

# The effect of hashrate, transaction volume, social media and macroeconomics on Bitcoin before and during the COVID-19 pandemic

Factors  
affecting  
Bitcoin price  
return

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## Abstract

**Purpose** – This research aims to determine the factors that affected Bitcoin price return in the period before and during the COVID-19 pandemic.

**Design/methodology/approach** – The independent variables used in this study are hashrate, transaction volume, social media and some macroeconomics variables. The data are processed using the vector error correction model (VECM) to determine the short-term and long-term relationships between variables.

**Findings** – The research shows that (1) Twitter and Gold significantly affected Bitcoin in the short term before the COVID-19 pandemic; (2) hashrate, transaction volume, Twitter and the financial stress index had a significant effect on Bitcoin in the long term before the COVID-19 pandemic; (3) the volatility index had a significant effect on Bitcoin in the short term during the COVID-19 pandemic; and (4) hashrate, transaction volume, Twitter and CHF/USD had a significant effect on Bitcoin in the long term during the COVID-19 pandemic.

**Research limitations/implications** – This research provides explanation about factors affecting Bitcoin so investors and regulators can pay more attention and prepare for the potential risks as well as to get a good understanding of market conditions for greater crypto adoption in the future.

**Originality/value** – The novelty in this study is the various factors driving the Bitcoin price were analyzed before and during the COVID-19 pandemic including the social media, as sentiment, interestingly, is being a predictive power for Bitcoin price return.

**Keywords** Cryptocurrency, COVID-19, Twitter, VECM method, Short and long-term relationships

**Paper type** Research paper

## 1. Background

The ongoing COVID-19 pandemic has made the world experience a significant risk showed by huge uncertainty jumps in all economic indicators (Altig *et al.*, 2020). One of the digital assets, cryptocurrency, has become a hot topic discussed by investors and public during the COVID-19 pandemic. Bitcoin is one of the most popular cryptocurrencies among investors due to its largest market capitalization in cryptocurrencies (Gurdgiev and O'Loughlin, 2020). Price changes in Bitcoin are very fast and difficult to predict. As investors in the market, they should probably turn their attention to cryptocurrencies. Bitcoin price has become a leading indicator of economic condition and remains higher during the COVID-19 pandemic. The price of Bitcoin increased significantly in October 2021 and reached to USD65,000. However, in an empirical study by Umar and Gubareva (2020), interestingly, the potential role of



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cryptocurrencies as alternative investment (asset diversification) has been particularly negatively impacted by the COVID-19 pandemic.

The fast price movements and fluctuations of Bitcoin are influenced by various factors. The internal and external factors are, for example, the supply of Bitcoin, the cost of producing a Bitcoin through the mining process, the market's demand, the other competing cryptocurrencies, government regulations, news and macroeconomics (Poyser, 2019). There is a perception that the price of Bitcoin is linked to its hashrate, the speed to solve hashes, over a long period of time in blockchain system (Fantazzini and Kolodin, 2020). In addition, other factors that influence Bitcoin price movements are also important to be considered, especially social media and macroeconomic factors. The exchange of information on social media has become active to this day, which makes social media as a reference in predicting cryptocurrencies price, especially through Twitter. Twitter has become a place of signaling through tweets made by professional investors (Mirtaheri *et al.*, 2019).

Macroeconomic factors such as equity indices, equity market volatility, foreign exchange and commodities have possibility to influence Bitcoin price. Not only that factors which may affect Bitcoin price, some other factors such as foreign exchange, crude oil and gold also possibly have correlation with Bitcoin. They are similar in term of their role of hedging.

This research is based on several research gaps from previous studies. According to Mai *et al.* (2018), social media sentiment is an important predictor of Bitcoin valuation, but not all social media have the same impact. Ciaian *et al.* (2016) found that the Dow Jones Index, exchange rates and oil prices significantly affect Bitcoin prices in the short term. Macroeconomic developments have the potential to encourage the use of Bitcoin in trading and exchange, thereby increasing demand, which will have a positive impact on Bitcoin price. Corbet *et al.* (2018) found a short-term relationship between Bitcoin and Ethereum in terms of blockchain position, hashrate and liquidity in their study. This is due to the fact that fundamentals have the ability to influence the prices of these two cryptocurrencies.

To avoid biased results when looking at only one factor at a time, the various factors driving the Bitcoin price must be analyzed concurrently. As far as we believe, that is our novelty in this paper. This study used internal and external factors simultaneously to compare conditions before and during the COVID-19 pandemic. This study applied the vector error correction model (VECM) to see the effect of internal and external factors on Bitcoin in the both long term and short term, as the ongoing COVID-19 pandemic has had a major impact on the world economy. This methodology also carried out the stationary test, lag length test, VAR stability test, cointegration test and Granger causality test. The variables in this study are found to have one or more cointegrating vectors. To avoid biased results, this study uses various factors that affect Bitcoin price. Therefore, this study will focus on whether the hashrate, transaction volume, social media and macroeconomics have an impact on Bitcoin price before and during the COVID-19 pandemic.

