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Is Sentiment on Twitter Effective on Bitcoin Price Prediction?

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Abstract

This research investigate how sentiment affects Bitcoin's pricing. Sentiment analysis is studied based on data that include sentiment scores and affiliated information from over 4 million posts on Twitter. The findings offer evidence that the number of tweets posted, unweighted sentiment compound score, and sentiment compound score weighted by retweets correlate more with Bitcoin's returns. The investigation also presents that the correlation of sentiment parameters such as weighted and unweighted compound scores on Bitcoin's price is not consistent over the time horizon, which forms a positive leading index, but turns negative as a simultaneous or lagged index. The degree of influence of Twitter information over Bitcoin's price is less significant 20 minutes before and after a tweet.

Keywords: Sentiment, Social Media, Bitcoin Price, Data Crawling, Database

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1. Introduction

The Efficient Market Hypothesis (EMH) proposed by Fama (1970) is the basis for examining if the returns in an asset market are efficient. The idea underlying EMH is that past information is not useful in predicting future returns; i.e., no extra gains in market return can be obtained by using already available information. It means the returns and the information over a period of time are independent of each other. EMH can be examined by fitting the correlation of returns for various incoming information. If any correlation exists, then it indicates market inefficiency.

With its status as the world's leading cryptocurrency by market capitalization, there has been a significant interest in the study of Bitcoin and calendar anomalies in its returns and volatility. The main benefit of researching Bitcoin's seasonality is that it helps further determine the validity of the efficiency market hypothesis. Another benefit is to allow investors to improve their investment portfolio performance. One crucial obstacle for the financial market in general is that investor sentiment is not directly observable. Different proxies have been used, such as analyst opinions and articles in newspaper (Sadka and Scherbina 2007). Recently, the availability of extensive online discussions can be helpful to analyze individuals' statements and opinions. Financial sentiment analyses have been conducted on information over the Internet to understand the effect of reactions and emotions on the financial market. Sentiment analysis is used to evaluate the emotion of investors to understand their attitudes and thoughts that affect trading behavior. For example, Antweiler and Frank (2004) investigated online posts on Yahoo! Finance and Raging Bull to predict market volatility and asset returns. Vega (2006) found that asset returns and volatility positively correlate with the number of analysts and media coverage and explained how it could be the case that both factors increase in order to meet the rise in information demand.

The arrival of massive amounts of information indicates that public available information generally arrives more frequently during business hours, when financial exchanges are open. Aharon and Qadan (2019) employed an active attention measure, Google search volume (GSV), to check the attention paid to Bitcoin on the Internet on daily basis. Baig et al. (2019) also employed GSV as a measure of investor sentiment and reported a strong positive relationship between GSV and Bitcoin price clustering. Lyócsa et al. (2020) used GSV activity as a gauge of panic sentiment and found that excess search volume represents a timely and valuable data source for forecasting stock price variation. For a statistical analysis of the relationship between investor sentiment and Bitcoin returns, Kapar and Olmo (2021) used weekly data between July 2010 and May 2019 and found that financial variables such as S&P 500 or the Federal Reserve financial stress index are not statistically significant to the dynamics of Bitcoin. However, the feedback effects of individual online interest (they used Google searches) are the only power variable for Bitcoin dynamics. Da et al. (2015) constructed a Financial and Economic Attitudes Revealed by Search (FEARS) index as a new measure of investor sentiment based on daily Internet search volume. AlNemer et al. (2021) and Anamika et al. (2021) offered similar research that used the monthly Sentix Investor Confidence index, which is based on a monthly online survey of 1600 financial analysts and institutional investors, to analyze investors' emotions. Interestingly, they found that a negative sentiment score usually indicates rising cryptocurrency prices.

For the characteristic of trading 24/7, one question arises: Other than the daily, weekly, or monthly information, is there any other information, such as high frequency posts on social media that may act as an index for Bitcoin's price movement? Naeem et al. (2021) compared the predictability of FEARS and Twitter Happiness sentiment on Bitcoin returns and noted that online investor sentiment is a significant predictor, and that Twitter is superior to Google as an online investor sentiment proxy, because of the nature of cryptocurrency participants who are typically young individuals and computer enthusiasts. Research has also been conducted to explore the relationship between investor sentiment on social media and Bitcoin price. For example, Kim and Kim (2014) used Internet messages posted on Yahoo! Finance to measure investor sentiment. Renault (2017) analyzed the messages published on StockTwits to construct intraday investor sentiment indicators. Sun et al. (2021) looked at posts on Chain Node to investigate the correlation between sentiment and the cryptocurrency market. Ranasinghe and Halgamuge (2021) collected 120,000 tweets from Twitter using keywords Bitcoin and BTC during a ten-day span (12/09/2018 to 22/09/2018) for sentiment analysis. Guégan and Renault (2021) used a database that includes about one million messages crawled from StockTwits for the analysis of the correlation between investor sentiment and Bitcoin returns. In general, Twitter and StockTwits are the two of the more common social media platforms for their abundance of users and many messages related to key words such as Bitcoin, hence providing a good representation of investor sentiment. Steyn et al. (2020) found that investor sentiment and emotions derived from stock market-related tweets are significant predictors of stock market movements. A similar analysis approach has been conducted (Li et al. 2019, Mohapatra et al., 2019, Sailunaz and Alhajj, 2019, Kraaijeveld and De Smedt, 2020, Lyu et al. 2020) to study the correlation between Twitter's sentiments and cryptocurrency price changes.

Another merit for using messages posted on social media is that they are time recorded. Both Bitcoin trading and social media operate 24 hours a day and 7 days a week. The relationship between investor sentiment and Bitcoin returns for corresponding time and for different time intervals can be studied. For example, Gao et al. (2021) studied how sentiment affects Bitcoin pricing on an hourly frequency. Guégan and Renault (2021) investigated the relationship for different time intervals ranging from one minute to one day. Jain et al. (2018) attempted to predict the prices of Bitcoin two hours in advance based on the number of positive, neutral, and negative tweets accumulated every two hours.

