CAN REDDIT SENTIMENT PREDICT BITCOIN RETURNS?

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I would like to express my gratitude to my family and friends for their unconditional support during my graduate studies.

Abstract

The goal of this study is to test whether Reddit sentiment can predict Bitcoin returns. I choose an available dataset that has all posts and comments from the Reddit platform containing 'Bitcoin' between 2016 and 2019. Using VADER, a language model pre-trained on the large corpora of social media text, I quantify the collected text and compute a daily sentiment score over the period. Then I conduct Granger causality tests to explore the relationship between Reddit sentiment and Bitcoin returns. In contrast to similar studies on Twitter sentiment and Bitcoin performance, I find that there is not enough evidence to state that Reddit sentiment has predictive power for Bitcoin returns.

Keywords: Natural Language Processing, Bitcoin, Sentiment Analysis, Granger Causality

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1. Introduction

Bitcoin is a decentralized electronic currency system introduced on January 3, 2009, by Satoshi Nakamoto, an anonymous individual or group. It operates on blockchain technology, that provides a transparent and secure platform for peer-to-peer transactions. The emergence of Bitcoin initiated a broader phenomenon known as the cryptocurrency market, which as of now totals 1.2 trillion US dollars in market capitalization and encompasses a wide range of nearly 10,000 different digital currencies (CoinGecko.com, 2023).

Cryptocurrencies have gained significant attention in recent years, with Bitcoin leading the way as the first and most prominent digital currency. The increased attention followed the rapid growth of Bitcoin over the course of 2017 and 2018. Since then, cryptocurrencies are constantly under the spot of the general public, market regulators, and professional investors. However, there is still limited understanding among academics of the nature of digital currencies and their price-driving factors. Some view them as a financial bubble lack of fundamental value, while some see them as potential alternatives to traditional fiat currency. Cryptocurrency market participants are primarily individual enthusiasts who often lack adequate trading knowledge and for whom social media might be an essential source of publicly available information in making investment decisions. Particularly important is the role of social media platforms, like Reddit and Twitter, in forming investors' sentiments.

This study follows a broad literature that investigates whether sentiment on social media could have predictive power for Bitcoin returns. I use comments and posts generated on Reddit and test if Reddit sentiment could be useful to predict Bitcoin returns. Using an available dataset from Kaggle.com containing all comments and posts mentioning 'Bitcoin' over the period between 2009 and 2019, I exploit natural language processing techniques to transform unstructured text data into structured quantitative data. I use VADER (Valence

Aware Dictionary and Sentiment Reasoner), a language model pre-trained on social media texts, to generate a sentiment score, ranging from -1 to 1, for each comment and post. I then aggregate the sentiment score to come up with a daily time series over the period between 2016 and 2019. This period is chosen as it includes the rapid growth of Bitcoin over the course of 2017, the consequent hype over cryptocurrencies on social media, and the following gradual decline over 2018. I then exploit Granger causality tests to see if daily sentiment scores could predict Bitcoin returns over the period in question. This paper is not trying to find an exact causal relationship between public mood on Reddit and Bitcoin performance; it only tests if public sentiment on Reddit could be useful to predict Bitcoin returns.

The subsequent sections of the paper are structured as follows: Section 2 provides a comprehensive literature review, Section 3 presents and describes the data, Section 4 describes the sentiment analysis, and Section 5 outlines the methodology employed. Section 6 discusses the results and highlights the limitations of this study, and finally, Section 7 concludes the work.

2. Literature Review

2.1 Sentiment Analysis and Cryptocurrency

A significant amount of research has been done to analyze the price-driving factors for cryptocurrencies. Kristoufek (2015) identifies two categories of factors that can potentially affect cryptocurrency prices: external factors (e.g., market trends, macro factors), and internal factors (e.g., supply and demand, mining difficulty). Other factors affecting cryptocurrency prices may include gold prices (Poyser, 2017), S&P 500 returns (Sovbetov, 2018), Twitter mentions (Li and Wang, 2017), the USD/EUR exchange rate (Georgoula et al., 2015), news sentiment and volume (Polasik et al., 2015), regulatory scrutiny, and Initial Coin Offerings.

Analysts traditionally used different indicators to measure sentiment: investor surveys, CBOE (Chicago Board Options Exchange) Volatility Index, and 50-day and 200-day Moving Averages. However, traditional metrics are used only as a proxy and may not be representative of the overall market sentiment. With the development of Natural Language Processing techniques, several studies have shifted focus to identify market sentiment from text data, including corporate reports, news articles, and comments on social media platforms (Mao et al., 2011 and Li et al., 2014). The emerging technique is widely known as sentiment analysis or opinion mining. Sentiment analysis allows the assignment of a certain score, either positive, negative, or neutral sentiment, to unstructured text data.

