“Major determinants of Bitcoin price: Application of a vector error correction model”

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MAJOR DETERMINANTS OF BITCOIN PRICE: APPLICATION OF A VECTOR ERROR CORRECTION MODEL

Abstract

Research in recent years has shown that Bitcoin is a virtual asset that is used as a medium of exchange and investment tool other than shares and bonds, the development of the digital era has opened up opportunities for Bitcoin to be chosen as part of an investor's portfolio. The focus of this study is to examine the impact of nine key determinants on Bitcoin price. The data used in the study are daily data starting from January 1, 2018 to January 1, 2022. The main data source is taken from Investing.com, and the estimation method applied is the Vector Error Correction Model (VECM). The main finding shows that Bitcoin Volume impacts Bitcoin Price negatively, which is in line with the demand theory. Another finding is related to the substitute effect of Ethereum Volume, Litecoin Volume, and Gold Volume, each of which influences Bitcoin Price positively, suggesting that these three commodities are substitutes to Bitcoin. In contrast, whereas Oil Volume has an insignificant effect on Bitcoin price in the short term, it has a negative significant impact in the long term. In addition, LQ45 stock index Volume influences Bitcoin Price positively in the short term, suggesting that LQ45 stock index and Bitcoin substitute for each other. Moreover, Google Trends impacts Bitcoin price positively in the long term. In terms of the income effect, either the Indonesian GDP or US GDP has a strong positive effect on Bitcoin price in both the short and long term.

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INTRODUCTION

Virtual commodities have become popular during the last decade. Bitcoin and Ether, for example, are free of a central authority to release brand-new products or confirm payment movement. Instead, the crypto network itself is involved in authorizing transactions and generating new products. Furthermore, individuals trading crypto on the blockchain are anonymous or at least "pseudonymous", and their real-life identities are not disclosed (Lucking & Aravind, 2019). Crypto currency is something new for the Indonesian people, its presence increased dramatically when the COVID-19 pandemic hit Indonesia. The increase in the number of Indonesian stock investors who are dominated by young beginner investors also has an impact on Bitcoin as one of the crypto currencies that the public is looking for because of its high value offered is fantastic. Virtual commodities can be threatened as part of "beyond broad money", despite the difficulty in measuring the total values. According to Vejacka (2014), a crypto-asset is a type of specific virtual commodity utilizing cryptographic and electronic communication, possessing a unique code for each entity. Due to their uniqueness, crypto-assets are no longer ordinary virtual currency but they have now been categorized as asset investments, as the

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character is similar to gold and the value fluctuates depending on market demand and supply. The current study focuses on Bitcoin as an asset and investigates the relationship of the price with its volume as well as other crypto's' volume of transactions to find out whether the other cryptos are substitution or complement assets.

Bitcoin is first invented by Nakamoto (2008). Originally, Bitcoin is a P2P payment method that makes direct web-based transactions between users without any financial institution as a medium. As it is commonly used as an electronic medium of exchange, Bitcoin is somehow considered by a certain group as an alternative currency (Platanakis & Urquhart, 2019). Bitcoin has value because it is frequently used as a medium of exchange (Joo et al., 2019), just like money. However, unlike original physical money, Bitcoin is available on a digital platform (Duarte et al., 2023). This sort of money increasingly attracts the interest of many parties. In Indonesia, the use of digital money has grown rapidly, since many companies facilitate the transaction, such as done by several companies, including Indodax, Triv.Co.id, Bitocto.Com, and many others. Hence, it is progressively important to study this growing interesting new sort of money, which is currently known better as a crypto-asset.

Bitcoin price can be determined by two factors: First is internal factors cover information regarding Bitcoin like the availability of coins and also the amount of demand and supply, while external factors cover other similar kinds of assets as well as other assets, such as gold price and stock price (Poyser, 2017). Bitcoin can be used for foreign trading and can be traded in several different currencies (Kim, 2017). Many governments have allowed or are considering allowing trading platform for this asset, and many businesses around the world have accepted it as a medium of exchange (Diaconaşu et al., 2022).

Prior research (Vujičić et al., 2018; Harm et al., 2016; Bhosale & Mavale, 2018) documents that there is a relationship between crypto assets, such as Ethereum and Litecoin. While Bitcoin strives to provide fast and safe transactions, Ethereum is more concerned with other issues. The popularity and profitability of Ethereum will increase as more intelligent agreements and distributed applications are developed (Harm et al., 2016). These two crypto currencies control the vast majority of the crypto currency market capitalization (Vujičić et al., 2018). The chart shows that the highest volatility of Bitcoin and the prices for Bitcoins experience a declining trend but at the same time, Ethereum and Litecoin comparatively show an increasing trend as they are newly introduced coins into the market (Bhosale & Mavale, 2018).

Yet comprehensive analyses on the substitution effect of other similar assets as well as the income effect from certain countries are still understudied. This study sheds light by investigating the substitution effect as well as the income effect of Bitcoin price.

1. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Bitcoin is a crypto-asset. It is commonly used as an instrument of investment besides gold or stock and to some extent is treated as a virtual currency. Bitcoin is considered to be a new innovation in digital investment with unique attributes (Mizerka et al., 2020; Lee at al., 2020). Bitcoin is defined as digital money within a decentralized peer-to-peer payment network (Baur et al, 2018; Luther & Smith, 2020). The price of the Bitcoin may be affected by its attractiveness as an investment opportunity (Kristoufek, 2018, Wong et al., 2018; Bouteska & Harasheh, 2023). Bitcoin also presents an opportunity for investment and trade (Chuen, 2015; Singh & Krishna, 2022). The most common use of Bitcoin is for investment, due to its high volatility and value (Hileman & Rauchs, 2017; Bakas et al., 2022). The extreme increase in Bitcoin price makes this topic progressively interesting to investigate, in relation to the volume of transactions. The Bitcoin price is mostly determined by the market's interaction of supply and demand (Jakub, 2015; Ciaian et al., 2016; Wang et al., 2016; Chen, 2021). Besides Bitcoin, there are

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several other crypto-assets on demand (Kjærland et al, 2018). The second in rank is Ethereum, with a market capitalization just below Bitcoin (Sifat et al., 2019). Due to its similar nature, Ethereum is considered a substitution asset for Bitcoin and an alternative investment for new players in the market (Onur & Yurdakul, 2022). Another well-known crypto-asset is Litecoin. The transaction volume of either Ethereum or Litecoin certainly interacts with Bitcoin price as these two former assets are also crypto-assets (Giudici & Hashish, 2019). The effects would be positive or negative, showing the liquidity interconnectedness of Bitcoin and Ethereum, as well as Bitcoin and Litecoin (Bouri et al., 2019).

In the equity market, Bitcoin is compared to other types of investments, such as gold, crude oil, or stock index as alternative investments (Yang et al., 2022; Tarchella et al., 2023; Mensi et al., 2023; Thaker & Mand, 2020). Gold is considered as a safe haven as it resists massive plunges in the equity market (Kyriazis, 2020; Baur & McDermott, 2016). Investment in gold assures investors during times of financial crisis and is regarded as an appealing alternative investment due to the ease of its transaction (Shabbir et al., 2019). Meanwhile, crude oil receives much intention from investors due to the soaring global demand. The West Texas Intermediate (WTI) is the most widely used crude oil price benchmark. In addition, a stock market index such as the LQ45 index is also being considered as an alternative to Bitcoin (Rudolf et al., 2021). The LQ45 stock price index generally consists of stocks that are considered the most liquid and have the largest market capitalization, the stocks that are incorporated in LQ45 represent around 65% of the capitalization of the IDX, which is an indicator of liquidity (Nurwulandari et al., 2021). To evaluate the possibility of these three types of investments as the alternative to Bitcoin, this current study proposed the substitution effect of the transaction volume of these three investments on Bitcoin price.

The role of information is very important in investing in Bitcoin, information can trigger investors' decisions in investing in Bitcoin (Guizani & Nafti, 2019). The Trends and sentiment analysis by Google search is an important factor affecting Bitcoin price (Kjærland et al., 2018). Google search analytics includes not only subjective information from text items like newspaper articles and product reviews, but also video and audio recordings, as well as the major. It also includes a supplemental analysis of macroeconomic conditions (Karalevicius et al., 2018). The positive and negative sentiment analysis in Google Search influences the price fluctuation in Bitcoin (Garcia et al., 2014; Kapar & Olmo, 2020). The positive sentiment boosts the Bitcoin price, whereas the negative sentiment pushes down the price (Valencia et al, 2019; Gurrib & Kamalov, 2022).

The change in macroeconomic condition is one of the considerations taken into account in investing. Gross Domestic Product (GDP) has a positive impact on Bitcoin price (Ismail & Basah, 2021; Gul et al., 2023). Macroeconomic factors, especially GDP, become market hypersensitive stimuli to the fluctuation of Bitcoin price (Corbet et al., 2020; Ben et al., 2023). GDP pictures the income of a country, and therefore the influence on Bitcoin price will reflect the income effect. Two GDP's are used in the analysis of the impact on Bitcoin price, the US GDP and the Indonesian GDP.

Based on the literature review, this study aims to analyze bitcoin price determinants based on transaction volume of the crypto currency itself (BTC, ETH, LTC), commodities (Gold & Oil), stock transaction volume (LQ45 Stock Index), trends or information (Google Trends) and macroeconomic conditions (USA GDP & IND GDP). Therefore, based on the literature review, the study tests the hypothesis formulated as follows:

H1: The transaction volume of Bitcoin influences Bitcoin price negatively.

H2: Ethereum volume influences Bitcoin price positively.

H3: Litecoin volume affects Bitcoin price positively.

H4: Gold transaction volume impacts Bitcoin price positively.

H5: Crude oil transaction volume influences Bitcoin price positively.

H6: LQ45 transaction volume affects Bitcoin price positively.

H7: Google Trends influences Bitcoin price positively.

H8: US GDP impacts Bitcoin price positively.

H9: Indonesian GDP affects Bitcoin price positively.

2. METHODS

This study implements quantitative explanatory research. It explores the relationships between several independent variables and one dependent variable. Daily dataset from January 1, 2018 to January 1, 2022 is utilized. The price of Bitcoin is a dependent variable. The nine independent variables are Bitcoin Volume, Ethereum Volume, LitecoinVolume, Gold Volume, Oil Volume, LQ45 Stock Index Volume, Google Trends, Indonesian Gross Domestic Product, and United States Gross Domestic Product. Bitcoin price is measured in rupiah, whereas the volume of Bitcoin is the unit of transaction of Bitcoin seven-day daily data in the Indonesian market. Ethereum volume is the unit of transaction of Ethereum in the Indonesian market. Similarly, the volume of Litecoin is measured using the unit of transaction of Litecoin in the Indonesian market. Vol Gold measures the unit of transaction of gold in kilograms in the Indonesian market, while Vol Oil is measured in barrels. LQ45 is the stock transaction volume of 45 top companies listed on the Indonesian Stock Exchange (IDX). Google Trends represents the number of documents searched in Google regarding Bitcoin. INDGDP is the actual Gross Domestic Product of Indonesia in rupiah measured under a certain consistent base year, and the seven-day daily data is interpolated using the procedure in the EViews application. Similarly, USGDP is also interpolated from the annual Gross Domestic Productof the US dollar. The data sources are from four main websites, namely investing.com, Coinmarketcap, Blockchain.info and The Indonesian Central Board of Statistics. The descriptive statistics for the selected variables are provided in Table 1.