Ordinary Least Square (OLS) regressions and Granger causality tests are commonly applied when studying the relationship between investor sentiment and Bitcoin price (Kim and Kim, 2014; Guégan and Renault, 2021; Renault 2017). A general finding is that the Bitcoin pricing mechanism can be partially revealed by sentiment found in social media. For example, Guégan, and Renault (2021) concluded that a significant relationship exists between investor sentiment and Bitcoin returns for time intervals of up to 15 minutes, while the relationship disappears as the amount of time in each interval increases. Gao et al. (2021) found that stronger bullish sentiment significantly foreshadows higher Bitcoin returns over the time range of 24 hours, while bearish and neutral financial Twitter sentiments do not. Xie (2021) analyzed hourly data and found that the sentiment and the posting of virtual investment community messages are largely driven by past market outcomes and provide limited value-relevant information for future price prediction. Öztürk and Bilgiç (2021) found that the 50 most influential accounts may provide information driving Bitcoin investors, while other Twitter accounts simply introduce some noise.

The preprocessing of Tweets and sentiment analysis are significant for providing and building an acute prediction of Twitter sentiments. A major task for big data experts is to find the optimum preprocessing strategies. For example, Pano and Kashef (2020) saw that splitting sentences and removing Twitter-specific tags or combination generally improve the correlation of sentiment scores with Bitcoin prices. Another concern in performing sentiment analysis is how to convert tweet text into a sentiment score that represents a tweet's emotion. For example, Tetlock (2007) and Jegadeesh and Wu (2013) used dictionary-based algorithms to analyze asset characteristics. Gao et al. (2021) targeted sentiment signals of tweets based on a list of positive, negative, and uncertain words according to the Loughran-McDonald finance-specific dictionary. Some well-known sentiment analysis tools are available for use. Among them, Valence Aware Dictionary and sEntiment Reasoner (VADER) is a popular choice. VADER is a lexicon-and-rule-based sentiment analysis tool that can handle words, abbreviations, slang, emoticons, and emojis commonly found in social media. It is typically much faster than machine learning algorithms, as it requires no training. Each body of text produces a vector of sentiment scores with negative, neutral, positive, and compound polarities. For example, Mohapatra et al. (2019) and Kraaijeveld and De Smedt (2020) used VADER to assign each tweet a compound sentiment score. Pano and Kashef (2020) performed VADER-based sentiment analysis of BTC tweets during the era of COVID-19.Öztürk and Bilgiç (2021) and Ibrahim (2021) also applied Valence

Aware Dictionary and Sentiment Reasoner (VADER) in a logistic model to calculate positive, negative, and neutral scores.

Understanding sentiment effect is helpful in developing models that forecast Bitcoin's price movement. Considering the characteristics of real-time, representativeness, and quantity, the abundant messages on social media may provide indicators for investor sentiment. This literature review indicates a wide array of questions. Some results about the sentiment effect on Bitcoin returns contradict one another. Is sentiment a significant factor to Bitcoin returns? Is sentiment score a positive indicator to rising Bitcoin prices? If sentiment score and Bitcoin returns strongly correlate, then what time lag is the most significant? Other parameters surrounding a tweet are not included in the discussion of sentiment scores, such as the number of favorites, retweets, and quotes. It is thus interesting to study how these affiliated factors affect the performance of Bitcoin's price.

The purpose of this research is to examine if EMH holds true for Bitcoin trading by examining how the Bitcoin price correlates with the sentiment scores of tweets. The remainder of this research runs as follows. Section 2 presents the data and the methodology. Section 3 cites the research findings. Section 4 provides the conclusion and discussion.

2. Data Description and Methodology

The minute data (44620 entries in total) between 2021/10/01/00:00 to 2021/11/01/00:00 were downloaded from https://www.CryptoDataDownload.com. . Some data (for example, for minute data 10/11/13:50-10/11/16:10 and 10/30/21:50-10/30/22:50) are missing or contain mistakes. These data are removed during follow-up analysis. The tweets posted on Twitter including Bitcoin keywords (bitcoin, bitcoins, BTC) were scraped for analysis by assuming that Bitcoin's market characteristics closely relate to these keywords. These key words cover discussions, comments, expectations, and emotions on Bitcoin's price movements. In total, 4,293,699 tweets posted between 2021/10/01/00:00 and 2021/10/31/00:00 are scraped. For each tweet, the compound sentiment score, which will be described later, is assessed using VADER. The numbers of favorites, retweets, and quotes for each tweet are also scraped. The rationale for considering such affiliated information is that some tweets receive more attention than others, and so these posts should have more weight than those that receive less attention.

The minute data are compiled into 10-minute intervals. The scraped Bitcoin-related tweets data corresponding to the 10-minute intervals are then used to evaluate the relationship between tweets and Bitcoin returns. The Bitcoin returns for each interval (R_m) are calculated as the logarithmic value of the closing price of minute t ($P_{m,t}$) divided by the closing price 10 minutes prior to it ($P_{m,t-10}$), that is,

$$R_{m,t} = \ln (P_{m,t}/P_{m,t-10}) \tag{1}$$

More than 4 million tweets posted in October 2021 are scraped on Twitter. This research explores the joint time-series behavior of the sentiment measures in these tweets and Bitcoin's return and price volatility. Using VADER, tweet text is converted into a sentiment score that is representative to its emotion (Hutto and Gilbert 2014). A sentiment lexicon is a mapping from tokens (words, stems of words, abbreviations, etc.) to a numerical indicator of sentiment. Each token carries a certain valence (negative, neutral, or positive sentiment) irrespective of context. VADER employs simple rules to improve its sentiment ratings for whole sentences with a corresponding valence between -1 (very negative) and 1 (very positive). VADER is an appropriate sentiment analysis tool in this study's analysis of Bitcoin for it is specifically trained for online datasets on social media and commonly applied in recent research. VADER is also embedded in Python packages.