The results of the current study reveal that different factors affect Bitcoin prices in short and long terms, before and during the pandemic. Twitter and Gold significantly affected Bitcoin in the short term before the COVID-19 pandemic. Hashrate, transaction volume, Twitter and the financial stress index had a significant effect on Bitcoin in the long term before the COVID-19 pandemic. The volatility index had a significant effect on Bitcoin in the short term during the COVID-19 pandemic. Hashrate, transaction volume, Twitter and CHF/USD had a significant effect on Bitcoin in the long term during the COVID-19 pandemic. In contrast, there is no evidence that S&P 500 Index, foreign exchange rate and crude oil had effect on Bitcoin.

Our paper has twofold implications. Firstly, analyzing how Bitcoin price influenced by economic and non-economic factors can be very beneficial to understand the movement of alternative asset, especially when investors and/or regulators want to make decision. Secondly, social media or news, empirically can be watched as indicator to explain Bitcoin price return.

The remaining sections of this study as follows. [Sections 2](#) provides literature review and hypothesis development. [Section 3](#) describes the research methods. [Section 4](#) reports the study's findings and discusses the main results. Lastly, [Section 5](#) concludes.

## 2. Literature review and hypotheses development

Development of Bitcoin has intrigued scholars' interest in decentralized finance. Bitcoin is a virtual currency that uses a cryptographic hash algorithm with a combination of private and public keys ([Lopez-Cabarcos et al., 2019](#)). Bitcoin was first invented and developed by Satoshi Nakamoto in January 2008, then first mined on January 3, 2009 ([Deniz and Teker, 2020](#)). Bitcoin became the basis for blockchain, which first appeared and was used on the largest scale, which then gradually separated blockchain technology from the Bitcoin network ([Wang and Su, 2020](#)). The three main aspects of blockchain technology are summarized according to blockchain technology analysis, namely cryptography, consensus mechanisms and smart contract ([Upadhyay et al., 2021](#); [Lim et al., 2021](#)).

There is abundant literature investigating factors affecting Bitcoin movements. One of them is the hashrate. The hashrate of a computer is the rate at which it completes Bitcoin operations ([Corbet et al., 2018](#)). Hashrate is measured in hashes per second where one hash is equal to double SHA-256 calculations ([Fantazzini and Kolodin, 2020](#)). In mining cryptocurrencies, Bitcoin in particular has a level of complexity that refers to a computational puzzle that is directly related to the hashrate, so that when the hashrate increases or decreases, the algorithm on Bitcoin will underlie to adjust the mining difficulty ([Kjaerland et al., 2018](#)). A higher hashrate at the time of mining will increase the miner's chances of finding the next block and receiving payment ([Corbet et al., 2018](#)).

[Kjaerland et al. \(2018\)](#) show that hashrate has a positive effect on Bitcoin. [Corbet et al. \(2018\)](#) also reveal that hashrate affects Bitcoin significantly. It occurs since there is a short-term relationship between Bitcoin and hashrate, which shows that fundamental factor affects the dynamics of the Bitcoin prices. Thus, we develop our [hypothesis 1](#), as below:

- H1.* Hashrate has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

Transaction volume is the traditional supply and demand transaction that may have an effect on cryptocurrencies, especially Bitcoin ([Kjaerland et al., 2018](#)). Transaction volume is measured by the total value of transactions on the Bitcoin network, which is then multiplied by the weekly average Bitcoin price ([Fantazzini and Kolodin, 2020](#)). If investor interest increases, the price of Bitcoin will be higher. Thus, we develop our [hypothesis 2](#), as below:

- H2.* Transaction volume has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

Since the emergence of social media platform, greater attention has been given to the empirical evidence of the effect of social media on financial assets. Bullish or bearish investor sentiment can drive the movement in Bitcoin ([AlNemer et al., 2021](#)). One way to provide or obtain information on Twitter is by using hashtags, user selection and keyword detection ([Mirtaheri et al., 2019](#); [Smuts, 2018](#)). Twitter has a short-term impact on cryptocurrencies ([Li et al., 2021](#)). [Kraaijeveld and Smedt \(2020\)](#) state that sentiment on Twitter has the ability to predict Bitcoin returns. [Kremser et al. \(2019\)](#) state Twitter has a significant influence on Bitcoin price in the long run. Thus, we develop our [hypothesis 3](#), as below:

- H3.* Twitter has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

The S&P 500 Index is used to measure global economic activity (Yilmazkuday, 2023). Sovbetov (2018) discovered that the S&P 500 Index has a long-term positive impact on Bitcoin but a short-term negative impact. The S&P 500 Index's long-term positive impact on Bitcoin confirms that when the S&P 500 rises, the USD rises against fiat currencies, including cryptocurrencies. The negative effect is caused in the short term by the negative correlation between the price of Bitcoin and the S&P 500 Index. Thus, we develop our hypothesis 4, as below:

- H4.* S&P 500 Index has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

In pursuance of Hoang and Syed (2021), the volatility index (VIX) is an indicator related to the volatility of the United States (US) financial market. Investor expectations and investment policies are built on the amount of uncertainty or risk represented by the VIX. The higher the VIX, the greater the fear of investors. Gaies *et al.* (2021) stated that VIX significantly affects Bitcoin returns in the short term. While in the research of Chang *et al.* (2021) stated that VIX has a significant effect on Bitcoin in the long run. Bitcoin investor sentiment is influenced by the VIX. When the VIX reaches a high level, the Bitcoin price can drop drastically. Thus, we develop our hypothesis 5, as below:

- H5.* VIX has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

The FSI is a description of the pressure on global financial markets which includes interest rates, credit and volatility. FSI is a benchmark for investors as market participants in making decisions and better investment risk management (Bouri *et al.*, 2018b). Gozbasi *et al.* (2021) state that FSI has a significant negative effect on Bitcoin in the short term since Bitcoin price has sensitivity to market risk. Gaies *et al.* (2021) state that FSI significantly affects Bitcoin returns in the short and long terms. Thus, we develop our hypothesis 6, as below:

- H6.* FSI has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

Foreign exchange (forex) is one of the most important economic indicators for all countries (Yasir *et al.*, 2019). The principle of foreign exchange is the same as the economic concept: supply and demand. Some previous studies and Urquhart and Zhang (2019) state that the price of Bitcoin is affected by the British pound sterling (GBP) positively and significantly. This shows the existence of hedging, that is, when the currency increases per US dollar, the price of Bitcoin will increase. Sathyanarayana and Gargesa (2019) and Majdoub *et al.* (2021) show that GBP has a significant negative effect on Bitcoin in the short and long terms. The existence of a significant influence signals that there is asymmetric conditional volatility in Bitcoin. Thus, we develop our hypothesis 7, as below:

- H7.* Foreign exchange rate has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

Crude oil is a combination of oil mixed with water to form a water-in-crude oil emulsion caused by factors such as high shear in coconut production wells and active chemicals that are naturally present in crude oil (Saad *et al.*, 2019). Crude oil is one of the most important commodities for the global economy. Oil prices are very important for global macroeconomic indicators. Fluctuations in oil prices will have both positive and negative impacts on each country. Jareno *et al.* (2020) find that crude oil has a significant negative effect on Bitcoin returns. Extreme market conditions tend to be sensitive to Bitcoin. Ciaian *et al.* (2016) also find that crude oil has an effect on cryptocurrencies in the short term but will have no effect in the long term. This occurs as a result of changes in the price of oil signaling the potential for

changes in the general price level to cause a depreciation or appreciation in the price of Bitcoin. According to Wang *et al.* (2016), the price of oil affects Bitcoin significantly in the short and long terms. In the short term, the price of oil has little impact on Bitcoin. The existence of a close relationship between oil prices and investor behavior illustrates the inflation expectations of investors to some extent, which will affect Bitcoin prices indirectly. Thus, we develop our hypothesis 8, as below:

- H8. Crude oil has a significant impact on Bitcoin price return in the short and long terms in the period before and during the COVID-19 pandemic.

Gold is among the most popular investments among investors. Gold has become a phenomenon that affects people of all income levels (Singh and Joshi, 2019). Gold has advantages as an investment option. Gold is considered a hedge for investment portfolios that affect investment decisions (Gonzalez *et al.*, 2021). This is due to the assumption that gold prices will continue to increase in the future (Hoang and Syed, 2021). Investor awareness of market risk in equity causes gold to be the best choice for hedging their investment portfolios (Robiyanto *et al.*, 2020). In the study of Jareno *et al.* (2020), the return of gold prices has a significant influence on Bitcoin in the short and long terms. The significant relationship shows that Bitcoin can be considered a safe haven in extreme shock. Bouri *et al.* (2018a) also state that gold has an influence on Bitcoin in the short and long terms because Bitcoin is sensitive to macroeconomic indicators. According to Zwick and Syed (2019), gold has a long-term relationship with Bitcoin since gold affects Bitcoin significantly, which shows gold can play a role in predicting the price of Bitcoin. Thus, we develop our hypothesis 9, as below:

- H9. Gold has a significant impact on Bitcoin return in the short and long terms in the period before and during the COVID-19 pandemic.