VECM is a constrained Vector Auto Regressive Model (VARM) with cointegration constraints written into the specification, making it suitable for usage with cointegrated stationary series (Husaini et al., 2011). The VECM requirement restricts endogenous variable long-term behavior to converge towards their cointegration correlation while permitting an extensive variety of short-term dynamics. Unlike VARM, VECM must be stationary to the first differentiation and all the variables should have the same stationary degree. In addition, the VECM is developed VARM for non-stationary data with a cointegration correlation. Because of this cointegration, it is known as restricted VARM (Nugroho et al. 2021). There are several steps in performing VECM tests. Firstly, the Unit Root Test is used to determine if data is stationary. Secondly, Lag Length Criteria is applied to choose the optimum lag. Johansen's Cointegration is used in the third stage to test the existence of a long-term relationship between the stationary variables. Fourthly, the Impulse Reaction Function is applied to check the reaction of a specific variable when there is a shock in that variable. Finally, the

Table 1. Descriptive statistics of the selected variables

Source: Calculated from the dataset taken from investing.com, Coinmarketcap, Blockchain.info, and the Indonesian Central Board of Statistics.

Variable	Mean	Median	Minimum	Maximum	Std Dev	Observations
Price BTC	2.668	1.348	47169000	9.58^{8}	2.588	1,461
Vol BTC	2.866.415	230	30	2100	2.148.195	1,461
Vol ETH	1.956.806	1535	170	15900	1.488.802	1,461
Vol LTC	1.512.400	1125	130	18600	1.341.470	1,461
Vol Gold	114930.3	11465	10	680820	136899.1	1,461
Vol Oil	4.652.610	476	0	993	2.425.194	1,461
Vol LQ45	3.9^{9}	1.699	1.07^{8}	97.211	43.110	1,461
GT	2.980.563	24	4	98	1.602.447	1,461
IND GDP	39.515	42.415	43.210	51.015	12.015	1,461
US GDP	52.515	57.715	64.612	70.015	18.115	1,461

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Variance decomposition is performed to test the influence of a certain variable on the variable itself and other variables. Variance decomposition evaluates the impact of various shocks by evaluating the proportionate amount of variance that each structural shock generates to the overall variance of each variable. The error term can be interpreted as an error in the one-step forecast (Bjornland, 2006).

The VECM for Bitcoin Price as an endogenous variable can be written as follows:

$$\begin{aligned}
&\log\left(PriceBTC_t\right) = \beta_0 + \beta_1 \log\left(PriceBTC_{t-1}\right) + \\
&+\beta_2 \log\left(priceBTC_{t-2}\right) + \beta_3 \log\left(VolBTC_{t-1}\right) + \\
&+\beta_4 \log\left(VolBTC_{t-2}\right) + \beta_5 \log\left(VolETH_{t-1}\right) + \\
&+\beta_6 \log\left(VolETH_{t-2}\right) + \beta_7 \log\left(VolLTC_{t-1}\right) + \\
&+\beta_8 \log\left(VolLTC_{t-2}\right) + \beta_9 \log\left(VolGOLD_{t-1}\right) + \\
&+\beta_{10} \log\left(VolGOLD_{t-2}\right) + \beta_{11} \log\left(VolOIL_{t-1}\right) + \\
&+\beta_{12} \log\left(VolOIL_{t-2}\right) + \beta_{13} \log\left(VolLQ45_{t-1}\right) + \\
&+\beta_{14} \log\left(VolLQ45_{t-2}\right) + \beta_{15} \log\left(GT_{t-1}\right) + \\
&+\beta_{16} \log\left(GT_{t-2}\right) + \beta_{17} \log\left(INDGDP_{t-1}\right) + \\
&+\beta_{18} \log\left(INDGDP_{t-2}\right) + \beta_{19} \log\left(USGDP_{t-1}\right) + \\
&+\beta_{20} \log\left(USGDP_{t-2}\right),
\end{aligned} \tag{1}$$

Where *PriceBTC* is Bitcoin price, *VolBTC* is the volume of Bitcoin trading in the Indonesian market, *VolETH* is the volume of Ethereum trading in the Indonesian Market, *VolLTC* is the volume of Litecoin trading in the Indonesian Market, *VolGOLD* is volume of Gold trading in the Indonesian market, *VolOIL* is the volume of oil trading in the Indonesian market, *LQ45* is the volume of LQ45 stocks trading in Indonesian stock exchange, *GT* is Google Trends, *INDGDP* is the real value of Indonesian Gross Domestic Product in rupiah, and *USGDP* is the real value of US Gross Domestic Product in US dollar.

3. RESULTS

Table 2 displays the unit root estimation results using the Augmented Dickey-Fuller (ADF) approach at the 1st difference. The test on the level shows that the observed variables are not stationary at the level. So, the unit root test is run on the 1st difference for each variable. The ADF statistics are larger than the critical values for all variables, implicating that all the observed variables are stationary at the 1st difference. The probability values in the last column of Table 2 show that the probability values of all variables are close to zero, with the same conclusion that all the variables are stationary at the 1st difference.