As social media platforms became an essential source of information for crypto market participants, several studies have been conducted to apply sentiment analysis to social media texts (e.g., tweets, posts on Reddit, or Bitcointalk.org) to predict price fluctuations for various cryptocurrencies. However, research on social media sentiment analysis and cryptocurrencies is still in its infancy; a significant amount of research has been done only in recent years. Most studies so far acclaim the predictive power of Twitter sentiment for cryptocurrency returns and trading volume both in short and longer terms (Mai et al., 2015 and Kim et al., 2016). Before the advancement of natural language processing-based sentiment analysis, academics used easily available metrics from social media to predict cryptocurrency performance. One of the recent works in this regard, Urquhart and Wang (2019) in "Does Twitter Predict Bitcoin?" used the number of tweets from Twitter as a measure of investor attention spanning from September 4, 2014 to August 31, 2018. They found that the volume of tweets is a significant driver of next-day trading volume and realized volatility using Granger causality tests.

Kraaijeveld and De Smedt (2020) focusing on the period between June 4, 2018 and August 4, 2019 used bivariate Granger-causality tests and lexicon-based sentiment analysis to analyze the predictive power of collected 24 million Tweets on the nine largest cryptocurrencies by market capitalization. They found that Twitter sentiment has predictive power for the returns of Bitcoin, Bitcoin Cash, and Litecoin. Some studies used a combination of Twitter and news headlines sentiment analysis to predict cryptocurrency price fluctuations. For instance, Lamon et al. (2017) combined nearly 3,600 crypto-related news headlines and around 30,000 Bitcoin-, Ethereum-, and Litecoin- related tweets between January 1, 2017 and November 30, 2017. Then using several algorithms, such as Logistic Regression and Naïve Bayes Classifier, they classified the collected text into sentiment scores. Further using these scores, they built a binary classification model to predict future price trends (up or down).

Other studies, instead of building their sentiment classification model, used available and already pre-trained language models to obtain sentiment scores. Sattarov et al. (2020) also used Twitter data to forecast Bitcoin returns. They collected 92,550 tweets over the period between 12th March and 12th May. Using the VADER sentiment analysis model, they obtained sentiment scores of the collected text data and using Random Forest Regression predicted Bitcoin price with nearly 67% accuracy. Raj Pand et al. (2018) could achieve better prediction accuracy using Recurrent Neural Networks also using Twitter Sentiment analysis - they could predict Bitcoin price with an accuracy of 81.39%. The authors collected tweets from January 1, 2015 to December 31, 2017, and then manually labeled 4,254 tweets and using different algorithms trained a model to predict Twitter sentiment.

In another prominent paper, Georgoula et al. (2015) collected nearly 2 million tweets containing the keywords 'Bitcoin' and 'BTC' from October 24, 2014 to January 12, 2015. They manually labeled sentiment scores to a large body of tweets, then used labeled data, and Support Vector Machines classified the remaining tweets by either positive, negative, or neutral sentiment. Then using a series of short-run regression they found that Twitter sentiment ratio is positively correlated with Bitcoin prices.

Overall, almost all studies confirm that social media sentiment, mainly expressed on Twitter, could predict the performance of several cryptocurrencies, including Bitcoin. Most of the studies use the Granger causality test to determine whether sentiment has predictive power for cryptocurrency performance. Although some studies used to develop and train their sentiment classification models, recently using already pre-trained language models became convenient in sentiment analysis. For instance, VADER, a language model suitable for social media analysis, on average, provides high levels of sentiment classification accuracy (Ottarov et al., 2020). There are also several language models (e.g., FinBERT) that are pre-trained using finance-specific dictionaries and are suitable to classify the sentiment of financial texts (Araci, 2019).

2.2 Limitations of the Current Literature

However, the current literature on social media sentiment analysis and its' predictive power on cryptocurrency returns is limited. First, the main limitation is its paucity. This reflects the young nature of the cryptocurrency phenomenon and the still-developing field of sentiment analysis using natural language processing techniques. Second, the majority of studies are focused on Twitter data, thereby omitting many other platforms where crypto-enthusiasts tend to gather their information about the markets. For instance, two of the largest subreddits on Reddit, r/CryptoCurrency and r/Bitcoin, have around 6.4 million and 5 million subscribers as of May 2023, respectively, generating tens of thousands of comments per day. In addition, Reddit platform users have proved their influence by playing a major role in GameStop's short squeeze in early 2021. Yet Reddit, as well as Bitcointalk.org, are largely omitted from researchers' perspectives. Third, as there are limitations to collecting data from Twitter's API (Application Programming Interface), the data often spans over a short period. Most studies focus on the period lasting several months, rarely on the period over a year. Fourth, while current pre-trained language models may perform well, they are not perfect and may fail in determining a subtle context of users' comments. Fifth, current literature does not account for the 'social influence' and treats all comments and tweets as having 'equal value'. In practice, however, comments that receive a greater number of upvotes may have a greater influence in shaping market sentiment. Sixth, the limitation of using the Granger causality test is that it requires two assumptions: stationarity and linear relations between the time series variables. These assumptions often may not be viable.

