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Effect of Covid-19 Sentiment on Financial Markets: Evidence from S&P 500 and Bitcoin

(Kesan Sentimen Covid-19 terhadap Pasaran Kewangan: Bukti dari S&P 500 dan Bitcoin)

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ABSTRACT

This study aims to investigate the influence of users' regarding Covid-19 sentiments in social media on the S&P 500 and Bitcoin returns. The social media used in this study is mainly Twitter. The vector autoregression approach was applied to examine trending issues, which involved daily data observation and observed from 17 August 2021 until 17 December 2021. These estimations revealed that past users' sentiments have significantly influenced the return of the S&P 500 and Bitcoin, as supported by the Granger causality test and variance decomposition. The findings of this study could be helpful for both policymakers and investors in their efforts to develop plans to lessen market volatility, particularly in terms of future unfavourable events. Investors could also use these findings to create profitable investing plans for when the market is turbulent.

Keywords: Return; sentiment analysis; Twitter; S&P 500; Bitcoin; COVID-19

ABSTRAK

Kajian ini mengkaji pengaruh sentimen pengguna mengenai Covid-19 dalam media sosial terhadap kadar pulangan S&P 500 dan Bitcoin. Media sosial yang digunakan dalam kajian ini adalah terutamanya Twitter. Pendekatan Vector Autoregression digunakan untuk mengkaji isu ini, yang melibatkan kekerapan data harian dan diperhatikan dari 17 Ogos 2021 hingga 17 Disember 2021. Hasil kajian ini mendedahkan bahawa sentimen pengguna telah mempengaruhi kadar pulangan S&P 500 dan Bitcoin dengan signifikan, dapatan ini turut disokong oleh ujian sebab-akibat Granger dan penguraian varians ralat ramalan. Penemuan kajian ini boleh membantu kedua-dua pembuat dasar dan pelabur dalam usaha mereka untuk merangka rancangan untuk mengurangkan kemeruapan pasaran, terutamanya dari segi peristiwa yang tidak diingini pada masa hadapan. Pelabur juga boleh menggunakan penemuan ini untuk merangka rancangan pelaburan yang menguntungkan apabila kegawatan pasaran.

Kata kunci: Kadar pulangan; analisis sentiment; Twitter; S&P 500; Bitcoin; COVID-19
JEL: E70, E71, G11, G14, G15, G41
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INTRODUCTION

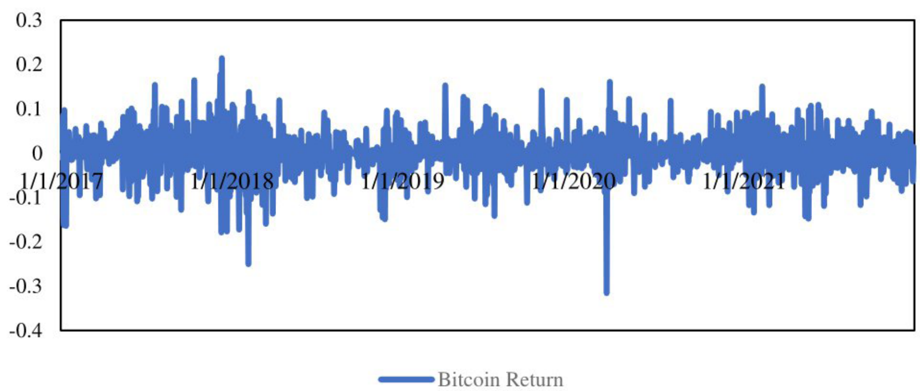
Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) is a novel coronavirus that began to spread in 2019 (2019-nCoV). The Coronavirus disease (Covid-19) started as a mystery illness that first appeared in Wuhan, China in December 2019. The World Health Organization (WHO) declared a public health emergency on 31st January 2020[1] to allow for the entire country to pay close attention to this issue and to take safety measures. On 11th March 2020[2], the WHO declared Covid-19 as a pandemic, as it has crossed borders and spread to many countries, and impacted millions of people. Consequently, this disease has not only infected the population but also affected the social and economic conditions of countries across the globe. On 2nd April 2020, the International Monetary Fund[3] reported that Covid-19 has caused a global financial crisis due to many countries taking tight actions to reduce the spread of the disease, which consequently slowed down economic activities.

Despite its severity, little is known on how this outbreak has affected stock markets and cryptocurrency, thus leaving a knowledge gap for future research. Previous studies (Ding et al. 2020; Kraaijeveld & De Smedt 2020; Reis & Pinho 2020) on behavioural economics have revealed that user sentiments can profoundly affect an individual's behaviour and decision-making process. At the initial stage of Covid-19, the implementation of macroeconomic policy to stabilize the financial markets was less efficient. Gao et al. (2021) reported that during the Covid-19 pandemic, the interest rate in the US in May 2020 was almost zero, yet the financial market still managed to endure the turbulence. It is thus important to understand the relationship between investor sentiments on certain issues and the financial markets in order to formulate emergency management strategies in the future.

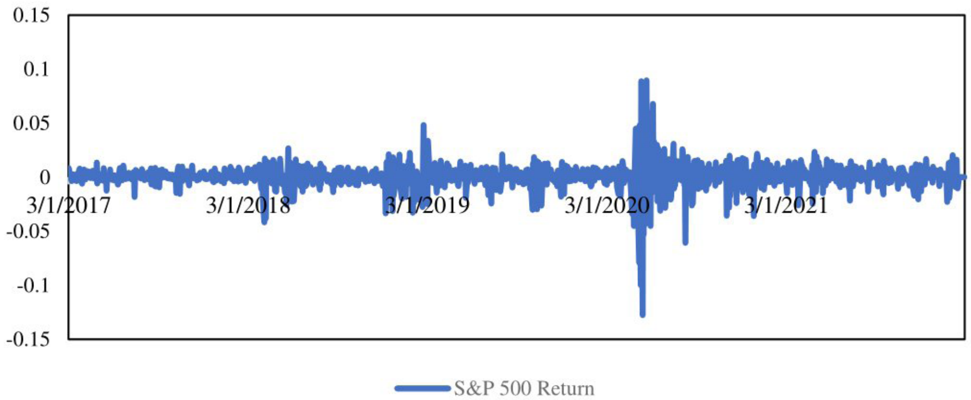
With this cognizance this research therefore aims to analyse the role of users' sentiment regarding the spread of Covid-19 in social media (Twitter) on the return of the S&P 500 and Bitcoin. This study involved daily observations made between 17 August 2021 and 17 December 2021 over a four-month period. The rather brief observation was due to several reasons. Firstly, during the period of data collection, Covid-19 cases and death rate in the US showed an increasing trend. Secondly, Bitcoin reached its highest price at this time, and the USD currency was used in almost 70% of Bitcoin transactions in 2021[4]. Thirdly, this analysis only involved real-time data collection from the Twitter developers by using RStudio software. Previous day's tweets were thus obviated. In other words, tweet collection cannot be skipped during the observation period. For these reasons, data collection was made for a short duration over specific event such as at peak Covid-19 occurrence recorded in the US, as explained above. Furthermore, most of past studies (Feng Mai et al. 2018; Kraaijeveld & De Smedt 2020; Steinert & Herff 2018; Shen et al. 2019) were conducted over two to three months when Twitter was used as a sentiment tool. In addition, the data analysis can be very beneficial to national policymakers, in order to assist them in understanding the causes of stock market volatility and thus to take appropriate actions against fortuitous future events such as Covid-19 (Kong et al. 2023; Siriopoulos et al. 2021). Similarly, investors can use the results to identify the opportune time to invest in financial assets and acquire the potential to build profitable and safe investment portfolios (Jong et al. 2020). The paper begins with an introduction in section one followed with the study background and literature review in section two and three, respectively. The methods are given in section four followed by the results in section five. Finally, the conclusion is presented in section six.