Because all the observed variables are stationary at the same degree, there is a possibility of cointegration among the variables. The next stage is to test the existence of cointegration under the system equations. Before proceeding with the cointegration test, it is useful to check the lag length for the system equations. The length test can determine an optimum lag for system equations in VARM or VECM. The test of lag length is based on five criteria tests: Sequential Modifier Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criteria (AIC), Schwarz Information Criteria (SC), and

Table 2. Unit root test (1st difference)

Source: Estimation results using Augmented Dickey-Fuller (ADF) method on the dataset.

No.	Variable	ADF Statistic	Critical Value			p-value
			1%	5%	10%	
1.	*Price* BTC	–24.70378	–3.434624	–2.863315	–2.567763	0.0000
2.	Vol BTC	–28.83620	–3.434636	–2.863320	–2.567766	0.0000
3.	Vol ETH	–24.75117	–3.434636	–2.863320	–2.567766	0.0000
4.	Vol LTC	–19.73553	–3.434646	–2.863324	–2.567769	0.0000
5.	Vol Gold	–35.20340	–3.434624	–2.863315	–2.567763	0.0000
6.	Vol Oil	–15.66254	–3.434692	–2.863345	–2.567780	0.0000
7.	Vol LQ45	–13.69135	–3.434683	–2.863341	–2.567777	0.0000
8.	Google Trends	–20.76072	–3.434667	–2.863334	–2.567774	0.0000
9.	INDGDP	–20.98596	–3.434652	–2.863327	–2.567770	0.0000
10.	*USGDP*	–20.78251	–3.434649	–2.863326	–2.567769	0.0000

Table 3. Lag length criteria

Source: Estimated results using some lag-length criteriaon the tabulated data.

Lag	LogLikelihood	LR	FPE	AIC	SC	HQ
0	–8723.304	NA	7.74^{-8}	12.00454	12.04085	12.01809
1	–7597.700	2234.189	1.89^{-8}	10.59478	10.99416	10.74379
2	–7152.079	878.3798*	1.18e–08*	10.11970*	10.88216*	10.40417*

Hannan-Quinn Information Criteria (HQ). The results of the five tests are presented in Table 3. Findings indicate that the lowest value of LR, FPE, and AIC is in lag 2, while SC is in lag 1. When the lag length tests have different optimum lags, the decision depends on the dominant findings. In this case, lag 2 would be the best lag length as it is confirmed by three selection criteria. Therefore, the estimation proceeds with the lag length 2 for the system equations.

After performing unit root and a lag length test, cointegration test is conducted to check the possibility of the stationary variables having linear combinations. Johansen's test is utilized to perform the cointegration check on the system equation. The results are presented in Table 4. The asterisk (*) sign indicates the possible existence of cointegration within the system equations.

From the probability value in the last column of Table 3, the hypotheses on the number of cointegration equations are rejected until nine possible cointegration equations. These findings suggest the possible existence of cointegration up to nine equations. It also suggests the long-run and the short-run equilibrium relationship. Furthermore, the existence of cointegration equations indicates the use of Vector Error Correction Model (VECM) for further estimation.

Table 5 and Table 6 present the estimation results for the system equations under VECM. The estimation results presented here are only the part that Price BTC is a dependent variable. The other parts of the estimation results for other variables are not presented here due to page limitation and will be provided upon request. Table 5 shows the error correction term, whereas Table 6 presents the estimation results for Price BTC as a dependent variable.

Table 5. Error correction terms

Source: Estimation of the dataset using VECM.

Error Correction	Coefficient Std. Error t-value
Price BTC	–0.004952**
	(0.00258)
	[–1.92156]

Notes: The numbers in parentheses are standard errors, whereas the numbers in square brackets are statistic values. Symbols ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4. Johansen's co-integration test

Source: Estimated results using Johansen's cointegration test on the tabulated data.

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Tracestatistics	0.05 Critical Value	Prob**
None*	0.537553	7408.000	239.2354	1.0000
At Most 1*	0.515798	6287.411	197.3709	1.0000
At Most 2*	0.499919	5233.620	159.5297	1.0000
At Most 3*	0.452977	4226.711	125.6154	1.0000
At Most 4*	0.425817	3350.168	95.75366	1.0000
At Most 5*	0.395975	2544.034	69.81889	1.0000
At Most 6*	0.316298	1811.519	47.85613	1.0000
At Most 7*	0.301922	1259.040	29.79707	1.0000
At Most 8*	0.239364	736.7957	15.49471	0.0001
At Most 9*	0.208231	339.2541	3.841466	0.0000

Notes: * denotes rejection of the hypothesis at the 5% level.** McKinnon-Haug-Michelis (1999) p-value.

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Table 6. Estimation results of the short-run (Vector Error Correction Model)

Source: Estimationof the dataset using VECM.

Variable	Coefficient (Std. Error) [t-value]
Vol BTC	−0.546271***
	(0.01578)
	[−34.6244]
Vol ETH	0.772170***
	(0.01425)
	[54.2022]
Vol LTC	0.238989***
	(0.01342)
	[17.8111]
Vol Gold	0.014539***
	(0.00418)
	[3.47663]
Vol Oil	0.006194
	(0.01122)
	[0.55186]
Vol LQ45	0.037236***
	(0.01637)
	[2.27459]
GT	0.080303*
	(0.04648)
	[1.72756]
IND GDP	0.052453***
	(0.00661)
	[7.93233]
US GDP	0.085544***
	(0.00577)
	[14.8186]

Notes: The numbers in parentheses are standard errors, whereas the numbers in square brackets are statistic values. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 shows that the error correction term has a negative value and is significant at the 5 percent level. The negative value indicates that the short-run disequilibrium tends to converse with the long-run equilibrium. The significance test confirms the significance of the convergence process. The magnitude of coefficient (i.e., −0.004952) shows that the process of convergence is at a low-speed level. In other words, there is a confirmation of the process of convergence from short-term disequilibrium to long-term equilibrium, for the Price BTC variable.