This study directly addresses two of the limitations. First, I analyze the data over a longer period of three years, from 2016 to 2019. Second, the study focuses on Reddit data only, thereby testing the effects of this social media platform on Bitcoin performance. The study does not address the limitation regarding the use of crypto-adjusted language model and the 'social influence' factor. Note that I use the Granger causality test in this study. Yet I acknowledge the limitation of using the Granger causality test, specifically as the relationship between sentiment and Bitcoin price (or returns) is more likely to be non-linear.

3. Data

In this section, I describe the data and explain basic data-cleaning techniques. The following data analysis, Granger causality and other statistical tests were conducted in Python using *statsmodels, pandas,* and *matplotlib* packages. The datasets and codes are available upon request.

3.1. Reddit Data

I use an available dataset from Kaggle. It contains nearly 4.2 million comments containing the word ‘Bitcoin’ from all subreddits between 2009 and 2019. The dataset includes information on the published date and time, subreddit, author, score (upvotes plus downvotes), and text body itself. It is important to note that the collection of comments in this dataset may not represent a comprehensive sentiment of all Reddit users. Comments that discuss Bitcoin, but that do not specifically mention ‘Bitcoin’, are omitted. Hence, I will assume that comments in this dataset are representative of the overall opinion of Reddit users regarding Bitcoin.

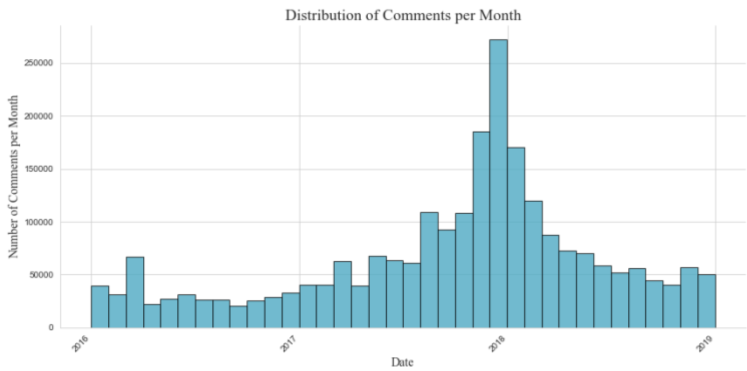

Figure 1. Comments per month

Figure 1 presents the distribution of the number of comments, aggregated by month. On average, the number of comments per month was around 50,000 (and nearly 250,000 comments during the end of 2017 and the beginning of 2018). The original dataset has 4,309,244 comments spanning from 2009 to 2019. After filtering for the period in question, and dropping missing values, the dataset has 2,444,081 comments. A small portion of non-English comments (40,263) was removed, thus leaving the final ready-for-analysis dataset with 2,403,818 comments spanning over 1096 days.

3.2. Financial Data

All quantitative data on Bitcoin was obtained from Yahoo Finance. This includes historical data on daily opening and closing, highest and lowest prices, and trading volume. I use the daily adjusted closing price as a proxy for the daily price. The period corresponds to that of the data from Reddit, from January 1, 2016 up to and including December 31, 2018. Note that Bitcoin prices slightly vary on different exchanges due to factors such as liquidity and market dynamics. Yahoo Finance collects Bitcoin historical data from various sources and aggregates the data, hence I assume the prices presented on Yahoo as an accurate measure of daily Bitcoin price.