For each tweet, the compound score, which is a weighted average of sentiment normalized to values between -1 (extremely negative) and 1 (extremely positive), is assessed using VADER. The compound scores of the tweets over a span of 10 minutes (usually more than 500 tweets) are compiled, and the mean value is set as the unweighted sentiment index. The standard deviation of the tweets over a span is also calculated as a proxy for disagreement. The numbers of favorites, retweets, and quotes for each Tweet are also scraped. The compound sentiment is weighted by multiplying the numbers of favorites, retweets, or quotes. The weighted compound scores of the tweets over a span of 10 minutes are also compiled, and the mean value is set as the weighted sentiment indices. These unweighted and weighted indices are then used to identify correlations with Bitcoin returns.

3. Analysis Results

A database containing tweets' information and Bitcoin returns is prepared for correlation analysis of tweets/Bitcoin returns. The duration for analysis is between 2021/10/01/00:00 and 2021/10/31/00:00. The data are compiled into 10-minute intervals. The 9 parameters crawled from the tweets include the following parameters: number of tweets (N), average sentiment compound score ($SC_{\_avg}$), average sentiment compound score weighted by favorite counts ($SC*F_{\_avg}$), average sentiment compound score weighted by quote counts ($SC*Q_{\_avg}$), average sentiment compound score weighted by retweet counts ($SC*RT_{\_avg}$), standard deviation of sentiment compound score ($SC_{\_sdv}$), standard deviation of sentiment compound score weighted by favorite counts ($SC*F_{\_sdv}$), standard deviation of sentiment compound score weighted by quote counts ($SC*Q_{\_sdv}$), and standard deviation of sentiment compound score weighted by retweet counts ($SC*RT_{\_sdv}$). The corresponding return (calculated using Equation (1)) and trade volume (Vol.) for each interval are appended into the database, as shown in Table I.

Table I. Partial rendering of database prepared for correlation analysis of tweets/Bitcoin price return

Time	N	$F_{\_AVG}$	$Q_{\_AVG}$	$RT_{\_AVG}$	$SC_{\_AVG}$	$SC*F_{\_AVG}$	$SC*Q_{\_AVG}$	$SC*RT_{\_AVG}$	$SC_{\_sdv}$	$SC*F_{\_sdv}$	$SC*Q_{\_sdv}$	$SC*RT_{\_sdv}$	R	Vol
10/1 00:00:00 ~ 10/1 00:09:59	696	114.101	2.856	24.249	0.238	75.559	2.161	16.528	0.423	1802.412	48.629	399.749	-0.0011	24.35
10/1 00:10:00 ~ 10/1 00:19:59	572	14.119	2.290	7.598	0.327	2.755	-0.218	5.772	0.421	67.767	5.265	138.504	0.0009	7.25
10/1 00:20:00 ~ 10/1 00:29:59	510	27.102	0.490	4.345	0.290	0.519	0.007	0.287	0.446	17.060	0.740	7.808	0.0014	9.54
: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;	: ; ;
10/30 23:30:00 ~ 10/30 23:39:59	595	23.345	0.440	4.575	0.320	-1.744	-0.074	-0.538	0.418	109.095	2.090	24.664	0.0013	21.79
10/30 23:40:00 ~ 10/30 23:49:59	652	13.505	3.104	4.952	0.362	4.357	2.088	2.491	0.442	93.690	53.052	59.046	-0.0001	0.68
10/30 23:50:00 ~ 10/30 23:59:59	571	30.420	0.681	5.356	0.283	1.267	0.014	0.402	0.421	25.588	0.189	8.131	0.0027	12.36

Table II provides summary statistics (mean, standard deviation, maximum, minimum, as well as the skewness and kurtosis) for the main variables of interest: numbers of tweets posted along with favorites, quotes, and retweet as well as sentiment scores evaluated using VADER. The subscript avg of variables indicates the average value, while the subscript sdv indicates the standard deviation of these variables in 10-minute span. As observed from the maximum and minimum values and the standard deviation, the numbers of tweets posted along with favorites, quotes, and retweets per 10 minutes are noisy. The average sentiment and the standard deviation of sentiment are also relatively noisy.

Table II. Statistics of the variables of concern in this research

	mean	sdv	max	min	skewness	kurtosis
N	842.8474	320.1097	7273.0000	205.0000	4.7802	60.5246
$F_{\_avg}$	29.0728	79.0354	3390.2924	0.5402	22.6668	822.6587
$Q_{\_avg}$	1.9346	5.4897	196.9930	0.0108	15.7561	446.3714
$RT_{\_avg}$	7.6911	14.6907	608.9022	0.2165	18.8052	676.3288
$SC_{\_avg}$	0.2932	0.0603	0.5221	-0.1000	-0.1737	0.9939
$SC*F_{\_avg}$	5.0774	23.7335	863.8589	-643.5862	7.9312	548.6948
$SC*Q_{\_avg}$	0.6519	2.5134	54.7711	-20.5679	7.4251	104.6010
$SC*RT_{\_avg}$	2.0816	5.4672	66.3059	-117.0713	0.4705	77.2312
$SC_{\_sdv}$	0.4299	0.0235	0.5109	0.3495	-0.0529	-0.0573
$SC*F_{\_sdv}$	190.0332	589.4334	18381.7140	0.9875	16.0629	404.4814
$SC*Q_{\_sdv}$	21.6945	68.6920	1798.3971	0.0260	9.7965	166.0829
$SC*RT_{\_sdv}$	66.9483	136.7258	3147.6412	0.3464	6.7671	89.0919
$R_{\_AVG}$	0.0001	0.0029	0.0356	-0.0531	-0.5308	43.2446
R_sdv	0.0007	0.0006	0.0144	0.0001	8.3187	145.5817
Vol	11.6649	27.2885	827.8801	0.0028	16.7427	413.2104

The statistics of Bitcoin return and trading volume are listed in Table I. The mean return for Bitcoin ($R_{\_avg}$) within a 10-minute span is calculated using Equation (3). The mean returns for Bitcoin per 10 minutes are positive (0.0001) with a standard deviation of 0.0029. This means the fluctuation of Bitcoin returns per 10 minutes is drastically high. The average and standard deviation of each variable within a 10-minute span are calculated similarly. For example, over the time span 10/1 00:00:00 ~ 10/1 00:09:59, there are 696 posts (Table I). Therefore, the average and standard deviation of 696 SC*F are calculated as $SC*F_{\_avg}$ and $SC*F_{\_sdv}$.