BACKGROUND OF THE STUDY

This study focuses on Bitcoin on August 2021[5], over 5,000 cryptocurrencies worldwide. Bitcoin represents nearly 50% of the market capitalization of the top 100 cryptocurrencies[6] and has the influence to drive the price of other cryptocurrencies in the desired direction (Hajam et al. 2023; Vidal-Tomás & Ibañez 2018). The Twitter media channel has also become an essential reference source for users to seek the latest information[7] on cryptocurrencies and serves as a platform of reference in making currency predictions (Kraaijeveld & De Smedt 2020; Öztürk & Bilgiç 2021; Philippas et al. 2019; Suardi et al. 2022; Steinert & Herff 2018). In addition, studies (Ranco et al. 2015; Soudeep 2021) have revealed that stock market movement predictions can be improved from sentiment analysis of tweet data. For instance, Yuexin et al. (2012) validated the strong correlation between the daily volume of tweets mentioning "S&P 500" and S&P 500 stocks. Moreover, Kraaijeveld & De Smedt (2020) indicated that Twitter could also reflect investor sentiments since the news would become viral first on the platform before its official announcement which will then exert an immediate impact on financial markets. Several past studies (Chen et al. 2020; Chundakkadan & Nedumparambil 2021; Corbet et al. 2020; Ding et al. 2020; Lyócsa et al. 2020; Reis & Pinho 2020) have also proven that investors' attention on Covid-19 has impacted the performance of S&P 500 and Bitcoin markets.



(a)



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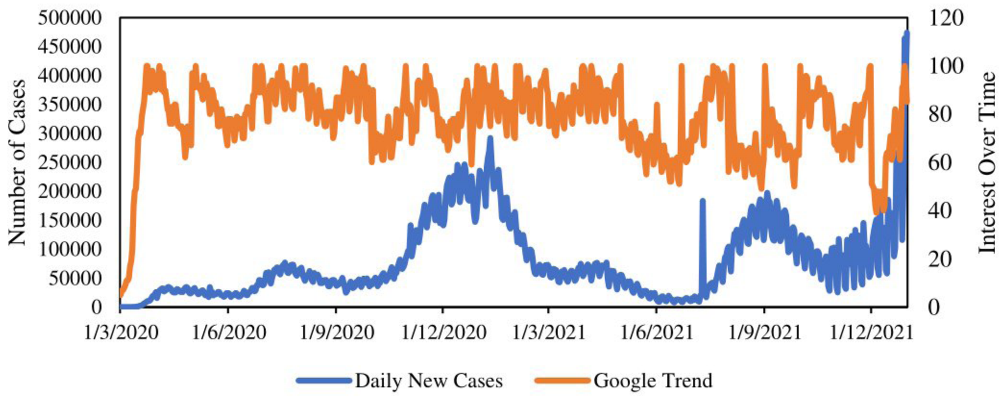
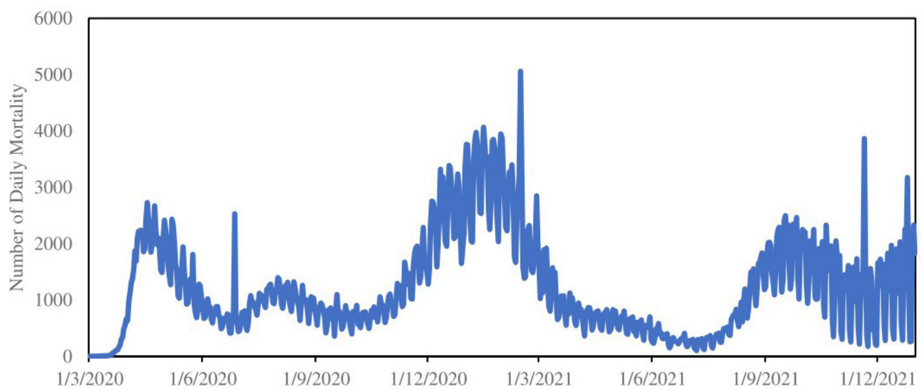


United States Daily Covid-19 Cases and Covid-19 Google Trend Data

(c)



United States Daily Mortality Rate

(d)

FIGURE 1. Market data of Bitcoin and S&P 500, United States Covid-19 daily cases and death rate, and Google trend data of Covid-19.

Notes: (a) Bitcoin Return; (b) S&P 500 Return; (c) United States Daily Covid-19 Cases and Covid-19 Google Trend Data; (d) United States Daily Mortality Rate.

Source: Author's calculation for return from the historical price of Bitcoin and S&P 500. https://coinmarketcap.com; https://trends.google.com; https://covid19.who.int/data.

Figure 1 demonstrates the return of Bitcoin and S&P 500 from 2017 until 2021. It also present the daily Covid-19 cases and mortality rate in the United States (US) together with Google trend data from January 2020 until December 2021. The Google trend data describe the users' web search interest in the keyword "Covid". An interest value of 100 indicates peak popularity for the term "Covid" and vice versa. Based on Figure 1, we find that the return of Bitcoin and S&P 500 displayed high fluctuation beginning March 2020. However, the fluctuation decreased after some time but the Bitcoin return still maintained high fluctuation until the end of 2021. Additionally, the daily Covid-19 cases in the US surged significantly from August 2021 and maintained an increasing trend until December 2021 at a higher level than that in early 2020. At the same time, the Google trend indicator had mostly shown a similar pattern to Covid-19, especially after mid-2021. During that time the mortality rate was still very high and Bitcoin peaked to its maximum price level of $67, 527.90 on 8th November 2021. Given that the rapid spread of Covid-19 has deeply influenced public emotions (Ding et al. 2020) investors' decision to invest in financial markets began to change discernibly. Since the Covid-19 scenario has also spread fear and anxiety among the people, it has also affected their investment decisions, causing them to omit the price data from previous historical assets (Del Lo et al. 2022; Siriopoulus et al. 2021).