Based on the VECM estimation results in Table 6, Bitcoin Price (Price BTC) is significantly influenced by the following variables: Bitcoin Volume (Vol BTC), Ethereum Volume (Vol ETH), Litecoin Volume (Vol LTC), Volume Gold (Vol Gold), Volume LQ45 (Vol LQ45), Google Trends (GT), Indonesian Gross Domestic Product (IND GDP), and United States Gross Domestic Product (US GDP). In contrast, Oil Price is found to have no significant effect on Bitcoin Price. This is indicated by the acquisition of a t-statistic value that is greater than the t-table for the nine variables.

The negative and significant coefficient of Bitcoin volume confirms the demand theory. From the magnitude of Bitcoin volume's coefficient, one can say that a 1% increase in Bitcoin Volume reduces the Bitcoin Price by 0.55%. In contrast, the positive and significant coefficient of Ethereum Volume confirms the substitution between Ethereum and Bitcoin. From the coefficient of Ethereum Volume, it shows that a 1% increase in Ethereum Volume raisesthe Bitcoin Price by 0.77%. The same is also found for Litecoin, with a positive and significant effect, suggesting for a substitution effect of Litecoin and Bitcoin.

Furthermore, the coefficient of Gold Volume is also positive and highly significant affecting Bitcoin Price, indicating that Gold is also a substitution for Bitcoin. When the volume of Gold Trading in the Indonesian Market increases by 1%, the Bitcoin price will increase by 0.014%. In contrast, Oil Volume is found to have an insignificant impact on Bitcoin Price, suggesting that Oil is neither a substitution nor a complement of Bitcoin. In addition, LQ45 Stock Trading Volume positively influences Bitcoin Prices, suggesting that LQ45 stock trading volume could be a substitution for Bitcoin. From the result of the Google Trends variable, one can say that Google Trends influences Bitcoin prices positively, indicating that buyers respond positively to good news in Google Trends. Then, the two economic variables such as Indonesian GDP and US GDP also impact Bitcoin Price positively, representing that either the income of Indonesian or American influence Bitcoin Price. These findings indicate that income does have a positive impact on Bitcoin Price.

As confirmed by the Error Correction Term (ECT) in Table 5, the findings of short-term relationships in Table 6 will converge to the long-term equilibrium relationship. To show the long-term relationship, the level estimation is conducted under the Ordinary Least Squared (OLS) method. Table 7 presents the long-term relationships.

Table 7. Estimation results of the long-run relationship (Ordinary Least Squared)

Source: Estimation of the dataset using OLS.

Variable	Coefficient (Std. Error) [t-value]
Vol BTC	–5545.121***
	(289.8275)
	[19.1324]
Vol ETH	2157.504
	(3503.325)
	[0.5381]
Vol LTC	31280.34***
	(4140.007)
	[7.55562]
Vol Gold	242.2830***
	(35.86208)
	[6.75597]
Vol Oil	–866.2828***
	(219.897)
	[3.93949]
Vol LQ45	–0.000042
	(0.000113)
	[0.37168]
GT	72848.68***
	(3330.19)
	[21.87523]
IND GDP	0.000074*
	(0.000041)
	[1.80488]
US GDP	0.000094***
	(0.000027)
	[3.48148]
Constant	0.000015***
	(0.000002)
	[7.5000]
F–test	153.1759
Adj. R^2	0.484023
N	1461

Notes: The numbers in parentheses are standard errors, whereas the numbers in square brackets are statistic values. Symbols ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The results of the long-term relationship in Table 7 show quite similar results to the short-run relationship in Table 6. The differences show the significance of variables Ethereum Volume (Vol ETH), Oil Volume (Vol OIL), and LQ45 Volume (Vol LQ45). Ethereum Volume is found to be insignificant in the long term. Similarly, the LQ45 Volume is also insignificant in the long run. In contrast, Oil Volume impacts Bitcoin Price negatively. These differences can be due to the difference in the method of estimation.

To check the stability of the results in VECM estimation, the Auto-Regressive (AR) Roots graph is performed. Figure 1 presents the results of AR Roots. Figure 1 shows that all variables symbolized by blue dots are in a circle, which indicates that the model is in a stable condition. A stable model is required to ensure that the results of the forecasting methods (Impulse Response Function and Variance Decomposition) are valid.

As the AR roots graph shows the stability of VECM model, the next stage performed is the impulse response function and the variance decomposition to assess the impact of a shock in one variable to other variables in the model.

The impulse response function (IRF) represents the effect of endogenous factors (current and future values) when random error is imposed by the standard deviation of the effect size. The VECM focuses on the path of the impulse response of every variable in the system, the consequences of time lags, and the stabilization process rather than specific model parameters (Liu et al., 2022). Shocks can be studied using impulse response analysis

Source: Estimated results using AR roots on tabulated data.