This database as shown in Table I is used to identify correlations between Twitter information and Bitcoin returns. Our empirical approach extracts a sentiment measure from tweets concerning Bitcoin. In particular, we take the sentiment measure as being relative to some time-variant-based level of expectations. It is of interest to understand if these parameters are leading or lagging indicators to Bitcoin returns. Therefore, the correlation between each parameter and Bitcoin returns is evaluated for different time lags. A +10 lag indicates the parameter value is 10 minutes ahead of the return, while a -10 lag indicates the parameter value is 10 minutes behind the return, and 0 indicates the parameter value is simultaneous with the return. The investigated time lags are -30, -20, -10, 0, +10,+20, and +30 minutes.

Table III to Table XI list the correlation analysis results of the 9 tweet parameters against Bitcoin returns. Table XII lists the correlation analysis results of trading volume against Bitcoin returns. These tables reports the correlation coefficient, standard deviation, t-statistics, p-value, and coefficient of determination (R^2). A positive correlation coefficient implies that this parameter possesses a positive correlation with Bitcoin returns and vice versa. The general trends observed from these tables are that p-values are not significant and R^2values are minimal for all cases. A large p-value indicates the correlation results are not statistically significant, and a small R^2 indicates the predictive ability of the regression model is not good.

Some further findings can still be drawn. First, the number of tweets (N) positively correlates with Bitcoin price return. This is consistent with the finding of Rognone et al. (2020) that Bitcoin reacts positively to both positive and negative news, because of investor enthusiasm for Bitcoin irrespective of the sentiment from news. The correlation is significant when N is used as a simultaneous or lagging index, and its predictive ability is relatively strong (Figure 1). Second, the unweighted sentiment compound score (SC_{avg}) generally negatively correlates with the return. The correlation is significant when SC_{avg} is used as a 10~20-minute lagging index, and its predictive ability is relatively strong. Though not significant, it is interesting to find that the coefficient turns from negative to positive when the lag exceeds 20 minutes (Figure 2). This means that Twitter sentiment, as a leading index by 20+ minutes, positively correlates with

Bitcoin returns, but as a simultaneous or lagging index it has a negative correlation. Third, the regression analysis results for the sentiment compound score weighted by favorites (SC*F_$_{avg}$) and quotes (SC*Q_$_{avg}$) are ambiguous. The correlation coefficients do not show trends, and neither p-values nor coefficients of determination support the analysis results. Only the sentiment compound scores weighted by retweets (SC*RT_$_{avg}$) have a statistically significant negative correlation with Bitcoin returns at -20 and +20 minutes. It is interesting to find that, though not significant, the correlation coefficient of SC_$_{avg}$ runs opposite to the correlation coefficients of SC*F_$_{avg}$ and SC*Q_$_{avg}$, but this opposite phenomenon is less obvious for SC*RT_$_{avg}$.

The standard deviation is an index showing disagreement of the data population. A large standard deviation among data can be a sign of fundamental uncertainty. One proposition is that when uncertainty increases, risk-averse traders require higher future returns to absorb the risk, which leads to a fall in price. Therefore, the standard deviations of the weighted and unweighted sentiment compound scores are included into analysis to examine this proposition. The analysis results are in Tables VIII to XI. Regretfully, the results are ambiguous, and the statistical analysis results are not significant enough to support nor negate the proposition. Here, SC_$_{adv}$ acts as a negative regression coefficient at a lag of -10 minutes, while it is positive at a lag of +10 minutes, while SC*RT_$_{sdv}$ acts as a positive regression coefficient at a lag of +10 minutes. The correlation analysis results of Bitcoin returns and trade volume (Vol) for different time lags are in Table XII which presents that trade volume generally positively correlates with Bitcoin price returns (Figure 3).

A comparison of the coefficients of determination for these analyzed cases is shown in Figure 4. It shows that the information retrieved from Twitter, including number of tweets posted (N), unweighted sentiment compound score (SC), and sentiment compound score weighted by retweets (SC*RT), along with trade volume (Vol), correlate with Bitcoin price returns. The average coefficient of determination for the 9 tweet parameters for different time lags is shown in Figure 5. As the time difference exceeds more than 20 minutes, the coefficient of determination becomes lower. This indicates that Twitter information correlates more with Bitcoin prices within a 20-minute span, no matter for leading or lagging.

Table III. Correlation analysis results of Bitcoin return and number of tweets for different time lags

N	-30	-20	-10	0	10	20	30
coefficient	3.8E-07	5.4E-07	5.6E-07	4.1E-07	1.4E-07	6.2E-09	-5.2E-08
sdv	1.4E-07	1.4E-07	1.4E-07	1.4E-07	1.4E-07	1.4E-07	1.4E-07
t-statistic	2.722	3.898	4.077	2.982	0.992	0.045	-0.379
p- value	0.007	0.000	0.000	0.003	0.321	0.964	0.705
R^2	0.042	0.059	0.062	0.045	0.015	0.001	0.006

Table IV. Correlation analysis results of Bitcoin return and average sentiment compound score for different time lags

$SC_{\_avg}$	-30	-20	-10	0	10	20	30
coefficient	-7.3E-04	-1.9E-03	-1.6E-03	-1.1E-03	-6.9E-05	3.2E-04	2.3E-04
sdv	7.3E-04	7.3E-04	7.3E-04	7.3E-04	7.3E-04	7.3E-04	7.3E-04
t-statistic	-0.993	-2.647	-2.250	-1.468	-0.094	0.440	0.312
p- value	0.321	0.008	0.024	0.142	0.925	0.660	0.755
R^2	0.015	0.040	0.034	0.022	0.001	0.007	0.005

Table V. Correlation analysis results of Bitcoin return and average sentiment compound score weighted by favorite counts for different time lags

$SC*F_{\_avg}$	-30	-20	-10	0	10	20	30
coefficient	7.8E-07	-1.0E-06	1.4E-06	2.9E-07	1.3E-06	-6.0E-07	-4.5E-07
sdv	1.9E-06	1.9E-06	1.9E-06	1.9E-06	1.9E-06	1.9E-06	1.9E-06
t-statistic	0.419	-0.555	0.742	0.157	0.723	-0.320	-0.242
p- value	0.675	0.579	0.458	0.876	0.470	0.749	0.809
R^2	0.006	0.008	0.011	0.002	0.011	0.005	0.004