### 3. Research methods

#### 3.1 Data

To study the effect of hashrate, transaction volume, social media and macroeconomics on Bitcoin, we did sample selection based on our secondary data. We used time series data from January 1, 2018, to December 31, 2021, which will be divided into 2 periods: January 1, 2018 to December 31, 2019 is the period before the COVID-19 pandemic; January 1, 2020 to December 31, 2021, the period during the COVID-19 pandemic. It covers 519 working days in the first period, and 518 working days in the second period. The daily data used is only 5 working days from Monday to Friday. It is adjusted for other variables used in this study, because the operational working day is only 5 days, from Monday to Friday.

Our paper considers the price of Bitcoin as dependent variables. For independent variables, we used hashrate (HR), transaction volume (TRVOL), Twitter, S&P 500 Index (SPX), volatility index (VIX), financial stress index (FSI), foreign exchange rate (GBP/USD, CHF/USD, EUR/USD, JPY/USD), crude oil (CRUDE\_OIL) and gold (GOLD). This study utilizes secondary data in time series from several official websites. This research retrieves the Bitcoin price data, hashrate and transaction volume from *blockchain.com*. Tweets data obtained via Twitter with the hashtag #Bitcoin using Python to determine how much influence each tweet uploaded by the user has in the hashtag. As for the index data for the S&P 500, VIX, foreign exchange, crude oil and gold through the Yahoo Finance website ([www.finance.yahoo.com](http://www.finance.yahoo.com)) returns of each variables are calculated. FSI data are taken from the OFR financial stress index through the website [www.financialresearch.gov](http://www.financialresearch.gov). Table 1 shows variable definition of all samples.

Table 2 provides the descriptive statistics of the variables before the COVID-19 period (Panel A) and during the COVID-19 period (Panel B). The number of observations in the

**Table 1.**  
Variable definition

| Variable  | Definition             | Measurement                                                                           |
|-----------|------------------------|---------------------------------------------------------------------------------------|
| BTC       | Bitcoin                | Price return of Bitcoin                                                               |
| HR        | Hashrate               | The estimated number of terahashes per second the bitcoin network is performing daily |
| TRVOL     | Transaction volume     | The number of coins or tokens traded                                                  |
| TWITTER   | Twitter                | Number of hashtag                                                                     |
| SPX       | S&P 500 Index          | Return of index                                                                       |
| VIX       | Volatility index       | Return of index                                                                       |
| FSI       | Financial stress index | Return of index                                                                       |
| GBP_USD   | Foreign exchange rate  | The value of the British pound against the US Dollar                                  |
| CHF_USD   | Foreign exchange rate  | The value of Swiss franc against the US Dollar                                        |
| EURO_USD  | Foreign exchange rate  | The value of euro against the US Dollar                                               |
| JPY_USD   | Foreign exchange rate  | The value of Japanese yen against the US Dollar                                       |
| CRUDE_OIL | Crude oil              | Price return of crude oil                                                             |
| GOLD      | Gold                   | Price return of gold                                                                  |

**Source(s):** Authors' own work

period before the COVID-19 pandemic was 519, while in the period during the COVID-19 pandemic, it was 518. During both periods, the average returns of the oil market as well as the average returns of gold are negative. It shows that gold returns are lower and negative during the COVID-19 period. In contrast, the mean returns of Bitcoin are positive during the COVID-19 period. The unconditional volatility of all return series is higher during the COVID-19 period. Both Bitcoin and gold have similar risk during both periods, shown by their standard deviation.

### 3.2 Methodology

The data analysis method used in this study is a quantitative data analysis method by using the vector error correction model (VECM). VECM is used to determine the short-term and long-term relationships between one variable and another. The VECM test stages carried out in this study were the stationary test, lag length test, VAR stability test, cointegration test, Granger causality test and VECM model estimation.

The VECM can be expressed as

$$\Delta y_t = \alpha \beta' y_{t-1} + \Gamma_1 \Delta y_{t-1} + \dots + \Gamma_{p-1} \Delta y_{t-p+1} + \Xi^+ D_t + u_t$$

where  $y_t$  is a  $K \times 1$  dimensional vector of variables observed at time  $t$ .

## 4. Results

### 4.1 Stationary test

A stationary test aims to minimize the data change drastically. The unit root test uses the augmented Dickey–Fuller (ADF) test. Table 3 shows the results of the unit root test before and during the COVID-19 pandemic:

Based on the table above, which shows the variables used in the study, it is stated that not all variables are stationary, so differencing is done. The goal of differencing is to convert