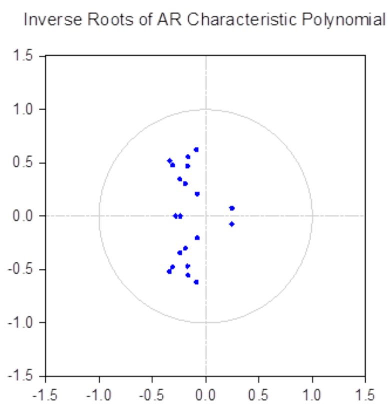

Figure 1. AR roots graph

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(Nugroho et al., 2021). The impulse response function (IRF) describes the amplitude and direction of a variable's relationship. IRF also demonstrates how variables interact with one another (Boamah et al., 2021). The IRF is conducted to analyze the dynamics of a model's response to certain stimuli and its effects concerning the observed variables. It also assesses the impact of shock in the currentand subsequent periods. Figure 2 shows the impulse response of the ten observed variables when a shock happens.

Source: Estimated results using impulse response function on tabulated data.

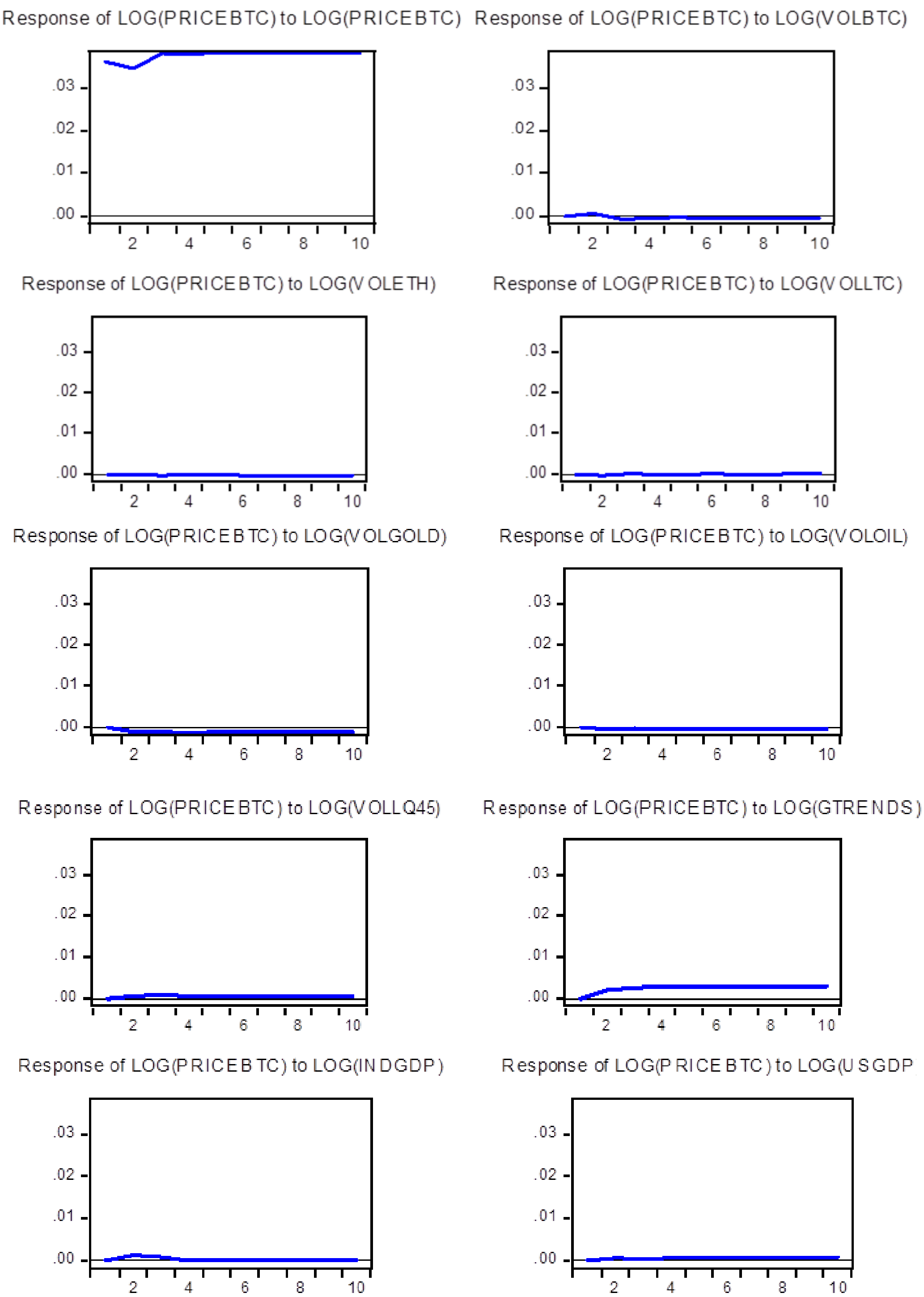

Figure 2. Impulse response function graph

The top-left panel of Figure 2 shows that the current price of Bitcoin (Price BTC) has a positive increasing response to the previous prices of BTC. The shock occurred in the 3rd to 4th period but was able to return to its equilibrium point in the 5th to 10th period. This impulse response indicates a strong impact of Bitcoin Price on the price fluctuation in the future. The second panel in the top-right side of Figure 2 shows that the response of Bitcoin price on the change in Bitcoin volume (Vol BTC) tends to be stable and positive in 10 periods, even though the shock occurred in the 2nd period but was able to return to its balance point in 4th to 10th period. Furthermore, the third panel of Figure 2 (the left side of the second row) pictures the response of Bitcoin price on the trading volume of Ethereum (Vol ETH). There is a strong influence of Ethereum volume on Bitcoin price, and the response is positive and stable, even though there was a shock in period 3 but the shock is temporary. A similar response is shown by the change in Litecoin volume (Vol LTC) where the Bitcoin price experiences a shock in the 2nd period and was quickly able to return to its equilibrium point in the 3rd until 10th period (see the left panel of the second row in Figure 2).