Table VI. Correlation analysis results of Bitcoin return and average sentiment compound score weighted by quote counts for different time lags

SC*Q_avg	-30	-20	-10	0	10	20	30
coefficient	4.5E-07	-1.5E-05	-1.3E-05	1.1E-05	4.3E-06	-4.0E-06	-6.2E-06
sdv	1.8E-05	1.8E-05	1.8E-05	1.8E-05	1.8E-05	1.8E-05	1.8E-05
t-statistic	0.025	-0.846	-0.711	0.646	0.247	-0.227	-0.352
p- value	0.980	0.398	0.477	0.518	0.805	0.821	0.725
R^2	0.000	0.013	0.011	0.010	0.004	0.003	0.005

Table VII. Correlation analysis results of Bitcoin return and average sentiment compound score weighted by retweet counts for different time lags

SC*RT_avg	-30	-20	-10	0	10	20	30
coefficient	-7.3E-04	-1.5E-05	1.3E-06	3.2E-06	1.3E-05	-1.4E-05	1.0E-06
sdv	7.3E-04	8.1E-06	8.1E-06	8.1E-06	8.1E-06	8.1E-06	8.1E-06
t-statistic	-0.993	-1.806	0.163	0.394	1.620	-1.717	0.124
p- value	0.321	0.071	0.871	0.694	0.105	0.086	0.901
R^2	0.019	0.028	0.002	0.006	0.025	0.026	0.002

Table VIII. Correlation analysis results of Bitcoin return and standard deviation of sentiment compound score for different time lags

SC_sdv	-30	-20	-10	0	10	20	30
coefficient	1.0E-05	1.2E-03	-4.1E-03	1.6E-03	4.8E-03	-3.1E-03	4.1E-04
sdv	8.1E-06	1.9E-03	1.9E-03	1.9E-03	1.9E-03	1.9E-03	1.9E-03
t-statistic	1.249	0.615	-2.122	0.815	2.515	-1.642	0.215
p- value	0.212	0.538	0.034	0.415	0.012	0.101	0.830
R^2	0.004	0.009	0.032	0.012	0.038	0.025	0.003

Table IX. Correlation analysis results of Bitcoin return and standard deviation of sentiment compound score weighted by favorite counts for different time lags

SC*F_sdv	-30	-20	-10	0	10	20	30
coefficient	-5.9E-08	-5.2E-09	9.0E-08	5.3E-08	1.4E-07	8.1E-09	-4.7E-08
sdv	7.5E-08	7.5E-08	7.5E-08	7.5E-08	7.5E-08	7.5E-08	7.5E-08
t-statistic	-0.779	-0.069	1.203	0.710	1.854	0.108	-0.627
p- value	0.436	0.945	0.229	0.478	0.064	0.914	0.530
R^2	0.012	0.001	0.018	0.011	0.028	0.002	0.010

Table X. Correlation analysis results of Bitcoin return and standard deviation of sentiment compound score weighted by quote counts for different time lags

SC*Q_sdv	-30	-20	-10	0	10	20	30
coefficient	-3.3E-07	-3.0E-07	3.9E-08	5.0E-07	3.3E-07	-1.6E-07	-6.5E-07
sdv	6.4E-07	6.4E-07	6.4E-07	6.4E-07	6.4E-07	6.4E-07	6.4E-07
t-statistic	-0.515	-0.467	0.060	0.780	0.516	-0.247	-1.015
p- value	0.607	0.640	0.952	0.436	0.606	0.805	0.310
R^2	0.008	0.007	0.001	0.012	0.008	0.004	0.015

Table XI. Correlation analysis results of Bitcoin return and standard deviation of sentiment compound score weighted by retweet counts for different time lags

SC*RT_sdv	-30	-20	-10	0	10	20	30
coefficient	1.3E-07	-4.9E-07	3.4E-07	4.1E-07	7.2E-07	-4.7E-07	-1.9E-07
sdv	3.2E-07	3.2E-07	3.2E-07	3.2E-07	3.2E-07	3.2E-07	3.2E-07
t-statistic	0.397	-1.524	1.044	1.273	2.240	-1.450	-0.592
p- value	0.691	0.128	0.296	0.203	0.025	0.147	0.554
R^2	0.006	0.023	0.016	0.019	0.034	0.022	0.009

Table XII. Correlation analysis results of Bitcoin return and trade volume for different time lags

Vol.	-30	-20	-10	0	10	20	30
coefficient	1.5E-06	5.8E-06	-1.2E-06	8.2E-06	1.4E-05	2.0E-06	-1.7E-06
sdv	1.6E-06	1.6E-06	1.6E-06	1.6E-06	1.6E-06	1.6E-06	1.6E-06
t-statistic	0.930	3.554	-0.716	5.067	8.397	1.209	-1.054
p- value	0.352	0.000	0.474	0.000	0.000	0.227	0.292
R^2	0.014	0.054	0.011	0.077	0.127	0.018	0.016

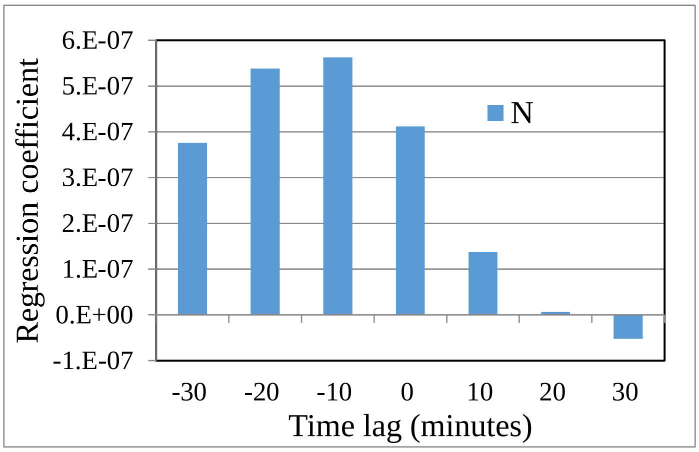

Figure 1. Regression coefficients of Bitcoin return and number of tweets for different time lags