LITERATURE REVIEW

Economic speculation during the pandemic has caused great uncertainty and volatility in global markets. Accordingly, understanding trends of market volatility and uncertainty during the pandemic period has the potential to produce a clear view regarding the fluctuating factors of S&P 500 and Bitcoin returns. Zhuo and Kumamoto (2020) showed that the rising number of positive Covid-19 cases and deaths had led to extreme changes in stock market volatility among the G7, BRICS, and four northern European countries. However, the empirical findings of studies by Del Lo et al. (2022) and Siriopoulos et al. (2021) indicated that positive cases of Covid-19 and the number of deaths had minimal impact on European and African stock markets. Besides this, Goodell and Goutte (2021) studied the relationship between daily global Covid-19 mortality rate and Bitcoin price by employing a wavelet coherence method. The results indicated that an increase in the death rate of Covid-19 led to a rise in the Bitcoin price. Although, Shields et al. (2021) reported that apart from deaths and positive Covid-19 cases, market uncertainty that can be described by financial behaviours, will influence the performance of the stock market. Thus, changes in investors' behaviour could affect global stock market trading, in parallel to the spread of Covid and which increased the feeling of doubt and fear in the population (Mnif et al. 2020).

The Efficient Market Hypothesis (EMH) assumes that stock market prices reflect all appropriate information and signals for resource allocation (Fama 1970). Therefore, the share price will bounce back to its original price without any shock when an event occurs in the market and new information reaches the public. In reality, investors may overreact to an event, which may have a negative impact on financial markets in the short term, given that previous stock price data were ignored (Ding et al. 2020). However, Kraaijeveld and De Smedt (2020) highlighted that the EMH is a standard neoclassical theory of financial markets, even though it does not give enough attention to the behaviour and emotions exhibited by investors. Hence, investment decisions can be influenced by investor sentiment and psychological factors, apart from the economic aspects of the stock markets. This statement has been value added by Wu and Hock Ow (2021) who indicated that news emotion from the Organization of the Petroleum Exporting Countries (OPEC) affects oil and gas company stock prices and assist market participants in formulating profitable investment decision. Furthermore, during the Covid-19 pandemic, several safety measures such as lockdown, border closures, social isolation, and other health interventions have created a condition of uncertainty in the global stock market and has exerted a significant impact on investors (Tanveer 2021).

The WHO frequently updated the news on current Covid-19 cases with stringent measures to be taken to curb the pandemic. This had led to panic, negative sentiments, and anxiety among people in various countries concerned with adverse impact on their national economy. These outcomes might have been the consequences of the closure of most economic activities globally. In consequence, investor sentiment may also be affected since it is closely related to emotions, pessimism, or even optimism, that could potentially affect investment decisions and financial asset prices (Hirshleifer et al. 2020; Jitmaneeroj 2017). Twitter was introduced in 2006 and this media gave users from all over the world a platform to express their feelings and emotions in the form of "tweets". The increase of users' access in Twitter indicated that they tend to respond immediately to an event by tweeting their comments. Such activities have indirectly influenced investors' behaviour when making investment decisions. Numerous studies have analysed the relationship between sentiments regarding cryptocurrency on Twitter and its currency markets (Garcia et al. 2015; Philippas et al. 2019; Steinert & Herff 2018).

User sentiments that were measured using Google Search have a greater impact on the stock markets. Papadamou et al. (2022) stated that the number of searches obtained from Google search data can be perceived as the behaviour of the general population for a given search, and such searches have become fruitful in analysing investor behaviour. This observation was in agreement with Ding et al. (2020). They examined the impact of investor sentiment, as assessed using Google search data with the keyword "Covid-19", on the stock market for 1,568 firms listed in NASDAQ. The empirical findings of their study were in line with the findings of other studies (Chundakkadan & Nedumparambil 2021; Lyócsa et al. 2020; Reis & Pinho 2020), that investor sentiment regarding Covid-19 has a significant effect on the rate of return, as well as stock market price. In addition, Conghui Chen et al. (2020) used the search term "Coronavirus" in Google trends as a measurement of the fear sentiment of users and also analysed its implication on the Bitcoin market. Their findings are in line with some studies (Hajam et al. 2023; Jieru Wan et al. 2023) which established that users' sentiment significantly influences the Bitcoin return. Information has thus become one of the important factors in financial market fluctuation.

In general, the spread of a new disease tends to affect the financial market of a country. Numerous studies have analysed the relationships between Covid-19, the stock markets, and cryptocurrencies (Goodell & Goutte 2020; Salisu et al. 2020; Shields et al. 2021; Zhuo & Kumamoto 2020). However, these studies were not focused on perspectives of user sentiment, even though investor sentiments regarding certain issues tend to influence investment decisions (Hirshleifer et al. 2020; Jitmaneeroj 2017). Corbet et al. (2020) investigated on Twitter the impact of user sentiments regarding Covid-19 on the cryptocurrency markets. Their findings revealed that cryptocurrencies were classified as hedging assets during the pandemic. But their studies did not explain the consequence of the type of users' sentiment on the cryptocurrency market nor compared it with other stock markets. Several studies though (Chen et al. 2020; Chundakkadan & Nedumparambil 2021; Ding et al. 2020; Lyócsa et al. 2020; Reis & Pinho 2020) had verified the impact of investor sentiment on stock markets and cryptocurrency markets using Google search. The combination of sentiment indicators on Twitter and users' interest in Google searches can be used to determine more clearly users' sentiment toward the Covid-19 outbreak. Admittedly, in mid-2017, most cryptocurrency prices rose sharply[6]. User activities on social media, such as Twitter and Google search, with interest in cryptocurrency also increased together with cryptocurrency price[8]. On the other hand, Americans are the most active Twitter users, with usage reaching the highest global level[9] of 24.32%. The official Federal Reserve Twitter account contained 768.9 thousand followers until 2021[10]. This is indicative that many investors are active in Twitter access in order to obtain current economic information. Hence, the two platforms are able to provide sufficient data for sentiment analysis of selected issues. Moreover, the inclusion of the macroeconomic variable can indicate in more detail the importance of user sentiment on the financial market. This study improves on the work of Mohamed Al Guindy (2022) and Ngo & Nguyen (2022) in further separating the sentiment into positive, negative, and neutral and also including the Google trend and macroeconomic variables together.