**Table 2.**  
Descriptive statistics  
test results

|                                     | Mean      | Minimum    | Maximum    | Std. dev. | Observations |
|-------------------------------------|-----------|------------|------------|-----------|--------------|
| <i>Before the COVID-19 pandemic</i> |           |            |            |           |              |
| BTC                                 | −0.0004   | −0.212381  | 0.225129   | 0.04549   | 519          |
| HR                                  | 1.7E+07   | 0          | 1.09E+08   | 2.8E+07   | 519          |
| TRVOL                               | 495,580   | 0          | 24,528,670 | 1,283,333 | 519          |
| TWITTER                             | 30592.1   | 0          | 111,394    | 20020.2   | 519          |
| SPX                                 | 0.00047   | −0.040979  | 0.049594   | 0.0092    | 519          |
| VIX                                 | 15.4169   | 0          | 37.32      | 5.00955   | 519          |
| FSI                                 | −2.3292   | −4.181     | 0.51       | 0.966     | 519          |
| GBP_USD                             | −0.002    | −1         | 0.020846   | 0.0442    | 519          |
| CHF_USD                             | −0.0019   | −1         | 0.012239   | 0.04406   | 519          |
| EURO_USD                            | −0.002    | −1         | 0.012473   | 0.04406   | 519          |
| JPY_USD                             | −0.0019   | −1         | 2.07E-02   | 0.04408   | 519          |
| CRUDE_OIL                           | −0.0035   | −1         | 0.146764   | 0.06514   | 519          |
| GOLD                                | −0.0016   | −1         | 0.07406    | 0.04614   | 519          |
| <i>During the COVID-19 pandemic</i> |           |            |            |           |              |
| BTC                                 | 0.004413  | −0.371695  | 0.211097   | 0.046795  | 518          |
| HR                                  | 4.4E+07   | 0.000000   | 1.99E+08   | 6.4E+07   | 518          |
| TRVOL                               | 738,828.5 | 0.000000   | 11,240,709 | 1,319,467 | 518          |
| TWITTER                             | 77822.06  | 13987.00   | 363566.0   | 51236.53  | 518          |
| SPX                                 | 0.000860  | −0.119841  | 0.093828   | 0.016152  | 518          |
| VIX                                 | 23.60726  | 0.000000   | 82.69000   | 11.06267  | 518          |
| FSI                                 | −2E+06    | −4,364,000 | 1,026,600  | 2,847,703 | 518          |
| GBP_USD                             | 6.77E-05  | −0.040944  | 0.029489   | 0.005725  | 518          |
| CHF_USD                             | 8.45E-05  | −0.022342  | 0.019785   | 0.004346  | 518          |
| EURO_USD                            | 1.69E-05  | −0.027752  | 0.014573   | 0.004166  | 518          |
| JPY_USD                             | −0.000104 | −0.026333  | 0.022206   | 0.004376  | 518          |
| CRUDE_OIL                           | −0.015344 | −3.059661  | 0.376623   | 0.180616  | 518          |
| GOLD                                | −0.003585 | −1         | 0.057879   | 0.063230  | 518          |

**Source(s):** Authors' own work

| Variable  | Before the COVID-19 pandemic |                             |      |                                          | During the COVID-19 pandemic |                             |      |                                          |
|-----------|------------------------------|-----------------------------|------|------------------------------------------|------------------------------|-----------------------------|------|------------------------------------------|
|           | Prob                         | At the level<br>Description | Prob | First difference<br>level<br>Description | Prob                         | At the level<br>Description | Prob | First difference<br>level<br>Description |
| HR        | 0.97                         | Non-Stationary              | 0.00 | Stationary                               | 0.85                         | Non-Stationary              | 0.00 | Stationary                               |
| TRVOL     | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.64                         | Non-Stationary              | 0.00 | Stationary                               |
| TWITTER   | 0.01                         | Stationary                  | 0.00 | Stationary                               | 0.01                         | Stationary                  | 0.00 | Stationary                               |
| SPX       | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| VIX       | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.01                         | Stationary                  | 0.00 | Stationary                               |
| FSI       | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.28                         | Non-Stationary              | 0.00 | Stationary                               |
| GBP_USD   | 0.08                         | Non-Stationary              | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| CHF_USD   | 0.12                         | Non-Stationary              | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| EURO_USD  | 0.23                         | Non-Stationary              | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| JPY_USD   | 0.16                         | Non-Stationary              | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| CRUDE_OIL | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |
| GOLD      | 0.00                         | Stationary                  | 0.00 | Stationary                               | 0.00                         | Stationary                  | 0.00 | Stationary                               |

**Source(s):** Authors' own work

**Table 3.**  
Stationary test results

nonstationary data into stationary data. The result is that the independent variable is stated to be stationary or that there is no unit root at the first difference level in the period before and during the COVID-19 pandemic.

4.2 Lag length test

A lag length test is carried out to find out how long the period of a variable is affected by endogenous variables in the previous time. The lag length test can see the stability of the VECM model by looking for the maximum lag. The results of the lag length test show that lag 9 is the optimum lag in the period before and during the COVID-19 pandemic. This can be seen from the lowest AIC value found at lag 9. To find out if the VAR estimate is in a stable state or not, it is necessary to carry out testing. In this study, the VAR stability test used roots of characteristic polynomials. Figure 1 is a picture of the results of the VAR stability test before and during the COVID-19 pandemic:

The picture on the left shows the results of the VAR stability test in the period before the COVID-19 pandemic and the picture on the right shows the results of the VAR stability test in the period during the COVID-19 pandemic. Based on the picture above, the roots of characteristic polynomial points are in a circle before and during the COVID-19 pandemic. The existence of a point inside the circle means that the VAR model is in a stable state. The stability of the VAR model can be assessed by the points that are not out of the circle or more than 1 or -1. The point of inverse roots of AR characteristic polynomial outside the circle indicates that the VAR model is not in a stable state.