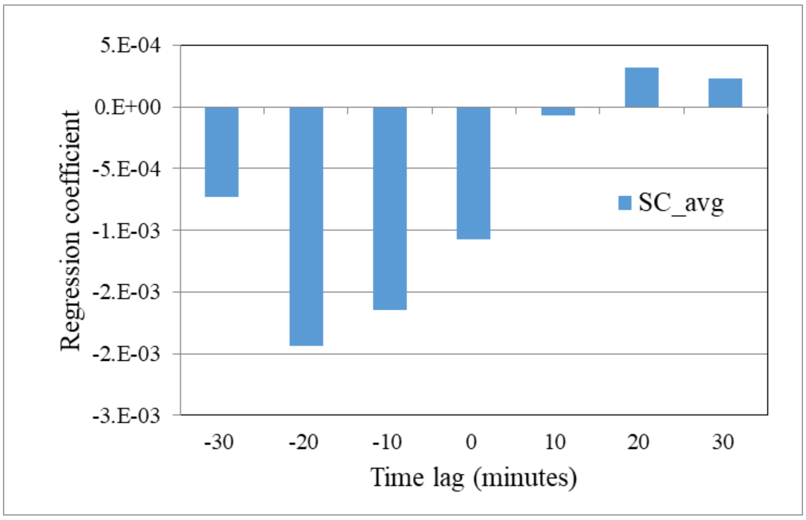

Figure 2. Regression coefficients of Bitcoin return and average sentiment compound score for different time lags

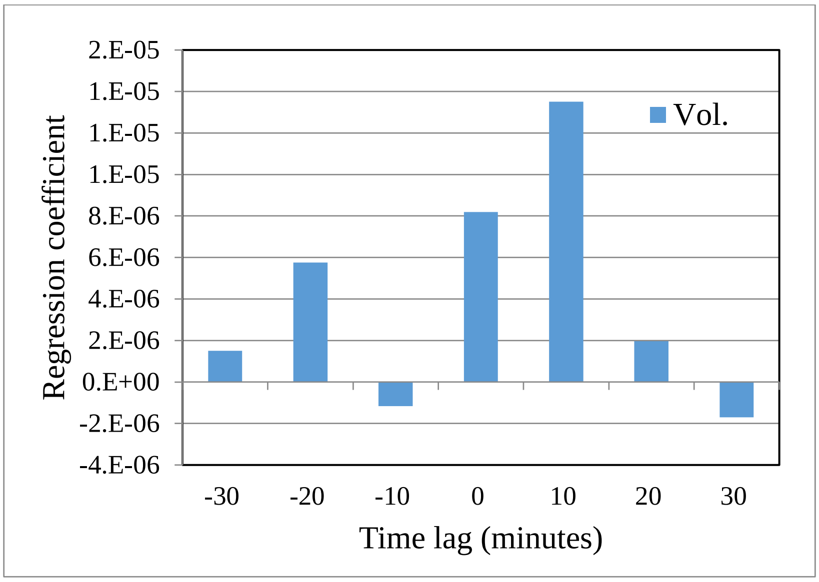

Figure 3 Regression coefficients of Bitcoin return and trading volume for different time lags

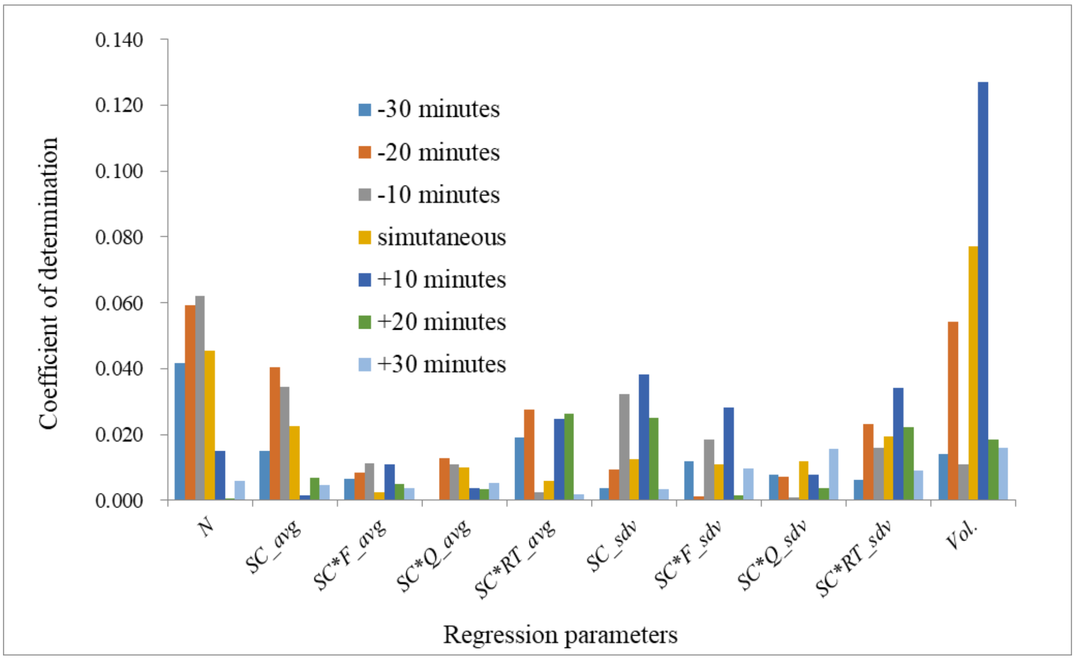

Figure **Error! No text of specified style in document.** Coefficients of determination for correlation analysis of Bitcoin return and variant parameters for different time lags