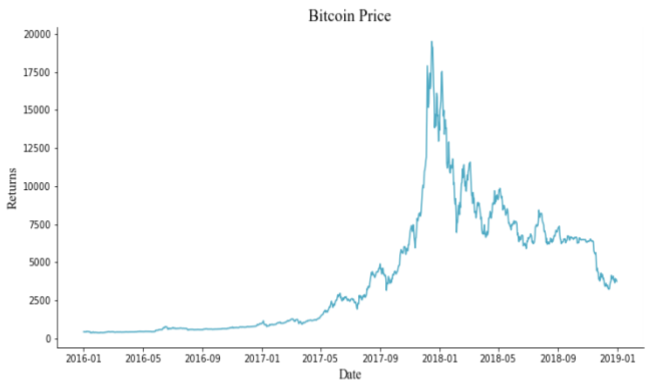

Figure 2. Bitcoin daily (adjusted closing) price, in USD

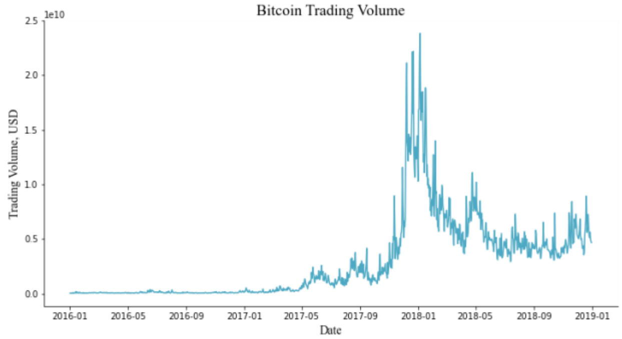

Figure 3. Bitcoin daily trading volume, in USD

Figure 2 depicts the Bitcoin price graph and Figure 3 illustrates Bitcoin's daily trading volume. It can be seen that the increased volume of daily activities on Reddit (see Figure 1) corresponds to the explosive price growth and trading volume during the end of 2017 and the beginning of 2018. Note that this correlation may be bidirectional. Rapid price growth of Bitcoin may have potentially attracted the attention of other investors, thereby increasing trading volume and increased activity on the Reddit platform; or, there could be a reverse causality, where increased attention of social media users further translated into higher trading volume and rapid price growth.

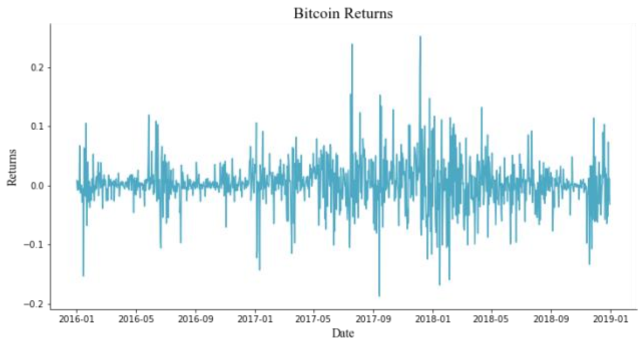

Figure 4. Bitcoin daily returns

Figure 4 presents the daily absolute returns of Bitcoin, measured as a gain or loss resulting from a price change during the day (expressed as a percentage of a prior day's price). Note that this paper tries to investigate whether Reddit sentiment could predict Bitcoin returns, not Bitcoin prices.

4. Sentiment Analysis

4.1. Text Pre-processing

Text data, especially social media text, contains noise in the form of special characters, punctuations, URLs, and irrelevant symbols. Therefore, it is necessary to pre-process raw text to ensure that sentiment analysis will focus on the actual and meaningful content. Beyond that, it may be necessary to further standardize the text data by tokenizing, lower-casing, and removing stopwords, so that VADER can analyze sentiment scores more accurately. Stopwords are commonly used words (such as 'you', 'and', 'the') that do not contribute much to the sentiment of a sentence. Tokenization involves breaking the text into individual words (or tokens). The following Table 1 depicts the pre-processing steps applied to the dataset:

	Processing technique	**Comment sample**
0.	Original Comment	Replying to **Author **jrond2678 The regulators are likely to ban Bitcoin very soon \n\n and all of you optimists will lose your money lol .. https://www.reuters.com/article/us-crypto-currencies-finra-idUSKCN1LR2AE this is only the beginning
1.	Removing URLs	Replying to **Author **jrond2678 The regulators are likely to ban Bitcoin very soon \n\n and all of you optimists will lose your money lol .. this is only the beginning
2.	Removing mentions	Replying to The regulators are likely to ban Bitcoin very soon \n\n and all of you optimists will lose your money lol .. this is only the beginning
3.	Removing all non-alphanumeric characters	Replying to The regulators are likely to ban Bitcoin very soon and all of you optimists will lose your money lol this is only the beginning
4.	Converting to lower-case	replying to the regulators are likely to ban Bitcoin very soon and all of you optimists will lose your money lol this is only the beginning
5.	Removing all stopwords	replying regulators likely ban Bitcoin very soon all optimists lose your money lol only beginning
6.	Removing all words with <3 characters	replying regulators likely ban Bitcoin very soon all optimists lose your money lol only beginning

Table 1. Text pre-processing steps

The following code snippet shows the pre-processing function. The pre-processing function given any raw text as an input returns pre-processed text. This step took around 10 hours to execute on all 2.4 million text data.

```
def text_preprocesser(text):

    text = re.sub(r'http\S+|www\S+', '', text)
    text = re.sub(r'\*\*Author\*\*:\s*[_\w]+', '', text)
    text= re.sub(r'\W',' ', text)
    tokens = word_tokenize(text.lower())
    tokens = [token for token in tokens if token not in stopwords.words('english')]
    tokens = [word for word in tokens if len(word)>=3]
    preprocessed_text = ' '.join(tokens)
    return preprocessed_text
```

Figure 5. Text pre-processing code snippet

4.2. VADER Sentiment Analysis

I use VADER, a language model pre-trained on social media texts, for sentiment analysis. Using text data as an input, VADER returns an array of scores: positive, neutral, negative, and compound. The former three can be interpreted as a probability of a text being classified as having respective sentiment. The compound score takes into account both the positive and negative sentiment words in the text and gives an aggregated measure of the overall sentiment expressed. The score ranges between -1 and 1, where the score between -1 and -0.05 is classified as negative, from -0.05 to 0.05 as neutral, and from 0.05 to 1 as positive. Table 2 presents actual comments and their respective VADER sentiment scores as an example.