4.3 Cointegration test

A cointegration test was conducted to determine the long-term relationship that exists between the dependent variable and the independent variable. If the variables are well integrated, then there is a stable long-term relationship. In this study, the cointegration test used the Johansen cointegration test method with a critical value of 5% or 0.05 (MacKinnon et al., 1999). The results of the cointegration test before and during the COVID-19 pandemic are shown in Table 4 as follows:

Based on the table above, it shows that there is a long-term relationship between variables in the period before and during the COVID-19 pandemic from rank 1 to 10. It can be seen that the *p*-value is smaller than the significant level of 0.05, so that the null hypothesis (*H*<sub>0</sub>) is rejected and the alternative hypothesis (*H*<sub>1</sub>) is accepted.

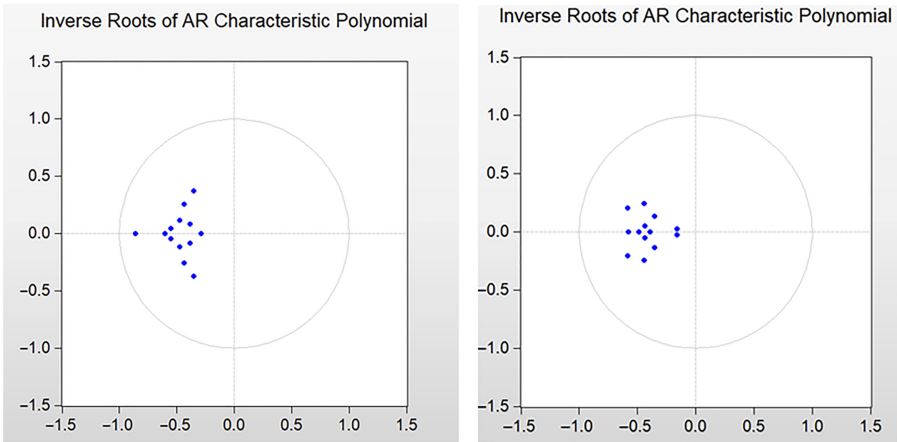


Figure 1.  
VAR stability test  
result

Source(s): Authors' own work

| Hypothesized<br>no. of CE(s) | Before the COVID-19 pandemic                       |                                                       | During the COVID-19 pandemic                       |                                                       |
|------------------------------|----------------------------------------------------|-------------------------------------------------------|----------------------------------------------------|-------------------------------------------------------|
|                              | Unrestricted<br>cointegration rank<br>test (Trace) | MacKinnon<br><i>et al.</i> (1999)<br><i>p</i> -values | Unrestricted<br>cointegration rank<br>test (Trace) | MacKinnon<br><i>et al.</i> (1999)<br><i>p</i> -values |
| At most 1 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0001                                                |
| At most 2 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 3 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 4 *                  | 0.0001                                             | 0.0001                                                | 0.0001                                             | 0.0000                                                |
| At most 5 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 6 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 7 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 8 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 9 *                  | 0.0000                                             | 0.0000                                                | 0.0000                                             | 0.0000                                                |
| At most 10                   | 0.0649                                             | 0.0649                                                | 0.0649                                             | 0.0000                                                |

**Source(s):** Authors' own work

**Table 4.**  
Cointegration test  
results

#### 4.4 Granger causality test

In this study, the Granger causality test was used to determine the causal relationship between the independent variable and the dependent variable. The significant level used in this test is 5% or 0.05 with a lag length of 9, which is adjusted to the optimum lag that has been carried out. Table 5 shows the results of the Granger causality test before and during the COVID-19 pandemic:

Based on Table 5, hashrate, transaction volume, VIX, FSI and crude oil are stated to have no causal relationship with Bitcoin in the period before and during the COVID-19 pandemic. While Twitter showed that there was a two-way causality relationship with Bitcoin in the period before the COVID-19 pandemic, and during the COVID-19 pandemic, Twitter was declared to have no causal relationship with Bitcoin. In CHF/USD, there was a two-way causality relationship with Bitcoin before the COVID-19 pandemic, but in the period during the COVID-19 pandemic, CHF/USD only had a one-way causality relationship where Bitcoin affected it. For GBP/USD and EUR/USD, it is stated that there is a one-way causality relationship with Bitcoin in which Bitcoin affects these two variables before and during the COVID-19 pandemic. At first, the S&P 500 Index did not have a causal relationship with Bitcoin, but during the COVID-19 pandemic, there was a one-way causal relationship. Gold

| Variable           | Before the COVID-19 pandemic   | During the COVID-19 pandemic   |
|--------------------|--------------------------------|--------------------------------|
| Hashrate           | No causality relationship      | No causality relationship      |
| Transaction volume | No causality relationship      | No causality relationship      |
| Twitter            | Two-way causality relationship | No causality relationship      |
| S&P 500 Index      | No causality relationship      | One-way causality relationship |
| VIX                | No causality relationship      | No causality relationship      |
| FSI                | No causality relationship      | No causality relationship      |
| GBP/USD            | One-way causality relationship | One-way causality relationship |
| CHF/USD            | Two-way causality relationship | One Way causality relationship |
| EUR/USD            | One-way causality relationship | One-way causality relationship |
| JPY/USD            | One-way causality relationship | Two-way causality relationship |
| Crude Oil          | No causality relationship      | No causality relationship      |
| Gold               | No causality relationship      | One-way causality relationship |

**Source(s):** Authors' own work

**Table 5.**  
Granger causality test  
results

also has a one-way causal relationship during the COVID-19 pandemic, which means gold is affecting Bitcoin.

4.5 VECM estimation test

For the 12 independent variables used, there is a cointegration relationship between them that needs to be estimated for the VECM model. It is necessary to estimate the VECM model according to the optimum lag that has been obtained previously. The optimum lag used is lag 9, so the estimated form of the VECM equation is VECM. Table 6 shows VECM estimation results.

Based on Table 6, only Twitter and gold had a significant effect on Bitcoin in the short term before the COVID-19 pandemic since the t-stat value is greater than 1.96. This effect is in accordance with the research of Li *et al.* (2021) and Mai *et al.* (2018) where Twitter is home to a social media platform that can signal investors. Significant relationship between gold and Bitcoin shows that Bitcoin can be considered a safe haven in extreme shocks (Jareno *et al.*, 2020). In the long term, before the COVID-19 pandemic, hashrate and transaction volume were declared to have a significant effect on Bitcoin. The existence of a relationship between miners and hashrate can increase the supply and demand for Bitcoin (Rehman and Kang, 2021). Representatives of investor interest can be seen through the transaction volume, which indicates that if investor interest increases, the price of Bitcoin will be higher over time (Sovbetov, 2018). Twitter and FSI were also found to have had a significant influence on Bitcoin in the long run before COVID-19 pandemic. This result is supported by the findings of Kremser *et al.* (2019), which state that Twitter is considered an important predictor for Bitcoin. Twitter is also associated with investor interest as outlined in his writings on the Twitter platform, which makes investors indirectly exchange information with one another that can predict the price of Bitcoin. The FSI, which is stated to have a significant effect on Bitcoin in the long term, is in line with research conducted by Gozbasi *et al.* (2021), which explains that increasingly depressed economic conditions make investors worry so that investors will make decisions to release their investments in Bitcoin so that the price of Bitcoin will decrease.

However, during the COVID-19 pandemic, only VIX affected Bitcoin significantly in the short term. This shows the increasing fear of investors, as seen from the increasing VIX (Lopez-Cabarcos *et al.*, 2019). Moreover, the emergence of the COVID-19 pandemic can make the VIX reach its highest level, which causes the Bitcoin price to collapse. In the long term,

| Variable  | Before the COVID-19 pandemic |           | During the COVID-19 pandemic |           |
|-----------|------------------------------|-----------|------------------------------|-----------|
|           | Short-term                   | Long-term | Short-term                   | Long-term |
| HR        | -0.9583                      | 23.1197   | -0.9950                      | -18.1460  |
| TRVOL     | -0.3017                      | 4.6971    | 1.4712                       | -2.3043   |
| TWITTER   | 1.9757                       | 6.4352    | 1.3453                       | 3.7280    |
| SPX       | -0.8288                      | -1.4517   | 1.0172                       | -0.2318   |
| VIX       | 0.0791                       | 0.0406    | 2.8564                       | 0.0191    |
| FSI       | -1.6271                      | 2.3302    | 1.2421                       | -0.3352   |
| GBP_USD   | -0.3184                      | -1.3147   | -0.4979                      | -0.0838   |
| CHF_USD   | 0.3352                       | 0.2542    | 0.8345                       | 1.9970    |
| EUR/USD   | -0.7553                      | 0.9089    | -0.6512                      | 0.0767    |
| JPY/USD   | -1.5224                      | -1.7383   | 1.9120                       | -0.6946   |
| CRUDE OIL | -0.2464                      | -0.2570   | 0.5475                       | -1.5922   |
| GOLD      | -2.1832                      | 0.6400    | -1.5366                      | -0.5945   |