In contrast, the response of Bitcoin Price to the change in Gold Volume, Oil volume, or LQ45 stock trading volume, independently, is negative throughout ten years. The negative response is immense especially for Gold volume and Oil volume, in the case that the shock is persistent for 10 periods, with no point to return to their balance point. For the Vol LQ45, even though the variable impacts Bitcoin price negatively, the effect of shock is slowing down in the 6th to 10th period.

In addition, the right panel in the fourth row of Figure 2 shows that the response of Bitcoin price on the Google Trends variable is positive for the whole period of observation. There is a shock during the 1st period, but a positive response appeared immediately after the shock, throughout the period of observation. Moreover, the responses of Bitcoin price on the change in Indonesia GDP (IND GDP) and on the change in the US GDP are quite similar. The Bitcoin price response to the change in Indonesian GDP happened in the 1st to 5th period, whereas in the 6th period, the Bitcoin price turns back to its equilibrium point, lasting until the 10th period. Similarly, the Bitcoin response to the change in US GDP happened also in the 1st to the 5th period, but the difference is that the shock effect from US GDP continued throughout all the periods.

Variance decompositions examine the impact of shocks on a component of each variable over time (Wang et al., 2016). The amount of contribution of each exogenous variable on the endogenous variable is pictured in the decomposed variances (Lestari, 2020). In addition, the decomposition evaluates the reaction of one variable to changes in other variables (Si et al., 2021). This method is used to reveal the causal relationship of explanatory variables to endogenous variables and to predict the rate of error of dependent variables (Alshehry & Belloumi, 2015).

Table 8 summarizes the variance decomposition effect for Price BTC, from the shocks given by each exogenous variable, including a shock in the Price BTC itself for 10 periods.

Table 8. Variance decomposition

Source: Estimated results using variance decomposition on tabulated data.

Period	Price BTC	Vol. BTC	Vol ETH	Vol LTC	Vol Gold	Vol Oil	Vol LQ45	Google Trends	IND GDP	US GDP
1	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	99.90	0.05	0.02	0.01	0.0001	5.65^{-7}	0.0001	4.23^{-5}	0.003	0.01
3	99.91	0.04	0.02	0.01	0.0001	4.83^{-7}	0.0001	3.62^{-5}	0.002	0.01
4	99.74	0.09	0.02	0.02	0.03	0.003	0.0002	0.08	0.002	0.009
5	99.58	0.11	0.02	0.02	0.05	0.003	0.01	0.11	0.01	0.07
6	99.50	0.11	0.02	0.02	0.07	0.003	0.02	0.13	0.02	0.10
7	99.45	0.10	0.02	0.02	0.08	0.004	0.02	0.14	0.03	0.13
8	99.41	0.10	0.02	0.01	0.09	0,008	0.03	0.15	0.03	0.14
9	99.36	0.10	0.01	0.01	0.10	0.01	0.04	0.16	0.03	0.16
10	99.33	0.10	0.01	0.01	0.11	0.01	0.04	0.17	0.03	0.17

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Table 9. Summary of hypothesis testing

Independent Variables	Dependent Variable: Price Bitcoin	
	Short Term (VECM Method)	Long Term (OLS Method)
Bitcoin Volume	Hypothesis 1 Supported: Impact Negatively	Hypothesis 1 Supported: Impact Negatively
Ethereum Volume	Hypothesis 2 Supported: Impact Positively	Hypothesis 2 Not Supported: Insignificant Impact
Litecoin Volume	Hypothesis 3 Supported: Impact Positively	Hypothesis 3 Supported: Impact Positively
Gold Volume	Hypothesis 4 Supported: Impact Positively	Hypothesis 4 Supported: Impact Positively
Oil Volume	Hypothesis 5 Not Supported: Insignificant Impact	Hypothesis 5 Supported: Impact Negatively
LQ 45 Index Volume	Hypothesis 6 Supported: Impact Positively	Hypothesis 6 Not Supported: Insignificant Impact
Google Trends	Hypothesis 7 Supported: Impact Positively	Hypothesis 7 Supported: Impact Positively
Indonesian GDP	Hypothesis 8 Supported: Impact Positively	Hypothesis 8 Supported: Impact Positively
United States GDP	Hypothesis 9 Supported: Impact Positively	Hypothesis 9 Supported: Impact Positively

Price BTC is dominantly influenced by itself in the first period of shock, but this influence is diminishing over the 10 observed years. In contrast, the shock from Vol BTC on Price BTC is almost zero at the beginning of the observed years, but the effect increases gradually to 11% in year 5 and year 6 and then stabilizes at 10% afterward. The effect of Vol ETH is very small and stable at the highest 2%. Similarly, the Vol LTC effect is also stable at the highest 2%. The effect of Vol Gold tends to increase over time and continues to increase until 11% in year 10. Similarly, the effect of Vol Oil also increases but in a very small magnitude during the 10 observed years. The same effect is also pictured in Vol LQ45, Google Trends, IND GDP, and US GDP. When each of the variables has a shock, the effect on Price BTC increases.

Based on the findings of the short-term as well as the long-term estimations, the summary of hypothesis testing results are provided in Table 9.