Comment	Positive	Negative	Neutral	Compound
Just wondering how many BTC an average Bitcoin holder hold?	0.065	0.043	0.892	0.031
Bitcoin is on the rise!!!	0.921	0.05	0.029	0.773
I am selling Bitcoin; the outlook is looking terrible.	0.011	0.502	0.487	-0.772

Table 2. Example of VADER sentiment scores

The following Figure 6 illustrates the distribution of compound sentiment scores for all 2.4 million comments. It is seen that the distribution is skewed toward more positive scores with a majority of comments falling in the range of being neutral. This means that, on average, Reddit users tend to think more positively about Bitcoin. In further steps, I only use the compound score as a proxy of Reddit sentiment and use 'compound score' and 'sentiment score' interchangeably.

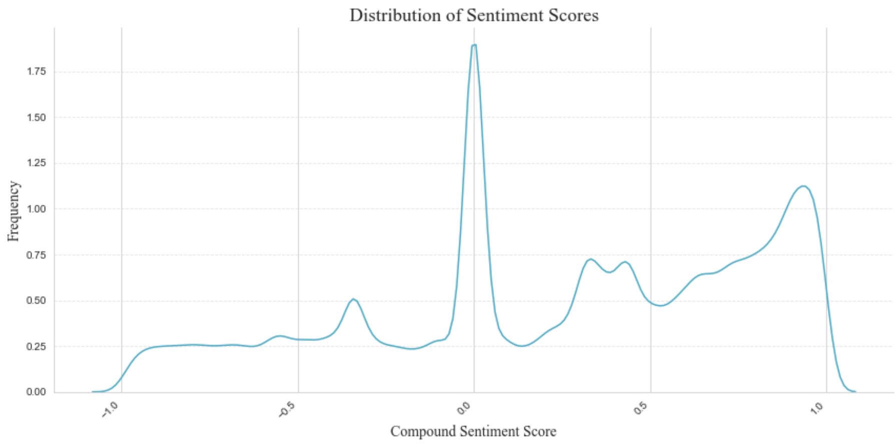

Figure 6. Distribution of compound sentiment scores

4.3. Daily Sentiment Score

I then aggregate all sentiment scores for each comment to form a daily sentiment score by simply taking the average of the sentiment scores for all comments for that day. Figure 7 illustrates the graph of daily sentiment scores.

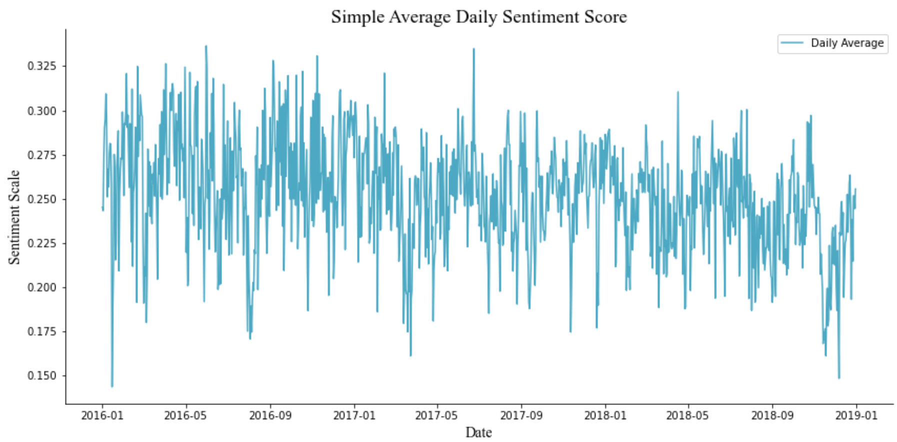

Figure 7. Daily sentiment scores

One could make two conclusions based on the above graph. First, daily sentiment score data is noisy. Second, an average daily sentiment is positive ranging from approximately 0.15 o 0.30. The latter observation aligns with other studies, that also report overall positive daily sentiment on Twitter regarding Bitcoin and other cryptocurrencies (e.g., Urquhart and Wang, 2019).

