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EMPIRICAL ANALYSIS OF BITCOIN AND MAJOR CRYPTOCURRENCIES PRICES

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ABSTRACT

Cryptocurrency is a relatively new phenomenon that is attracting a lot of interest. On the one hand, it is built on a brand-new technology whose full potential has yet to be realized. On the other hand, it performs similar services to other, more traditional assets, at least in its current form. The development of theoretical models of cryptocurrencies has received a lot of academic attention. Many elements have been mentioned in the theoretical literature on cryptocurrencies as potentially important in cryptocurrencies' pricing. The cryptocurrencies with a market value of over \$100 million between January 1, 2018 and May 12, 2021 were selected for this research. Time-series analysis was done to investigate the price relationship among the cryptocurrencies. The results pointed out as major cryptocurrencies' prices are linked to Bitcoin prices.

Keywords: Cryptocurrencies; Bitcoin; Binance; Ethereum; Time-Series

1 INTRODUCTION

Cryptocurrencies have been known since the popularity of Bitcoin (BTC). For their online transaction platforms, many cryptocurrencies utilize blockchain technology (Yermack, 2017). The blockchain can considerably boost the liquidity of the securities market values due to its ability to reduce costs and time in negotiations (Aste, 2016). The launch of this virtual money appears to be a response to current environmental problems. Its growing popularity proves that it is the most effective solution to the present issues. At the same time, the relevant authorities are battling to maintain control, limiting the virtual currency market's expansion, and creating uncertainty (Mikołajewicz-Woźniak & Scheibe, 2015).

Bitcoin's fusion of two domains of knowledge, technology and economics, provides a glimpse of models that could solve social issues, including inflation,

economic cycles, untrustworthy financial institutions, and a lack of universal financial services (Hendrickson et al., 2016). The encryption is built on the ideas of open source and peer-to-peer networks, signifying a commitment to social solidarity and mutual aid (Scott, 2016). However, speculators, profit-driven entrepreneurs, market fundamentalists, and libertarian technophiles became identified with Bitcoin (Yelowitz & Wilson, 2015).

Cryptocurrencies have gained traction as a payment option due to public criticism of credit and debit card networks' fees, as the technology would push the card networks to reduce their charges to traders (McCallum, 2015). Cryptocurrencies are encoded using an anonymous technique that is extremely liquid, low-cost, and quick, making them more desirable. In a larger sense, the system is not controlled by a central body, which reduces privacy concerns, and it may be connected to any type of asset, such as gold or silver, which makes it more appealing (Chu et al., 2015).

However, there has been little research in the literature on the financial aspects of cryptocurrencies, let alone attempts to find relationships between existing cryptocurrencies other than Bitcoin when considering it as an investment choice. This study is relevant in proposing the verification of the level of correlation between major cryptocurrencies, in this opinion.

According to Huhtinen (2014), the importance of the topic arises from the decentralization of monetary system technology, which signals the growth of interactions between actors. Regarding economic relevance, it is also worth noting that futures Bitcoin contracts are already traded on two US futures and options exchanges: the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME), the latter of which is one of the world's largest exchanges markets. As a result, it is clear that institutional investors' money can be transferred to Bitcoin and appreciated as a result, as has happened in the past (Bohme et al., 2015).

As a result, a study examining the relationship between various types of cryptocurrencies is required, resulting in the following research question: What effect will Bitcoin's resurgence have on the major cryptocurrencies? This dilemma comes from the idea that the higher the correlation between assets, the bigger the cumulative return loss due to higher volatility, and thus rebalancing assets can provide risk and return advantage to a negatively correlated active investor.

2 LITERATURE REVIEW

Recently several types of research have been out to understand cryptocurrencies better genesis, behaviour, and mechanism. After Narayanan et al. (2016) analyzed blockchain systems with the environment of cryptocurrencies, Noga (2017) examines the function of currency as well as artificial currencies. Moreover, Conti et al. (2018) and Tschorsch and Scheuermann (2016) clarify

the technical side of BTC and blockchain in terms of security, network, and privacy implications.