METHODS

The study methodology is described in this section. The first step was data gathering, and followed with an estimation of the return and volatility of Bitcoin and S&P 500, and also the tweet data cleaning process. The third step was to analyse the sentiment on cleaned tweets, followed with preparation of the datasets, and finally in estimating the model using the Var approach.

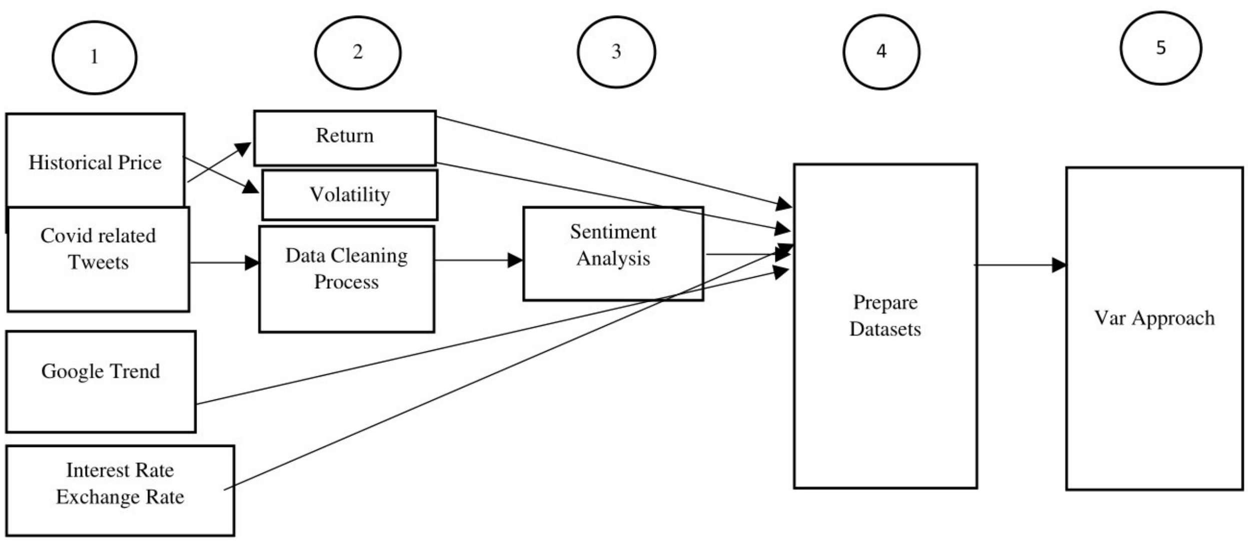


FIGURE 2. Various stages of the methodology
Source: Author's Sketch on Methodology Framework

Figure 2 illustrates an overview of the methodology used in this study. The first step was data collection, which consisted of daily observations from 17 August to 17 December 2021. This study focused on Bitcoin and S&P 500 since findings of previous studies (Kraaijeveld & De Smedt 2020; Öztürk & Bilgiç 2021; Philippas et al. 2019; Suardi et al. 2022; Steinert & Herff 2018; Yuexin et al. 2012) had established that users' sentiment in Twitter influenced the Bitcoin and S&P 500 markets performance. The actual closing price data for S&P 500 were sourced via Investing.com[11] and from coinmarketcap.com for Bitcoin. A total of 2,158,000 tweets were collected from the Twitter Application Programming Interface[12] (API) using "Covid" as a keyword in the R-Studio software[13]. The value of Google trend data has a range from 0 to 100 and this study used the same keyword to gather Google trend data in Twitter using the Rstudio software. In addition, the US interest rate (Effective Federal Fund Rate) and exchange rate (USD/EUR) were used as macroeconomic data that were gathered from Investing.com and Fred[14]. The same macroeconomic data were applied for Bitcoin due to the high amount of USD used in Bitcoin transactions.

The second step involved collecting historical price data for the S&P 500 and Bitcoin, as well as tweets related to Covid-19. Starting with S&P 500 and Bitcoin data, the asset price, $P_{i,t}$, was used to compute the return, as shown in Equation (1):

$$Return_{i,t} = \frac{P_{i,t} - P_i(t-1)}{P_i(t-1)} \tag{1}$$

This study subsequently employed the generalized autoregressive conditional heteroskedasticity (GARCH) approach to determine the variance of asset returns. The conditional mean and variance specifications are as follows:

$$\begin{aligned} Return_{i,t} &= \beta_0 + \beta_1 Return_{i,t-1} + \varepsilon_{i,t} \\ \varepsilon_{i,t} &= \eta_{i,t}\sqrt{h_{i,t}},\ \eta_{i,t} \sim N(0,1) \end{aligned} \tag{2}$$

$$\sigma_{i,t}^2 = x + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2 \tag{3}$$

Where $Return_{i,t}$ and $Return_{i,t-1}$ are the rates of return of S&P 500 and Bitcoin at time t and $t-1$, respectively. $\varepsilon_{i,t}$ is an error term, $x > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\eta_{i,t}$ are independent and similar random variables that are distributed with zero mean and unit variance, and $h_{i,t}$ is the variance-covariance matrix. After that, the collected tweets were cleaned to filter out noise elements. The Valence Aware Dictionary for sEntiment Reasoning (VADER) (Hutto & Gilbert 2014) was used to determine user sentiments in this study. This dictionary is advantageous for analyzing certain punctuations and symbols, as well as numbers in tweets. Thus, his research followed the data-cleaning process demonstrated by Öztürk and Bilgiç (2021), which used the VADER dictionary. Among the data clean-ups made in this analysis were tweets cleared from punctuations, except #, $, @, ', ', !, ", ?, ., and webpage links, while all uppercase letters were converted to lowercase letters.