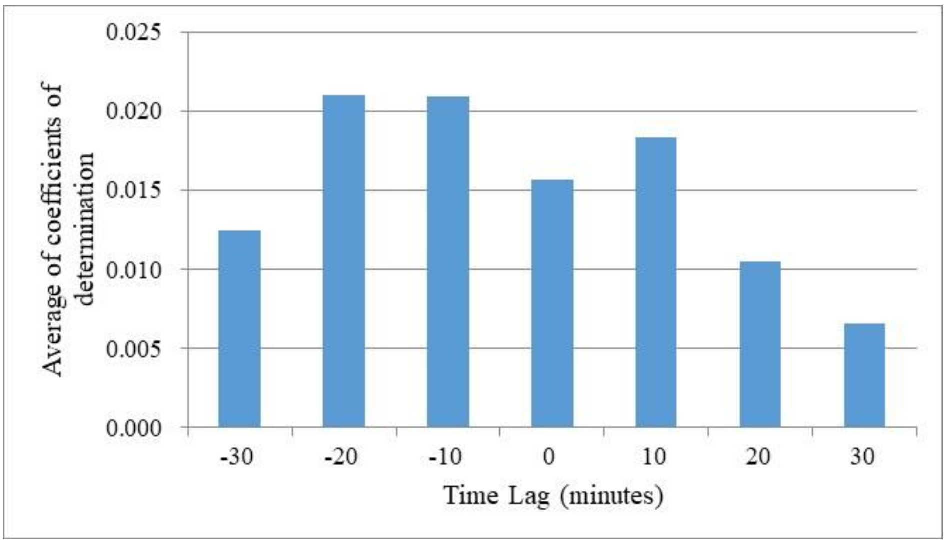

Figure 5 Average coefficient of determination for 9 tweet parameters for different time lags, for regression analysis of Bitcoin return

4. Conclusions and Discussions

Investors aim to profit from their decisions over investment assets, and Bitcoin is one of the most popular assets that have emerged in the last decade. This research examines if Bitcoin's price satisfies the efficient market hypothesis (EMH) and specifically examines any sentiment effect in Bitcoin can also be integrated into profit models. As Bitcoin is a purely belief-driven asset and has no concrete fundamental value, optimistic sentiment over it can lead to an increase in its price, while the emergence of negative sentiment could erode the beliefs among Bitcoin investors that then lead to a situation in which disagreement predicts low returns. Therefore, it is of interest to study how sentiment-related information revealed in Twitter affects the return and volatility of Bitcoin.

This study of the sentiment effect is based on minute-level Bitcoin price data and Bitcoin-related tweets posted on Twitter in October 2021. In total, more than 4 million tweets are crawled and processed for sentiment compound scores, using the VADAR-based sentiment analysis package embedded in python. The affiliated information, including favorites, quotes, and number of retweets, are also crawled for weighing their sentiment scores. The analysis results show that the information retrieved from Twitter, including number of tweets posted during the time period, unweighted sentiment compound score, sentiment compound score weighted by retweets, and trade volume, correlate more with Bitcoin returns. The number of tweets and trade volume positively correlate, while the unweighted and retweet weighted compound scores generally negatively correlate with Bitcoin returns. For the correlation with volatility in Bitcoin, a similar conclusion is reached except for the weighted compound scores is positively correlated. It is found that Twitter information correlates more with volatility than with Bitcoin returns, and the correlation is mostly with volatility simultaneously, but less correlated as time elapses.

A common proposition is that tweets about Bitcoins are representative for revealing the sentiment of Bitcoin investors. However, the analysis results indicate that the correlated effect of sentiment parameters, such as weighted and unweighted compound scores on Bitcoin price, is not consistent over the time horizon. This analysis provides a detailed investigation and discovers that when the time difference exceeds more than 20 minutes, no matter for leading or lagging, the correlation between Twitter information and Bitcoin price is less significant. Tweets’ sentiment is a positive leading index, but it turns negative for a simultaneous or lagging index. This finding conforms to the fact that recent research results about the relationship between investor sentiment and Bitcoin contradict each other.

Considering their characteristics of real-time, representativeness, and quantity, the abundant messages on social media may provide an indicator for investor sentiment. One concern of this research is in the selection of crawling techniques and the sentiment analysis tool. Using different keywords on different social media platforms may scratch different posts, making it a potential issue for follow-up analysis. The same can be said towards the different sentiment analysis tools that may output different sentiment scores. The question of how to capture objective sentiment data from social media would be an interesting topic for further study.

One limitation of this research is that the sentiment analysis results are based on the data of the selected time period, and the results may not be appropriate for extrapolating to other durations. Another limitation of this research is that the p-values are not significant, and the R^2 values are insignificant for the single variable linear regression models examined in sentiment analysis. Some recent studies (e.g., Kristoufek 2013; Stavroyiannis et al. 2019) proposed that the relationship between cryptocurrency prices and investor sentiment is not linear. For example, Li et al. (2019) applied the Extreme Gradient Boosting Regression Tree Model to investigate investors' sentiment effect on cryptocurrency's price fluctuation. They reported that general sentiment is a powerful indicator that can better predict cryptocurrency price movements. This makes advanced models developed by machine learning a relevant approach to further study the lead-lag interactions between sentiment variables and Bitcoin price action.

References:

1. Aharon, D.Y., and Qadan, M. (2019) “Bitcoin and the Day-of-the-week Effect.” *Finance Research Letters, 31,* 415–424.

2. AlNemer, H. A., Hkiri, B., and Khan, M. A. (2021) “Time-Varying Nexus between Investor Sentiment and Cryptocurrency Market: New Insights from a Wavelet Coherence Framework.” *Journal of Risk and Financial Management, 14*(6), 275.

3. Anamika, C., M., and Subramaniam, S. (2021) “Does Sentiment Impact Cryptocurrency?” *Journal of Behavioral Finance,* 1-17.

4. Antweiler, W. and Frank, M. (2004) “Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards.” *The Journal of Finance, 59*(3), 1259–1294.

5. Baig, Ahmed, Blau, B. M., and Sabah. N. (2019) “Price Clustering and Sentiment in Bitcoin.” *Finance Research Letters, 29:* 111–116.

6. Da, A., Engelberg, J, and Gao, P. (2015) “The Sum of All FEARS Investor Sentiment and Asset Prices.” *Review of Financial Studies, 28*(1):1-32.