4. DISCUSSION

From the findings of long-run estimations, one can evaluate the results and compare them with the previous empirical studies' results. The negative and significant effect of Bitcoin Volume on Bitcoin Price conforms to the demand theory and is consistent with the past research by Gemici and Polat (2019). As Bitcoin is a high-risk investment instrument, an increase in its price will go with a reduction in the trade volume. For technical analysts and traders, the Bitcoin market fluctuates from time to time as price and volume are determined by a single market mechanism. This implies that Bitcoin volume could aid in predicting the underlying mechanisms of Bitcoin price fluctuations (El Alaoui et al., 2019).

The trading volume of Ethereum has a positive effect on Bitcoin price. This indicates a possible substitution between Bitcoin and Ethereum. This finding is consistent with a study by Angela and Sun (2020), which stated that there is a significant relationship between Bitcoin and Ethereum due to the nature of crypto currency. Investors who invest (speculate) in crypto currencies benefit from diversifying their holdings of this currency (Baumöhl, 2019). Diversification is a way to reduce investment risk so that Bitcoin investors will choose to also invest in Ethereum. According to Beneki et al. (2019), Bitcoin and Ethereum have shown significant price gains, and these two cryptocurrencies are primarily used to diversify digital currency portfolios.

This finding is similar to Gemici and Polat (2021), who found that Bitcoin is affected by Litecoin and there is a causality effect from Litecoin to Bitcoin. Another finding, which is equally important, is that the trading volume of Gold impacts Bitcoin price positively. The possible interpretation of this result is that Gold is an alternative commodity for Bitcoin. Investors can choose to invest in either Gold or Bitcoin, and these two commodities substitute each other. Surprisingly, the effect of Oil Volume is negative on Bitcoin price. While the Volume of LQ45 stock index has no significant effect on Bitcoin Price in the long-run. Google Trends is found to influence Bitcoin price positively. The positive effect of Google Trends is also found by Bakas et al. (2022), who examine Google Trends as one of the key factors affecting Bitcoin volatility. The same result is also shown by Hung

(2022) who discovers evidence that the stock market was a net transmitter of volatility in the oil and gold markets, but a net receiver of Bitcoin's volatility. The influence of oil was first carried over to gold, and the influence of the Bitcoin market and gold was carried over to Bitcoin. Similarly, the findings of this study confirm the findings of Charfeddine et al. (2020), the dynamic interrelationship between oil price, gold price and stock market certainly affects Bitcoin price volatility. In addition, the findings are also in line with Ghorbel et al. (2022) that investors may diversify their investment portfolios and lower potential risks by including Bitcoin, Litecoin and Gold when investing in the stock market.

The two economic variables in this study, i.e., IND GDP and US GDP, show a strong positive significant link with Bitcoin price. In the United States, Bitcoin is considered one of the payment methods in e-commerce and is accepted as a payment method in many restaurants, hotels, and shops around the world. Therefore, it should come as no surprise that US GDP influences Bitcoin price positively. The United States is one of the world's most convenient countries for Bitcoin commerce (Inshyn et al., 2018). This research differs from Qudah and Aloulou (2020), who found insignificant correlation between GDP per capita and Bitcoin Prices in GCC countries. The difference in research method could be a possible reason.

CONCLUSION

This study examines nine key determinants of Bitcoin price using time-series analysis. Following the procedure of Vector Error Correction Model (VECM), all variables under concern (i.e., Bitcoin price, Bitcoin volume, Ethereum volume, Litecoin volume, Gold volume, Oil volume, LQ45 volume, Google trends, IND GDP, and US GDP) are stationary at first difference. The variables have cointegration relationships under the Johansen test. Based on the VECM estimation results, either Bitcoin Volume, Ethereum Volume, and Litecoin Volume influences Bitcoin prices positively. Daily transaction volume is an indicator used by Bitcoin traders and investors in determining price movements. The large transaction volume of either Bitcoin or Ethereum or Litecoin shows market movement, and this data is used to predict potential price movements and profits obtained by a trader or investor. Similarly, volume of LQ45 stock index influences Bitcoin positively, reflecting that stocks and Bitcoin have a similar risk profile, namely they are part of traded assets, and Bitcoin is one of investors' portfolios. Furthermore, Google trends have a positive effect on Bitcoin, showing that information is a powerful tool used by investors in determining investment decisions. The publication of positive or negative news about Bitcoin influences the psychology of Bitcoin traders or investors, so that it provides a direct effect on decisions to buy or sell the asset in the crypto currency market. Similar findings are shown in Indonesian GDP and US GDP, as each factor influences Bitcoin Price positively, picturing the importance of economic conditions as crucial determinant affecting Bitcoin Price. As for income effect, an increase in income rises the investors' ability to purchase Bitcoin and, in turn, increases its price. In addition, the volume of Oil does not affect the volatility of Bitcoin price in the short-run. The short-term disequilibrium found in the VECM is converging to the long-run equilibrium at a low speed.

AUTHOR CONTRIBUTIONS

Conceptualization: Dermawan Jaya Hartono, Suyanto Suyanto.
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Formal analysis: Dermawan Jaya Hartono, Suyanto Suyanto.
Funding acquisition: Suyanto Suyanto.
Investigation: Dermawan Jaya Hartono.
Methodology: Dermawan Jaya Hartono, Suyanto Suyanto.
Project administration: Suyanto Suyanto.
Resources: Suyanto Suyanto.
Software: Dermawan Jaya Hartono.

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Validation: Suyanto Suyanto.
Visualization: Dermawan Jaya Hartono.
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Writing – review & editing: Dermawan Jaya Hartono, Suyanto Suyanto.

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