The sentiment analysis was implemented for the cleaned tweets, as the third step in the methodology. The VADER approach is a lexicon and rule-based sentiment analysis, which is specifically trained and suitable for sentiments expressed on social media (Elbagir & Jing 2019; Kraaijeveld & De Smedt 2020). Furthermore, VADER has several additional benefits compared to machine learning methods, whereby this technique is relevant for analysing tweet content and extracting additional sentiment values from emotions, emojis, punctuations, use of grammar, slang, and acronyms (Valencia et al. 2019). This technique can produce three types of sentiments, namely, positive, negative and neutral sentiment. Each collected tweet in this study was classified into these sentiment types based on the compound score. VADER was used to estimate the compound score, thus, a tweet with a score of -1 was classified as a negative sentiment, and a tweet with a +1 score was deemed a positive sentiment. Hutto and Gilbert (2014) have also stated that compound scores of ≥ 0.05 indicated positive sentiments, while neutral sentiments ranged between > -0.05 and < 0.05, and ≤ -0.05 for negative sentiments. This range of scores was also applied in previous studies (Kraaijeveld & De Smedt 2020; Öztürk & Bilgiç 2021; Suardi et al. 2022) that used the VADER dictionary. The compound score for the tweet is based on the tweet itself. For example, the compound score for a tweet "*4 months ago I had covid while the markets were crashing to hell, today bitcoin and eth hit new all-time highs and I'm clos*…" ("*the stock market is up, covid infections are down and millions of good-paying jobs have been created #buildbackbetter*") is -0.6808 (0.25) and the tweet is categorized on negative (positive) sentiment. After completing the sentiment analysis, the total number of positive, neutral, and negative sentiments were counted and grouped into daily tweet datasets separately. The cleaning process and sentiment analysis were conducted using Python software[15].

In the fourth step the datasets for S&P 500 and Bitcoin were prepared independently. Since the sentiment data highly fluctuated compared with other variables, this study had to renormalize the variables. All the time series were standardized using the Z-transformation: $Z_t = (X_t - \mu_x)/\sigma_x$, where μ_x and σ_x are defined as the mean and standard deviation of each time series, respectively. Consequently, all data have a similar scale and variance, which enabled researchers to determine their impact differences in numerical analysis (Garcia et al. 2015). The descriptive statistics of the datasets for the S&P 500 and Bitcoin are listed in the Appendix, Table 1. Before conducting the VAR analysis, this study evaluated the stationary of each time series using the Augmented Dickey Fuller (ADF) test (Fuller 2009). Under the ADF test, time series were deemed stationary when the p-value was below 0.05. Next, the differentiation method ($\Delta X_t = X_t - X_{(t-1)}$) was used for time series that were not stationary at all levels. The unit root test for each S&P 500 stock and Bitcoin asset dataset is presented in the Appendix, Table 2.

Lastly, to analyse the implication of Covid-19 sentiment on the return of the S&P 500 and Bitcoin, a VAR model was utilized in the following form:

$$Y_{i,t} = a + \sum_{i=1}^{p} A_i\, Y_{i,t-i} + \sum_{j=1}^{k} \beta_i\, X_{i,t-j} + \varepsilon_{i,t} \quad (4)$$

where α is a vector of constant and $\varepsilon_{i,t}$ is a vector of independent white noise innovations. $Y_{i,t}$ is the vector y of variable return for S&P 500 and Bitcoin. $X_{i,t-j}$ represents the vector that contains different variables, such as positive sentiment, neutral sentiment, negative sentiment, volatility, Google trend, interest rate, and exchange rate. The lag selection was based on the Schwarz Criterion (SC), the Akaike Information Criterion (AIC), and the Hannan-Quinn (HQ) Criterion. However, the suggested lag for S&P 500 stock and Bitcoin assets has an autocorrelation problem. To solve this problem, the lag apart from the suggested lags was chosen, which was lag 2 for Bitcoin and lag 3 for S&P 500. With this VAR model, this study then performed a linear Granger causality test (Granger 1969). For a linear system, the Granger causality test can be expressed as follows:

$$\Delta Y_{i,t} = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta Y_{i,t-1} + \sum_{i=1}^{m} \beta_{2i}\, \Delta X_{i,t-1} + \varepsilon_{i,t} \quad (5)$$

This study has conducted the Variance Decomposition (VDC) analysis, which is a vital method in a VAR model (Dizaji 2019; Siriopoulos et al. 2021). The VDC can decompose the forecast error of the S&P 500 and Bitcoin current returns shock to different variables. The forecast error of VDC is highly dependent on the ordering of the variable. Consequently, the results of VDC could change based on the ordering. Thus, Dizaji (2019) suggest that variable ordering should follow economic theory from most exogenous variable to endogenous. Following that Google trend and sentiment variables is admittedly the most exogenous variable in our model; hence it is listed as the first and second variable. Macroeconomic variables come next in the Cholesky ordering, after the first and second variables. Subsequently, volatility and return are the two most endogenous variables in the Var system and are ordered as the fourth and fifth variables. This study has also conducted a diagnostic test of the estimated VAR model using the inverse roots of the AR characteristic polynomial (VAR stability) and the VAR residual serial correlation Lagrange Multiplier (LM) test for S&P 500 and Bitcoin datasets separately. The VAR stability results indicated that the absolute values of Eigenvalue were less than one and all points were positioned in the circle. The VAR residual serial correlation LM test showed no serial correlation problem in the VAR estimation. Thus, the diagnostic criteria indicated that the estimated VAR model was stable and satisfactory. The diagnostic test results are reported in the Appendix, Figure 1 (Eigenvalue Stability), and Table 3 (LM Autocorrelation).

RESULTS

1. VAR ESTIMATION

TABLE 1. VAR Results for return of Bitcoin and S&P 500

	Bitcoin	S&P 500
	Return	Return
Panel A: VAR Estimates		
Constant	0.0073	0.1046
	(0.0879)	(0.1195)
$Return_{t-1}$	0.0599	-0.0398
	(0.0919)	(0.1362)
$Return_{t-2}$	-0.2940***	-0.0840
	(0.0941)	(0.1377)
$Return_{t-3}$		-0.0561
		(0.1380)
Positive $Sentiment_{t-1}$	0.1990*	-0.3512**
	(0.1113)	(0.1623)
Positive $Sentiment_{t-2}$	-0.2856**	-0.3500**
	(0.1162)	(0.1600)
Positive $Sentiment_{t-3}$		0.1538
		(0.1568)
Neutral $Sentiment_{t-1}$	0.1150	0.1325
	(0.1107)	(0.1401)

continue ...