**Table 6.**  
VECM estimation test  
results

**Source(s):** Authors' own work

hashrate, transaction volume, Twitter and CHF/USD had a significant effect on Bitcoin where the value of  $t$ -statistics is more than 1.96. The hashrate and transaction volume will affect the supply and acceptance of Bitcoin. The higher the hashrate, the greater the chance for a miner to get Bitcoin, which makes the miner provide a greater supply to the market, thus making the Bitcoin price increase. The effect of bullish or bearish messages on Twitter is to increase or decrease the volume of transactions in the market in the next few days, which makes the Bitcoin price move (Kraaijeveld and Smedt, 2020). The reaction to the message was caused by the relationship of irrational factors that turned out to have an influence on cryptocurrency. Investor sentiment formed from tweets within Twitter had a considerable impact on Bitcoin. The results of the VECM estimation on CHF/USD are in line with research by Levulyt and Šapkauskienė (2021), which states that an increasing currency will make the price of Bitcoin also increase where movements in the cryptocurrency market follow the movement of the traditional currency market. Before and during the COVID-19 pandemic, the S&P 500 Index, GBP/USD, EUR/USD, JPY/USD and crude oil were found to have no significant effect on Bitcoin in the short and long term. This result is not in line with the research conducted by Sovbetov (2018), who revealed that S&P 500 Index has a negative and positive impact on Bitcoin in the short and long terms, respectively. Also, the result is not in accordance to the previous research by Urquhart and Zhang (2019), Sathyanarayana and Gargesa (2019) and Majdoub *et al.* (2021) which stated that that foreign currency has an impact on Bitcoin. This occurred since some macroeconomic indicators are said to be insignificant to Bitcoin, which is based on a  $t$ -statistic that is smaller than the  $t$ -table (1.96). There may be difficulties in predicting the price of Bitcoin due to the high volatility of the cryptocurrency market.

## 5. Conclusions

This study attempts to observe the influence of internal and external factors on Bitcoin in the period before and during the COVID-19 pandemic using the VECM, for data from January 2018 to December 2021. The importance of conducting this research is supported by the development of digital asset, Bitcoin. Hashrate and transaction volume were found to have a long-term significant effect on Bitcoin before and during the COVID-19 pandemic, which is in accordance with a study conducted by Rehman and Kang (2021) and Sovbetov (2018). The results show that if the hashrate and transaction volume increase, the supply opportunities in the market will also increase. In addition, for short-term and long-term effect, Twitter is also an influential factor of Bitcoin both in the pre-COVID-19 pandemic and during the COVID-19 pandemic. The role of social media in moving the price of Bitcoin is unavoidable, as the study by Kremser *et al.* (2019) shows the predictive role of social media for Bitcoin. Every tweet that contains both positive and negative sentiment still has an effect on the movement of Bitcoin.

The results of the VECM estimation also supported the study of Gozbasi *et al.* (2021) in which Bitcoin was significantly affected by FSI in the long term before the COVID-19, as Bitcoin price is sensitive to market risk. In the short term, gold has shown a significant negative impact on Bitcoin in the pre-COVID-19 pandemic, while VIX had a significant impact on Bitcoin during the COVID-19 pandemic. Lopez-Cabarcos *et al.* (2019) support that VIX affects Bitcoin significantly, which shows that the pressure in the market is getting higher and investors are increasingly afraid to invest in the market. The result is also in line with the study of Jareno *et al.* (2020), which considers gold to have a more prominent advantage over Bitcoin. Investors prefer gold because it is less risky and easier to understand than other investments such as gold and forex. According to Levulyt and Šapkauskienė (2021), CHF/USD is one of the foreign currencies that has had an impact on Bitcoin in the long term during the COVID-19 pandemic. When comparing forex and gold with Bitcoin, with a complex system, Bitcoin will be more difficult to understand. It takes time to delve deeper into Bitcoin.

For other factors, the S&P 500 Index, GBP/USD, EUR/USD, JPY/USD and crude oil were found to have no significant effect on Bitcoin in the short and long terms.

Investors or potential investors can pay more attention and prepare for the potential risks. Investors can also consider price trends and security risks before including Bitcoin to their portfolio. The other implication is that factors such as social media or news can be watched as indicator or motivation to make decision. In addition, suggestions for regulators to increase market protection can be done by laws. Regulators can also increase awareness and update information periodically to get a good understanding of market conditions for greater crypto adoption in the future.

The limitations of this study reside in the period that focuses only on the health crisis. Moreover, the data retrieval from Twitter is very limited and not grouping based on the positive or negative sentiment. For further research, it is recommended to have a longer research period and the latest year in order to provide an updated picture of Bitcoin. It can add other possible variables that affect Bitcoin, use other hashtags and analyze positive or negative sentiment. They can also use other cryptocurrencies, not only Bitcoin, such as Ripple and Ethereum.

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