	Compound	**Positive**	**Neutral**	**Negative**	**ΔCompound Score**
count	1095	1095	1095	1095	1095
mean	0.2517	0.1842	0.7142	0.1015	0.0080
std	0.0311	0.0063	0.0106	0.0081	0.1278
min	0.1433	0.1567	0.6591	0.0751	-0.4445
25%	0.2326	0.1798	0.7073	0.0957	-0.0729
50%	0.2523	0.1839	0.7145	0.1009	0.0016
75%	0.2728	0.1882	0.7219	0.1064	0.0763
max	0.3365	0.2087	0.7485	0.1377	0.6985

Table 3. Descriptive statistics of sentiment scores

Table 3 provides descriptive statistics for daily sentiment scores, including daily positive, negative, and neutral scores. The period in question contains 1096 days. However, the first day is omitted in the analysis as it serves as a basis for calculating Bitcoin return and change in compound sentiment score for the second day. Note that I also calculate the change in compound score measured as the percentage change from the previous day. I include the change in sentiment score as it also could be interesting to see if changes in sentiment, rather than the sentiment score itself, Granger cause returns (or vice versa).

5. Methodology

The following diagram summarizes the methodology of this study. Ultimately, this paper tests whether Reddit sentiment Granger causes returns, or vice versa.

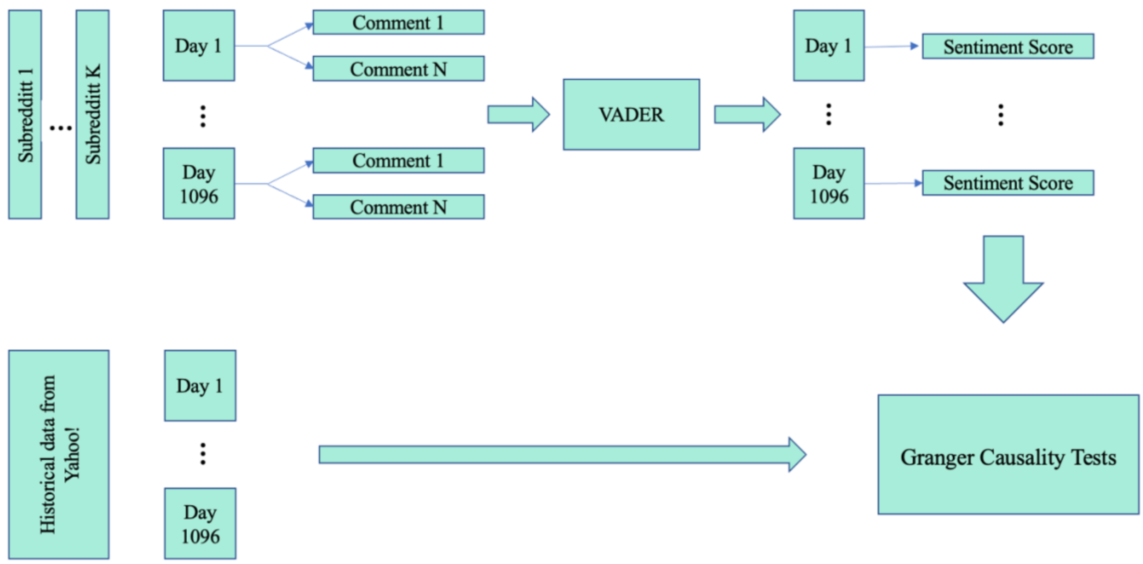

Figure 8. Methodology diagram

Granger causality is a statistical test that helps to identify whether one time series can be used to predict another time series. It is based on the idea that if a time series X "Granger causes" another time series Y, then the past values of X provide valuable information in predicting the future values of Y (beyond what can be predicted using only the past values of Y itself). In other words, Granger causality tests whether the inclusion of past values of one variable improves the prediction of another variable (Granger, 1969). In the context of this study, the Granger causality test will help to find if Reddit sentiment is useful to predict Bitcoin returns. The results of this test, if positive, may showcase that the Reddit platform has an impact for Bitcoin price fluctuations. That would be the first step to identify whether Reddit sentiment could be further used in building prediction models to forecast Bitcoin and potentially other cryptocurrency returns.

5.1. Checking for Normality

Beyond checking data visualizations, it may be important to conduct several tests to check for data distribution. I conduct the following two tests to see if returns and sentiment scores data is normally distributed:

1. Shapiro-Wilk test (Null hypothesis: variables follow a normal distribution)
2. Jarque-Bera test (Null hypothesis: skewness and kurtosis match a normal distribution)

The following Table 4 presents the results of these tests for sentiment, change in sentiment, and returns data. For all variables, p-value is less than 1% (except for the Jarque-Bera test for sentiment), so the null hypothesis can be rejected in each case. Jarque-Bera test's p-value for sentiment score is around 2%, so still we reject the null hypothesis at a 5% level of significance.