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Neutral Sentiment$_{t-2}$	-0.1609	0.1671
	(0.1067)	(0.1467)
Neutral Sentiment$_{t-3}$		-0.0474
		(0.1396)
Negative Sentiment$_{t-1}$	-0.0292	0.0527
	(0.1295)	(0.1681)
Negative Sentiment$_{t-2}$	-0.1324	0.0985
	(0.1251)	(0.1675)
Negative Sentiment$_{t-3}$		0.0810
		(0.1554)

	Bitcoin	S&P 500
	Return	Return
Panel A: VAR Estimates		
Volatility$_{t-1}$	0.1043	-0.5106**
	(0.1502)	(0.2331)
Volatility$_{t-2}$	0.0865	0.2379
	(0.1537)	(0.2577)
Volatility$_{t-3}$		-0.1353
		(0.2679)
Google Trend$_{t-1}$	0.0831	-0.2661
	(0.1360)	(0.1969)
Google Trend$_{t-2}$	0.1496	0.3876
	(0.1282)	(0.2421)
Google Trend$_{t-3}$		-0.1139
		(0.1711)
Interest Rate$_{t-1}$	-0.2645**	0.0548
	(0.1226)	(0.1694)
Interest Rate$_{t-2}$	0.0410	-0.1002
	(0.1241)	(0.2141)
Interest Rate$_{t-3}$		0.1297
		(0.1695)
Exchange Rate$_{t-1}$	0.2213	-1.0220*
	(0.5190)	(0.5867)
Exchange Rate$_{t-2}$	-0.7603	-0.9057
	(0.5254)	(0.6757)
Exchange Rate$_{t-3}$		-0.2937
		(0.6454)
Panel B: Test for Granger-causality		
Positive Sentiment	6.9577**	11.7924**
Neutral Sentiment	2.6542	2.8405
Negative Sentiment	1.8896	1.5708
Volatility	3.6584	7.0777*
Google Trend	5.4504*	2.8161
Interest Rate	4.8032*	0.6993
Exchange Rate	2.5289	3.8056

continue ...

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Observations	120	83
R^2	0.24	0.34
Durbin-Watson Stat	2.09	1.94

Note: Panel A is VAR estimation and Panel B is Granger causality test. Standard error values are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Source: Author's calculations

Table 1 lists the findings of the VAR models, with the coefficient estimates shown in Panel A and the Granger causality results shown in Panel B. Based on the VAR estimation of Bitcoin, the results showed that previous positive sentiments did affect Bitcoin return, with a significant positive at lag 1 and a significant negative at lag 2 at the 10% and 5% significance levels, respectively. These results were supported by the Granger causality results, as they indicated successful rejection of the null hypothesis, which is positive emotion with Granger cause return at the 5% significance level. According to Chen et al. (2020), this mix of positive and negative relationships at lags between user sentiment and Bitcoin return was due to Bitcoin prices being incredibly volatile during the coronavirus outbreak. Moreover, the reaction of Bitcoin return with sentiment was more consistent with transient sentiment shocks (Hasan 2022). This study also found that past interest rates had significantly affected return at lag 1 on the 5% significance level. This observation demonstrated that an increase in interest rate will lead to a reduction in return the following day. Furthermore, the Granger causality test showed that the previous interest rate led the Granger to return to be at 10% significance level. This outcome was consistent with those of past studies (Ting et al. 2021), whereby Bitcoin return was negatively correlated with the US interest rate. Also, the Bitcoin market tends to be impacted by the Federal Reserve Bank's decision on the macroeconomic variable since the USD captured approximately 70% of Bitcoin transactions in 2021.

Meanwhile, the VAR estimation for S&P 500 revealed that preceding positive sentiments significantly influenced returns at lag 1 and lag 2, both at 5% significance level. These findings illustrated that an increase in positive sentiments will lead to a decrease in the returns at lag 1 and lag 2. The findings are supported by the Granger causality results at 5% significance level, as shown in Panel B of Table 1, and are consistent with Reis and Pinho (2020). The authors discovered that the US stock market would respond more in anticipation of current sentiments, which is a measure of present and potential worry and anxiety. Ding et al. (2020) also pointed out that market perceptions of the pandemic have a considerable impact on the stock price. Nevertheless, this study has discovered that S&P 500 returns at lag 1 were influenced by prior volatility at 5% significance level, which suggested that an increase in volatility will cause a decrease in return the following day. Moreover, the Granger causality test has shown that information on preceding volatility can be very useful in predicting future returns.

On the other hand, the estimation results showed that S&P 500 returns were not considerably influenced by past exchange rates since the coefficient was only statistically significant at the 10% significance level. This observation is supported by the Granger causality results listed in Panel B of Table 1, which does not reject the null hypothesis since the exchange rate does not Granger cause return. Based on these results, S&P 500 returns were unaffected by factors, such as Google trend, interest rate, and exchange rate. Thus, user sentiments on Twitter have the potential to influence the S&P 500 market, apart from investors' attention in Google searches and macroeconomic indicators. Additionally, the US has the highest number of Twitter users compared to other countries.

VARIANCE DECOMPOSITION METHOD

TABLE 2. Variance decomposition of return

Assets	Days	S.E	Google Trend	Positive Sentiment	Neutral Sentiment	Negative Sentiment	Interest Rate	Exchange Rate	Volatility	Return
S&P 500										
	1	0.97	1.42	7.10	0.43	0.31	0.81	0.47	0.00	89.45
	2	1.09	3.48	13.61	2.46	0.90	0.90	3.14	5.31	70.20
	3	1.14	3.29	14.94	3.74	0.90	1.32	2.99	7.28	65.55
	4	1.16	3.77	15.39	3.65	1.75	1.72	2.95	7.08	63.69
	5	1.18	4.67	15.39	3.95	1.72	1.80	2.90	7.41	62.17
	6	1.19	5.15	15.21	4.41	1.98	1.91	2.88	7.49	60.98
	7	1.20	5.33	15.45	4.35	2.11	2.13	2.89	7.57	60.17

continue ...

... continued

	8	1.20	5.31	15.39	4.34	2.12	2.29	2.90	7.78	59.87
	9	1.20	5.30	15.43	4.37	2.16	2.30	2.90	7.79	59.75
	10	1.20	5.29	15.40	4.46	2.19	2.30	2.90	7.78	59.67
	11	1.20	5.31	15.40	4.46	2.23	2.31	2.92	7.83	59.55
	12	1.20	5.34	15.41	4.45	2.23	2.32	2.92	7.82	59.50
	13	1.20	5.35	15.41	4.46	2.23	2.32	2.92	7.83	59.48
	14	1.20	5.35	15.41	4.47	2.24	2.33	2.92	7.83	59.46
	15	1.20	5.35	15.41	4.47	2.24	2.33	2.92	7.83	59.46
Bitcoin										
	1	0.94	0.04	0.50	0.61	0.10	0.39	1.22	0.11	97.04
	2	0.99	0.05	3.48	1.34	0.13	4.22	1.22	0.46	89.09
	3	106	3.04	3.76	1.39	0.74	3.67	1.96	1.40	84.03
	4	1.07	3.94	4.32	1.77	0.73	3.74	1.92	1.58	81.99
	5	1.08	3.87	4.31	1.79	0.79	3.89	2.35	1.59	81.39
	6	1.08	3.87	4.32	1.80	1.03	3.89	2.35	1.64	81.09
	7	1.08	3.86	4.35	1.80	1.10	3.89	2.36	1.67	80.97
	8	1.09	3.86	4.35	1.81	1.11	3.88	2.36	1.69	80.93
	9	1.09	3.86	4.35	1.81	1.13	3.89	2.37	1.72	80.88
	10	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.74	80.85
	11	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.76	80.84
	12	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.77	80.82
	13	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.78	80.81
	14	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.78	80.81
	15	1.09	3.86	4.35	1.81	1.14	3.89	2.36	1.79	80.80