Since the introduction of cryptocurrencies, researchers have broadened their studies from the investment asset's universe; for example, the predictability of the "financial return assets" within financial literature (Golez & Koudijs, 2018), predicting the values of cryptocurrencies based on the stock returns (Campbell & Shiller, 1988; Fama & French, 1988; Van Binsbergen & Kojien, 2010). Some of the empirical investigations are drawn partially from calculation and forecasting processes. The risk-reward characters of cryptocurrencies are examined in detail (Liu & Tsyvinski, 2021). According to Malladi et al. (2019), BTC forecasting with fewer predictors was investigated. They discovered that the direction of returns, but not its amount, could be accurately estimated.

According to Van Wijk (2013), most of the factors influencing Bitcoin prices are related to the US economy. Using daily and weekly data inside a dynamic conditional correlation (DCC) model, Bouri et al. (2017) revealed that BTC might function as an effective diversifier in the majority of situations. Ciaian et al. (2016) found three major determinants of BTC pricing: market dynamics of supply and demand, the introduction of more information (trust), and speculators. Furthermore, they disproved previous findings that global macro-financial developments influence BTC's price.

Other studies, such as those conducted by Cheah and Fry (2015) and Katsiampa (2017), contend that recent cryptocurrency price volatility is the consequence of market emotion, with the latter being associated with significant "memory." According to those researchers, the "memory" of Bitcoin price shocks is a semi-important driver of cryptocurrency pricing. According to Dyhrberg (2016), BTC can be an appropriate tool for risk-averse investors as a buffer against negative market shocks, whereas BTC can hedge against a market-specific risk. Cheah et al. (2018) conducted the most current Bitcoin price study. They model cross-market BTC pricing using a fractionally cointegrated VAR approach. They describe cross-market BTC pricing as long-memory processes with dynamic dependency in a fractionally cointegrated VAR framework. According to their findings, the long memory is present in both individual and five-market systems, exhibiting nonhomogeneous informational inefficiency and a cointegration connection with slow shock adjustment.

In this study, the relationship between cryptocurrency prices has been investigated by using time-series analysis.

3 METHODOLOGY

In this work, the three largest cryptocurrencies with a market value of over \$100 m between January 1, 2018 and May 12, 2021, using 1,224 daily data, were collected on CoinMarketCap. Other cryptocurrencies (such as Ethereum and Litecoin) could have been used but decided against it deliberately because

other cryptocurrencies have significantly lower market capitalizations and can be safely ignored. Thus, the final sample was three cryptocurrencies with higher market value, as shown in Equation 1.

$$BTC = \alpha + \beta_1.ETH + \beta_2.BNB + \varepsilon \quad (1)$$

Where:

- α : refers to the intercept parameter;
- β = corresponds to the slope of the control variables;
- BTC = Bitcoin;
- BNB = Binance;
- ε = disturbance (error or residue) model.

The return is calculated in the logarithm, which is the natural logarithm of the arithmetic return, for the specified cryptocurrencies. The use of this methodology is justified by the statistical qualities of most time-series returns, such as stationary and ergodic (Morettin & Toloï, 2006). Based on this assumption, the calculation for the return of cryptocurrencies will be:

$$R_i = \ln(P_t / P_{t-1}) = \ln(P_t) - \ln(P_{t-1}) \quad (2)$$

where:

- R_i = the cryptocurrencies return;
- P_t = a number of daily closing cryptocurrencies in period t ;
- P_{t-1} = a number of daily closing cryptocurrencies in period $t-1$.

Figure 1 illustrates the daily price volatilities of BTC, BNB, and ETH from January 1, 2018 to May 12, 2021. BNB price is less volatile compared to BTC and ETH. The price of these three major cryptocurrencies has sharply increased after January 1, 2021. BTC price was roughly \$10,000 until the beginning of January 2021. After that, it has gone up to about \$60,000. BNB price was below \$100 between January 1, 2018 and January 1, 2021, and it increased to \$665. ETH price was below \$500 most of the time, but it has sharply increased to \$4,211 on May 12, 2021.

