419	true	false
Financial (finetuned)	Stock price	0.4976	false	true
Financial (finetuned)	Stock price	0.9206	true	true

Table 8: Granger Causality measurements (p-value) for AMC (sentiment data)

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measures further highlights the complexity of social media-driven market behavior, warranting further investigation into how different forms of online expression influence stock price movements.

7 Conclusions and Future Work

Overall, sentiment values were neither strongly correlated nor causally related to either company's stock price. The model finetuned by us supplied the best results, but they were still statistically insignificant. Surprisingly, simpler metrics like the number of comments or Google Trends values were meaningfully correlated. Furthermore, the Granger Causality values imply a strong causal relationship for these simple metrics, although the *stationary* modification is needed for that to be true. Interestingly, it seems that this causal relation is symmetric - the number of comments and Google searches impact the stock price change, and the stock price change impacts the number of comments and Google searches. More research is needed to determine if some other method of determining sentiment can be found to provide values with a causal relationship with the stock price. Furthermore, it should be checked if the findings in this paper can be replicated for different companies and periods.

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References

1. Abhinav Anand and Jalaj Pathak: The role of Reddit in the GameStop short squeeze. Econom. Lett. **211**, 110249 (Feb 2022)
2. André Betzer and Jan Philipp Harries: How online discussion board activity affects stock trading: the case of GameStop. Financ. Mark. Portf. Manag. **36**(4) (2022)
3. Anna Mancini, Antonio Desiderio and others: Self-induced consensus of Reddit users to characterise the GameStop short squeeze. Sci. Rep. **12**(13780), 1–11 (2022)
4. Clive William John Granger: Investigating causal relations by econometric models and cross-spectral methods. Econometrica **37**(3), 424–438 (1969)

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5. Daniel Kent and others: Investor Psychology in Capital Markets: Evidence and Policy Implications. Journal of Monetary Economics **49**(1), 139–209 (Jul 2001)
6. Danqi Hu, Charles M. Jones, Valerie Zhang and Xiaoyan Zhang: The Rise of Reddit: How Social Media Affects Retail Investors and Short-sellers' Roles in Price Discovery. SSRN Electronic Journal (1) (Jan 2021)
7. David C. Broadstock, Dayong Zhang: Social-media and intraday stock returns: The pricing power of sentiment. Finance Research Letters **30**, 116–123 (Sep 2019)
8. Gareth Campbell, John D. Turner and Clive B. Walker: The role of the media in a bubble. Explorations in Economic History **49**(4), 461–481 (Oct 2012)
9. Gawron, K., Pogoda, M., Ropiak, N., Swędrowski, M., Kocoń, J.: Deep neural language-agnostic multi-task text classifier. In: 2021 International Conference on Data Mining Workshops (ICDMW). pp. 136–142. IEEE (2021)
10. Štefan Lyócsa, Eduard Baumöhl and Tomáš Výrost: YOLO trading: Riding with the herd during the GameStop episode. Finance Research Letters **46** (May 2022)
11. Johan Bollen, Huina Mao, Xiaojun Zeng: Twitter mood predicts the stock market. J. Comput. Sci. **2**(1), 1–8 (Mar 2011). https://doi.org/10.1016/j.jocs.2010.12.007
12. Kochanek, M., Cichecki, I., Kaszyca, O., et al.: Improving training dataset balance with chatgpt prompt engineering. Electronics **13**(12), 2255 (2024)
13. Kocon, J., Baran, J., Kanclerz, K.: Multi-modal personalized hate speech analysis using differential dataset cartography. In: DE-FACTIFY@ AAAI (2023)
14. Kocoń, J., Cichecki, I., Kaszyca, O., Kochanek, M., et al.: Chatgpt: Jack of all trades, master of none. Information Fusion **99**, 101861 (2023)
15. Kocoń, J., Zaśko-Zielińska, M., Miłkowski, P.: Multi-level analysis and recognition of the text sentiment on the example of consumer opinions. In: RANLP (2019)
16. Koptyra, B., Ngo, A., Radliński, Ł., Kocoń, J.: Clarin-emo: Training emotion recognition models using human annotation and chatgpt. In: ICCS. Springer (2023)
17. Llukan Puka: Kendall's Tau. SpringerLink pp. 713–715 (Dec 2014)
18. Miłkowski, P., Gruza, M., Kazienko, P., Szołomicka, J., Woźniak, S., Kocoń, J.: Multiemo: language-agnostic sentiment analysis. In: International Conference on Computational Science. pp. 72–79. Springer (2022)
19. Miłkowski, P., et al.: Multitask personalized recognition of emotions evoked by textual content. In: 2022 PerCom Workshops. IEEE (2022)
20. Ngo, A., Kocoń, J.: Integrating personalized and contextual information in fine-grained emotion recognition in text: A multi-source fusion approach with explainability. Information Fusion p. 102966 (2025)
21. Ngo, A., et al.: Studemo: A non-aggregated review dataset for personalized emotion recognition. In: Perspectivist Approaches to NLP@ LREC2022. pp. 46–55 (2022)
22. Patrick Schober, Christa Boer and Lothar A. and Schwarte: Correlation Coefficients: Appropriate Use and Interpretation. Anesth. Analg. **126**(5), 1 (Feb 2018)
23. Simon Behrendt and Alexander Schmidt: The Twitter Myth Revisited: Intraday Investor Sentiment, Twitter Activity and Individual-Level Stock Return Volatility. Journal of Banking & Finance **96** (Sep 2018)
24. Stephen Wooley, Andrew Edmonds, and others: Extracting Cryptocurrency Price Movements from the Reddit Network Sentiment. ICMLA pp. 16–19
25. Suwan(Cheng) Long, Brian M. Lucey, Larisa Yarovaya and Ying Xie: "I Just Like the Stock": The Role of Reddit Sentiment in the GameStop Share Rally (2022)
26. Tolga Buz and Gerard de Melo: Should You Take Investment Advice From WallStreetBets? A Data-Driven Approach. arXiv (May 2021)
27. Woźniak, S., Kocoń, J.: From big to small without losing it all: Text augmentation with chatgpt for efficient sentiment analysis. In: 2023 IEEE International Conference on Data Mining Workshops (ICDMW). pp. 799–808. IEEE (2023)

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