Source: Author's calculations

Table 2 shows the influence of several variables, namely, Google trend, positive sentiment, neutral sentiment, negative sentiment, interest rate, exchange rate, volatility, and return on the forecast error variance (FEV) of S&P 500 and Bitcoin current returns after a 15-day forecasting horizon. This study found that S&P 500's return shock can explain the greatest part of its own FEV but in a decreasing trend in the following days. On the first day of the forecast, the S&P 500 return illustrated 89.45% of its return, although it only interpreted 59.46% on the 15th day. Apart from the influences of its return shocks, sentiment variables (especially positive sentiments) on Covid-19 showed their importance in the S&P 500 market compared with volatility, Google trend, exchange rate, and interest rate by explaining the FEV of S&P 500 current return with more than 15% starting from the fourth until the 15th day. These outcomes were in agreement with the VAR estimations, which showed S&P 500 current return being negatively influenced by positive sentiment. Volatility shock has also contributed to the fluctuation of the S&P 500 current return, which recorded more than 7% from the third until the 15th day. Meanwhile, neutral sentiment and negative sentiment only explained less than 5% and 3%, respectively, on the FEV of the S&P 500 current return on most days. On the other hand, the highest outcome for Google trend based on the FEV of the S&P 500 current return was 5.35% on the last three days of the forecast. Interest rate and exchange rate can only explain the FEV of the S&P 500 current return at lower than 3% most of the forecast period. These results once again confirmed the influence of user sentiments on the S&P 500 market.

As expected, the largest portion of the FEV of Bitcoin current return can be explained by the Bitcoin return itself compared to other indicators. On the first day of the forecast, the return displayed 97.04% of the FEV of Bitcoin current return and this value decreased on the remaining days reaching 80.80% on the 15th day. Furthermore, the positive sentiment shock has priority in showing the FEV of Bitcoin current return after the return variable, which was higher than 4% on the fourth day and this value was consistent until the 15th day. Neutral sentiment and negative sentiment could only explain lower than 2% of the FEV of Bitcoin current return most of the days. Similar to the S&P 500 market, positive sentiments can illustrate quite a large portion of the FEV of Bitcoin current return after its return shock, and the relationship between positive sentiment and Bitcoin return was also significant in VAR findings. Moreover, volatility contributed less than 2% to the FEV of Bitcoin current return from the third to the 15th day of the forecast. Interest rate and exchange rate recorded the highest FEV of Bitcoin current return at 4.22% on the second day and 2.37% on the ninth day, respectively. Google trend showed its highest explanation of the FEV of Bitcoin current return on the fourth day at 3.94%.

This study has examined the influence of user sentiments regarding Covid-19 on Twitter on the returns of the S&P 500 and Bitcoin. Previous studies have reported that changes in investor behaviours as a result of Covid-19 exert an impact on a country's financial market (Del Lo et al. 2022; Shields et al. 2021; Siriopoulos et al. 2021). Furthermore, the emergence of financial market uncertainty due to Covid-19 was the main reason for stock markets experiencing a negative return (Hussain & Omrane 2021; Salisu et al. 2020). Financial markets are also easily influenced by current issues and information on these issues on social media (Beckers 2018). Kong et al. (2023) and Siriopoulos et al. (2021) suggested that policymakers need to know the real reasons for the fluctuations in the financial markets in relation to unprecedented events such as Covid-19 to restabilize the markets by taking the appropriate measures. These results confirmed that positive sentiments can have a significant negative impact on S&P 500 return. These findings have also revealed that the return had decreased, even when there was positive news about Covid-19 on Twitter. This could have happened due to the large number of reported cases and deaths caused by the pandemic, which increased drastically in the US and hold the first position in the stated criteria[16]. Nippani and Washer (2004) reported that shareholders were not interested in investing in countries that were affected by new diseases for the reason that most economic activities cannot operate as usual and the money supply was reduced in the market during the Covid-19 lockdown period. The findings of this study were further strengthened by the arguments in earlier studies (Hirshleifer et al. 2020; Jitmaneeroj 2017), whereby investor sentiments regarding certain issues tend to influence their investment decisions and the financial asset prices. Furthermore, Huerta et al. (2021) agreed that users' discussions on Twitter will have an impact on their behaviour. Kraaijeveld and De Smedt (2020) also pointed out that psychological and sentiment perspectives can play significant roles in investment decisions, which is consistent with the behavioural science theory. Investors can also use this knowledge to formulate beneficial investment strategies (Hasan 2022).

CONCLUSION

This paper has presented the significant role of user sentiments on the returns of the S&P 500 and Bitcoin, whereby the fluctuations in their returns were influenced by the sentiment indicator. We revealed empirical findings that S&P 500 return was negatively impacted by users' positive sentiment on Twitter, thus policymakers in the US should accordingly emphasize the importance of user behaviour on Twitter regarding certain issues in the process of formulating related government policies. One of the beneficial steps that policymakers can take is to spread the news about monetary policy plans that will be implemented during a financial crisis and ways to strengthen financial markets on Twitter. Subsequently, policymakers could build a good impression regarding the financial market among the investors and the common public. In the same way, the findings of this study could help investment managers to draw profitable structural investment portfolios, especially in an unwanted situation like Covid-19. Based on the findings of this study, Bitcoin return was affected by users' positive sentiment but showed mixed positive and negative results. This mix could have occurred since Bitcoin prices went through high fluctuations during the pandemic period and the impact of these sentiments was only temporary. This observation was proven by the high demands and elevated prices of Bitcoin during the Covid-19 pandemic, which demonstrated that investors preferred to invest in the Bitcoin market compared to other assets. However, this research has limitations in terms of data collection from other social media platforms such as Facebook, TikTok, and YouTube. Further, data from Twitter can manually be collected only in real-time thus obviating the compilation of earlier twits. Future research may consider comparing the stock markets between countries with low and high active Twitter usage. Investors should get a clear understanding on the impact of user sentiments on Twitter in countries with active and inactive users.