Variable	Shapiro-Wilk Test Statistic	Shapiro-Wilk p-value	Jarque-Bera Test Statistic	Jarque-Bera p-value
sentiment	0.9961	0.0075	7.8043	0.0202
Δsentiment	0.9875	0.0000	93.9228	0.0000
returns	0.9194	0.0000	1064.9446	0.0000

Table 4. Results of Shapiro-Wilk and Jarque-Bera tests

Overall, these results indicate that all three variables (Reddit sentiment, change in Reddit sentiment, and returns) do not follow the normal distribution as supported by the results of Shapiro-Wilk and Jarque-Bera tests.

5.2. Stationarity

Stationarity is a key concept in time series analysis. It refers to the constancy of certain statistical properties over time. Stationarity specifies that the mean, variance, and autocovariance of a time series remain constant over the entire period. In the context of the Granger causality test, stationarity is a crucial assumption. Non-stationary variables may lead to spurious relationships, thereby producing misleading causal inferences. Therefore, it is necessary to verify stationarity before proceeding with Granger causality tests.

I use the Augmented Dicky-Fuller test to check for stationarity. It evaluates the null hypothesis that a unit root is present in the time series against the alternative hypothesis stating that the time series is stationarity. It calculates a test statistic and compares it to critical values to determine the significance of the results. If the test statistic is more negative than the critical values and the associated p-value is below a predetermined significance level (typically 0.05), we reject the null hypothesis and conclude that the variable is stationary (Dickey and Fuller, 1979).

The following Table 5 presents the results of the Augmented Dickey-Fuller test. We see that the p-value associated with compound sentiment score, sentiment change, and returns time series is near zero, thus suggesting that there is enough evidence to assume that these time series are stationary.

Variable	ADF Test Statistic	ADF p-value
sentiment	-8.1948	0.0000
Δsentiment	-16.2455	0.0000
returns	-32.7391	0.0000

Table 5. Results of the Augmented Dickey-Fuller test

Having verified stationarity, we may further proceed with the Granger causality tests.

5.3. Granger Causality

It's important to note that Granger causality does not establish a definitive causal relationship, but rather provides evidence of a predictive relationship between variables. This paper conducts two Granger causality tests. First, I test if sentiments could Granger cause returns, or vice versa. Second, I check if the change in sentiments could Granger cause returns, or vice versa.

From	To	Lag(s)	Test Statistic	p-value
sentiment	returns	[1]	1.8424	0.1747
sentiment	returns	[2]	1.7751	0.4117
sentiment	returns	[3]	1.7395	0.6282
sentiment	returns	[4]	2.0111	0.7337
sentiment	returns	[5]	2.5510	0.7688
returns	sentiment	[1]	7.9733	0.0047
returns	sentiment	[2]	12.1616	0.0023
returns	sentiment	[3]	13.1749	0.0043
returns	sentiment	[4]	13.7882	0.0080
returns	sentiment	[5]	15.1798	0.0096

Table 6. Results of the Granger causality test

The results of the Granger causality tests between the sentiment score and returns are presented in Table 6. The tests were conducted in both directions to explore the causal relationship between the two variables. In the direction from sentiment to returns, various lagged values were considered, up to lag 5. The test statistics for each lag ranged from 1.8424 to 2.5510, with corresponding p-values ranging from 0.1747 to 0.7688. The findings indicate that there is insufficient evidence to support the presence of Granger causality from Reddit sentiment to Bitcoin returns.

In the direction of Bitcoin returns to Reddit sentiment also up to 5 lag values were considered. The test statistics for each lag ranged from 7.9733 to 15.1798, and the corresponding p-values ranged from 0.0047 to 0.0096. These results suggest a significant Granger causality relationship from Bitcoin returns to Reddit sentiment.

Thus, the Granger causality tests indicate a unidirectional causal relationship, with Bitcoin returns exerting a significant influence on Reddit sentiment. However, there is not enough evidence to support the presence of Granger causality from sentiment to returns.

Table 7 presents the results of the Granger causality tests between the change in sentiment (Δsentiment) and returns variables. Similarly, the test was conducted in both directions and up to lag 5 values were considered. The test statistics ranged from 0.0001 to 2.0267, with corresponding p-values ranging from 0.9922 to 0.8454. The results indicate that there is no significant evidence to support the presence of Granger causality from the change in Reddit sentiment to Bitcoin returns. On the other hand, test findings suggest a significant Granger causality from Bitcoin returns to the change in Reddit sentiment.

From	To	Lag(s)	Test Statistic	p-value
Δsentiment	returns	[1]	0.0001	0.9922
Δsentiment	returns	[2]	0.5771	0.7493
Δsentiment	returns	[3]	0.8204	0.8446
Δsentiment	returns	[4]	1.7596	0.7799
Δsentiment	returns	[5]	2.0267	0.8454
returns	Δsentiment	[1]	1.3336	0.2482
returns	Δsentiment	[2]	2.2878	0.3186
returns	Δsentiment	[3]	7.3882	0.0605
returns	Δsentiment	[4]	9.4673	0.0504
returns	Δsentiment	[5]	13.5040	0.0191

Table 7. Results of the Granger causality test (continued)

Overall, the Granger causality tests indicate that Bitcoin returns have predictive power for Reddit sentiment, while there is no evidence that Reddit sentiment and change in Reddit sentiment may predict Bitcoin returns. The results may be surprising, specifically as they contrast the widely acknowledged belief in the literature that social media sentiment has predictive power for digital currency returns. The following discussion presents potential explanations for these results and outlines the limitations of the employed methodology.