7. Fama, E. F. (1970) “Efficient Capital Markets: A Review of Theory and Empirical Work.” *The Journal of Finance, 25*(2), 383-417.

8. Gao, X., Huang, W., and Wang, H. (2021) “Financial Twitter Sentiment on Bitcoin Return and High-Frequency Volatility.” *Virtual Economics, 4*(1), 7-18.

9. Guégan, D., and Renault, T. (2021) “Does Investor Sentiment on Social Media Provide Robust Information for Bitcoin Returns Predictability?” *Finance Research Letters, 38,* 101494.

10. Hutto, C and Gilbert, E. (2014) “Vader: A Parsimonious Rule-based Model for Sentiment Analysis of Social Media Text.” *Proceedings of the International AAAI Conference on Web and Social Media.*

11. Ibrahim, A. (2021) “Forecasting the Early Market Movement in Bitcoin Using Twitter's Sentiment Analysis: An Ensemble-Based Prediction Model.” *2021 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS),* 1-5. IEEE.

12. Jain, A.; Tripathi, S., Dwivedi, H.D., and Saxena, P. (2018) Forecasting Price of Cryptocurrencies Using Tweets Sentiment Analysis. *Proceedings of the Eleventh International Conference on Contemporary Computing (IC3).* Institute of Electrical and Electronics Engineers (IEEE), Noida, India, 2–4 August 2018; 1–7.

13. Jegadeesh, N and Wu, D. (2013). “Word Power: A New Approach for Content Analysis.” *Journal of Financial Economics*,110(3), 712–729.

14. Kapar, B., and Olmo, J. (2021) “Analysis of Bitcoin Prices Using Market and Sentiment Variables.” *The World Economy, 44*(1), 45-63

15. Kim S.-H. and Kim D. (2014) “Investor Sentiment from Internet Message Postings and The Predictability of Stock Returns.” *Journal of Economic Behavior and Organization, 107,* 708–729.

16. Kraaijeveld, O.; De Smedt, J. (2020) “The Predictive Power of Public Twitter Sentiment for Forecasting Cryptocurrency Prices.” *Journal of International Financial Markets, Institutions, and Money,* 65, 101188.

17. Kristoufek, L. (2013) “Bitcoin Meets Google Trends and Wikipedia: Quantifying the Relationship between Phenomena of the Internet Era.” *Scientific Reports, 3,* 3415.

18. Li, T. R.; Chamrajnagar, A. S.; Fong, X. R.; Rizik, N. R.; Fu, F. (2019) “Sentiment-based Prediction of Alternative Cryptocurrency Price Fluctuations Using Gradient Boosting Tree Model.” *Frontier Physiology,* 7.

19. Lyócsa, S., Baumöhl, E., Výrost, T. Molnár. P. (2020) “Fear of the Coronavirus and the Stock Markets.”*Finance Research Letters, 36,* 101735.

20. Lyu, H.; Chen, L.; Wang, Y.; Luo, J. (2020) “Sense and Sensibility: Characterizing Social Media Users Regarding the Use of Controversial Terms for COVID-19.” *IEEE Transaction and Big Data,* 1.

21. Mohapatra, S.; Ahmed, N.; Alencar, P. (2019) “A Real-Time Cryptocurrency Price Prediction Platform Using Twitter Sentiments.” *arXiv:*2003.04967.

22. Naeem, M. A., Mbarki, I., and Shahzad, S. J. H. (2021) "Predictive Role of Online Investor Sentiment for Cryptocurrency Market: Evidence from Happiness and Fears." *International Review of Economics and Finance, 73,* 496-514.

23. Qadan, M., Aharon, D. Y., and Eichel, R. (2021) "Seasonal and Calendar Effects and the Price Efficiency of Cryptocurrencies."*Finance Research Letters,* 102354.

24. Öztürk, S. S., and Bilgiç, M. E. (2021) "Twitter and Bitcoin: Are the Most Influential Accounts Really Influential?." *Applied Economics Letters,* 1-4.

25. Pano, T., Kashef, R. A. (2020) "Complete VADER-based Sentiment Analysis of Bitcoin (BTC) Tweets during the Era of COVID-19." *Big Data and Cognitive Computing, 4,* 33.

26. Ranasinghe, H., and Halgamuge, M. N. (2021) "Twitter Sentiment Data Analysis of User Behavior on Cryptocurrencies: Bitcoin and Ethereum." *Analyzing Global Social Media Consumption,* 277-291, IGI Global.

27. Renault T. (2017) "Intraday Online Investor Sentiment and Return Patterns in the U.S. Stock Market." *Journal of Banking and Finance, 84,* 25–40.

28. Rognone, L., Hyde, S. and Zhang, S. (2020) "News Sentiment in the Cryptocurrency Market: An Empirical Comparison with Forex." *International Review of Financial Analysis, 69:* 101462.

29. Sadka, R and Scherbina A. (2007) "Analyst Disagreement, Mispricing, and Liquidity." *The Journal of Finance, 6*(5), 2367–2403.

30. Sailunaz, K., and Alhajj, R. (2019) "Emotion and Sentiment Analysis from Twitter Text." *Journal of Computational Science, 36,* 101003.

31. Stavroyiannis, S., Babalos, V., Bekiros, S., Lahmiri, S., and Salah G. (2019) "The High Frequency Multifractal Properties of Bitcoin." *Physica A: Statistical Mechanics and its Applications,* 520: 62–71.

32. Steyn, D. Greyling, T., Rossouw, S., and Mwamba, J. H. (2020) "Sentiment, Emotions and Stock Market Predictability in Developed and Emerging Markets." *No 502,GLO Discussion Paper Series from Global Labor Organization.*

33. Tetlock, P. C. (2007) “Content to Investor Sentiment: The Role of Media in the Stock Market.” *The Journal of Finance, 62*(3), 1139–1168.

34. Vega, C., (2006) “Stock Price Reaction to Public and Private Information.” *Journal of Financial Economics, 82* (1), 103–133.

35. Xie, P. (2021) “The Interplay between Investor Activity on Virtual Investment Community and the Trading Dynamics: Evidence from the Bitcoin Market.”*Information Systems Frontiers,* 1-17.