NOTES

1 https://www.who.int/docs/default-source/coronaviruse/situationreports/20200131-sitrep-11-ncov.pdf?sfvrsn=de7c0f7_4.
2 https://www.who.int/docs/default-source/coronaviruse/situationreports/20200311-sitrep-51-covid- 19.pdf?sfvrsn=1ba62e57_10.
3 https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression.
4 http://data.bitcoinity.org/markets/volume.
5 https://www.statista.com/statistics/863917/number-crypto-coins-tokens/
6 https://coinmarketcap.com.
7 https://www.statista.com/topics/737/twitter 2021.
8 https://bitinfocharts.com and https://trends.google.com.
9 https://www.statista.com/statistics/number-of-active-twitter-users-in-selected countries.
10 https://twitter.com/i/flow.
11 https://www.investing.com.
12 https://developer.twitter.com/en/docs/twitter-api.
13 RStudio. (2011). Version 3.6.2. Affero General Public License v3.
14 https://fred.stlouisfed.org.
15 https://www.python.org.
16 https://www.worldometers.info/coronavirus/#countries.

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APPENDIX

TABLE 1. Descriptive statistics

1. S&P 500

	Return	Volatility	Positive Sentiment	Neutral Sentiment	Negative Sentiment	Google Trend	Exchange Rate	Interest Rate
Mean	4.08E-17	-9.44E-17	-2.86E-16	1.23E-16	3.62E-16	-2.70E-16	-3.35E-15	4.18E-16
Median	0.1356	-0.4778	0.1159	0.0750	0.1987	0.0685	-0.1712	-0.0700
Maximum	2.4032	2.7756	3.8834	4.1439	1.8896	2.7856	1.9609	3.9874
Minimum	-2.7855	-1.0652	-2.6531	-3.0123	-2.9805	-1.9474	-1.5973	-4.1273
Std. Dev.	1	1	1	1	1	1	1	1
Skewness	-0.3350	1.0339	-0.3934	0.0123	-1.3952	0.6251	0.3852	-0.5044
Kurtosis	3.2678	3.0206	6.0993	6.6659	4.9228	4.1670	1.9074	11.4687

Source: Author's calculations

2. Bitcoin

	Return	Volatility	Positive Sentiment	Neutral Sentiment	Negative Sentiment	Google Trend	Exchange Rate	Interest Rate
Mean	-5.05E-17	1.26E-17	1.05E-16	2.49E-16	8.85E-16	1.27E-16	-1.30E-15	-3.89E-16
Median	0.0659	-0.2400	0.1353	0.0018	0.1609	-0.0854	-0.1488	-0.0540
Maximum	2.6648	2.7570	4.0942	4.2498	1.8545	2.7658	1.9734	4.3707
Minimum	-3.3183	-1.5501	-2.7796	-3.0607	-3.1313	-2.1220	-1.5797	-4.4786
Std. Dev.	1	1	1	1	1	1	1	1
Skewness	-0.3574	0.8505	-0.5268	0.1028	-1.4305	0.4122	0.3596	-0.4300
Kurtosis	3.7295	3.1845	5.9867	6.2536	4.9755	3.5083	1.9299	12.1510

Source: Author's calculations

TABLE 2. Augmented Dickey Fuller unit root test

Variable	ADF			
	Level		1st diff	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
S&P 500				
Return	-9.7629***	-9.6963***	-8.7047***	-8.6523***
Volatility	-2.7198*	-2.8884	-11.3407***	-11.2722***
Positive Sentiment	-7.2054***	-7.1137***	-8.4829***	-8.6232***
Neutral Sentiment	-7.4722***	-7.4077***	-11.1001***	-11.1355***
Negative Sentiment	-5.6737***	-5.7392***	-12.3261***	-9.7379***
Google Trend	-4.5694***	-4.5510***	-12.2557***	-12.2040***
Interest Rate	-6.9407***	-6.9989***	-9.3194***	-9.3308***
Exchange Rate	-0.09101	-2.9217	-11.4424***	-11.4758***
Bitcoin				
Return	-9.4388***	-9.6187***	-10.6463***	-10.6001***
Volatility	-3.7242***	-3.718**	-11.6701***	-11.6212***
Positive Sentiment	-7.2054***	-7.1137***	-8.4829***	-8.6232***
Neutral Sentiment	-7.4722***	-7.4077***	-11.1001***	-11.1355***
Negative Sentiment	-5.6737***	-5.7392***	-12.3261***	-9.7379***
Google Trend	-4.5694***	-4.5510***	-12.2557***	-12.2040***
Interest Rate	-7.2793***	-7.3833***	-9.5047***	-9.5521***
Exchange Rate	-0.3484	-2.9206	-12.4644***	-12.4917***

Note: *Null hypothesis rejection at 10%, **Null hypothesis rejection at 5% and *** Null hypothesis rejection at 1%.
Source: Author's calculations

TABLE 3. VAR residual serial correlation LM test

Assets	Lags	LM Test	P-Value
S&P 500	1	0.8263	0.8173
	2	0.9846	0.5154
	3	0.9795	0.5259
	4	0.9304	0.6263
Bitcoin			
	1	1.0918	0.3008
	2	1.1776	0.1741
	3	1.0970	0.2919

Note: *Ho no serial correlation at lag order h
Source: Author's calculations

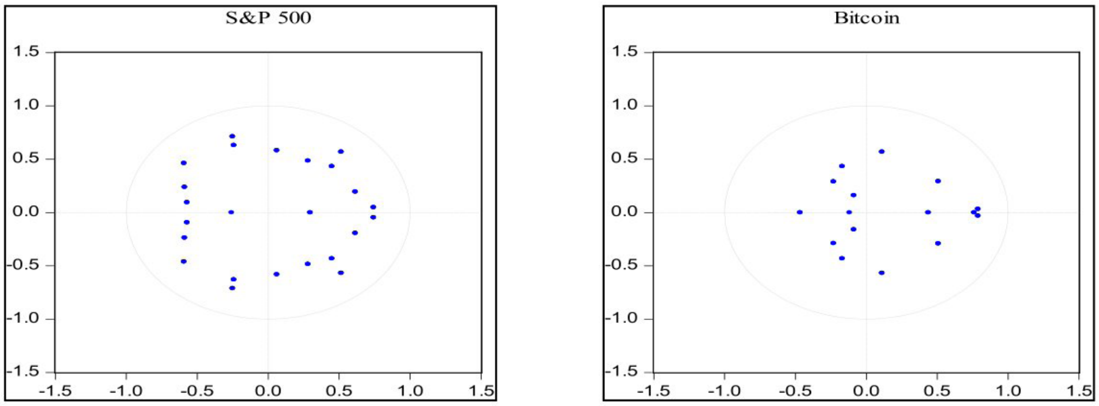

FIGURE 1. Inverse roots of AR characteristic polynomial.
Source: Author's calculations