6. Discussion

6.1. Discussing Results

This study suggests that social media sentiment on Reddit does not have enough predictive power for Bitcoin returns, thereby suggesting that Reddit may not be an important determinant of Bitcoin price. But note that Bitcoin returns do have predictive power for Reddit sentiment. The results of this study contrast with the results of the studies that tested the predictive power of Twitter sentiment. One potential explanation could be related to the distinct nature and characteristics of these social media platforms. Twitter focuses on real-time microblogging with a character limit of 280 characters. Its' emphasis on quick and concise communication may better reflect public sentiment. While Reddit is a community-structured curated platform focused more on in-depth discussions. Therefore, it could well be that as Twitter users generate unique sentiment that further drives the cryptocurrency price fluctuations, then Reddit users tend to follow up and discuss the recent price changes on the platform. This explanation, however, does not fit with other studies which showed the predictive power of Reddit posts on selected stock returns. It may be that public sentiment on social media forms differently for stocks and cryptocurrencies, which could explain the observed difference between the results of this study and the rest of the literature.

6.2. Limitations of the Study

There might be other explanations related to the limitations of this study. This work is based on several assumptions, which may not be viable. First, I assumed that all Reddit posts and comments containing "bitcoin" are representative of the overall crypto investors' sentiment on Reddit. This may not be true as discussions on Bitcoin may not necessarily include the word "Bitcoin" itself, hence a large body of user-generated comments may be omitted in the dataset. Second, I assumed that the VADER sentiment analysis provides accurate estimates of Reddit sentiment. This assumption again may not be viable. Although

VADER provides a quite well classification of positive, negative, and neutral posts, it is not perfect and may fail to capture the subtle context or specific crypto-related jargon. Beyond that, the study did not account for 'social influence', which may be important as more upvoted comments may have a greater impact on daily sentiment score. I also acknowledge the limitation of my Granger causality setting. Granger causality assumes a linear relationship between variables along with stationarity. However, the relationship between Reddit sentiment and Bitcoin return may be complex and non-linear, hence allowing for potentially distorted results of Granger causality tests.

6.3. Future Research Directions

Based on the results and limitations of this study, future research could be done in the following directions. First, further analysis of the impact of social media sentiment should be done, potentially combining all major platforms like Twitter, Reddit, Bitcointalk, and others. While it could be computationally demanding given the API query limitations, the results may shed light on the relative importance of some social media platforms in crypto markets. Second, pre-training and developing more accurate language models may be necessary to produce better estimates of sentiment analysis. Potentially, tuning existing language models for the specific crypto-jargon and/or developing crypto-language dictionaries may further help to produce better sentiment classification. Beyond that, just adjusting the dictionaries may not be enough; the context and semantics also matter. For instance, there was a comment that heavily criticized the central bank system with a subtle mention of Bitcoin's potential when the central bank fails to control the monetary system. That was classified as carrying a negative sentiment. Thus, VADER failed to identify the subtle semantics of the cryptocurrency concept: negative things about the controlled monetary system are likely to be positive for cryptocurrencies, in general. Therefore, it may be necessary to develop new crypto-adjusted language models to obtain more accurate sentiment scores.

7. Conclusion

In conclusion, this master's thesis aimed to test if Reddit sentiment could predict Bitcoin returns. The main dataset comprised all posts and comments mentioning 'Bitcoin' on Reddit between January 1, 2016 and December 31, 2018. Utilizing VADER, a language model trained on social media text, the text data was quantified into sentiment scores, allowing for the calculation of a daily sentiment score throughout the period. Next Granger causality test was conducted to investigate the relationship between Reddit sentiment and Bitcoin returns. The findings indicate that there is no sufficient evidence to suggest that Reddit sentiment possesses predictive power for Bitcoin returns. However, there is enough evidence to state that Bitcoin returns Granger cause Reddit sentiment. This contrasts with similar studies that acknowledge the predictive power of Twitter sentiment for Bitcoin and other cryptocurrencies price fluctuations. Based on these results, I make two conclusions. First, Reddit as a social media platform may not be relevant in the context of opinion formation regarding Bitcoin returns. Second, since Bitcoin returns Granger cause Reddit sentiment, it may be that the nature of the Reddit platform (as opposed to Twitter's) may be more appropriate for discussing already happened price change, rather than preceding one.

8. References

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