Figure 2 shows the daily return of BTC, BNB, and ETH. It can be seen that the daily return of these three major cryptocurrencies is moving in the same direction most of the time. There was a significant loss on BTC (-22.80%) and ETH (28.84%) on March 12, 2020, while the highest daily return of BTC was 9.83% on October 26, 2019, and the highest daily return of ETH was 14.00% on January 3, 2021. BNB lost 22.85% of its value on March 13, 2020 and the highest daily return of BNB was 36.05% on January 6, 2018.

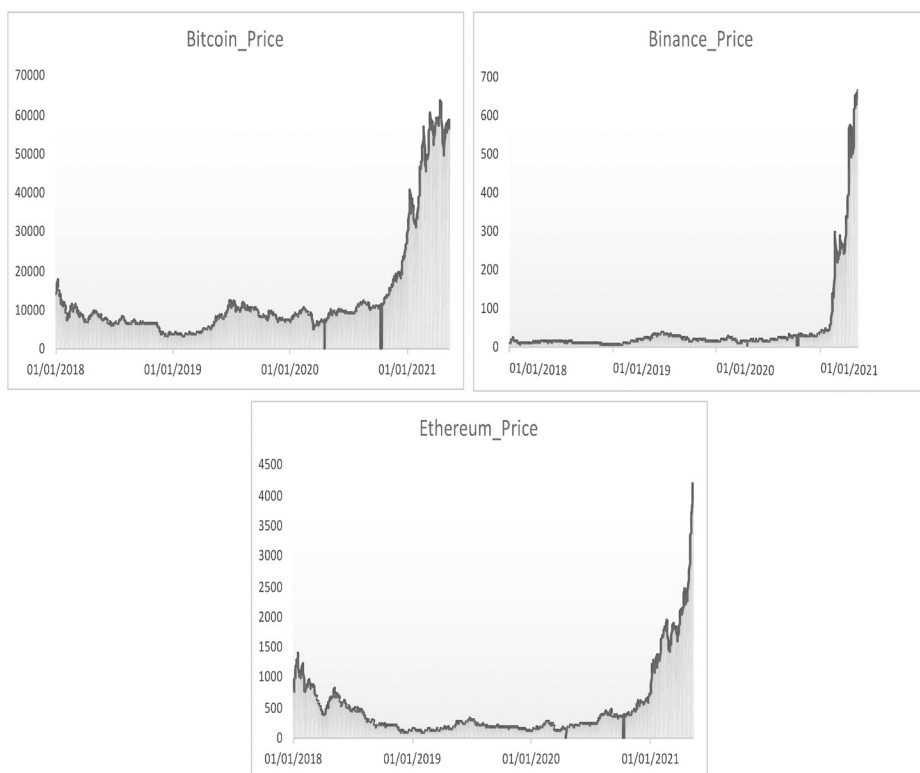


Figure 1. Historical price changes of Bitcoin, Binance, and Ethereum

4 RESULTS

In this section, empirical findings have been discussed.

Summary statistics of major cryptocurrencies' volatilities are provided in Table 1.

BTC, BNB, and ETH prices are very volatile between the period of January 1, 2018 and May 12, 2021. BTC price was only \$3,240.38 on December 15, 2018, but it went up by \$60,076.34 to \$63,316.72 on April 14, 2021. The minimum BNB and ETH prices were \$4.55 and \$84.36 on December 15, 2018, respectively. BNB price increased by \$661.31 to \$665.86, while ETH price went up by \$4,126.67 to \$4,211.03 on May 12, 2021. On the other hand, BNB has the highest daily return (36.5%), while Bitcoin has the lowest daily return (9.83%).

According to Table 2, there is a positive and significant correlation among the three major cryptocurrencies prices. BTC price is highly correlated with BNB and ETH prices. When the BTC price increases by 1 unit, BNB and ETH prices go up by 0.849 and 0.900 units, respectively. In addition to this, ETH and BNB prices are highly correlated with each other (0.865).

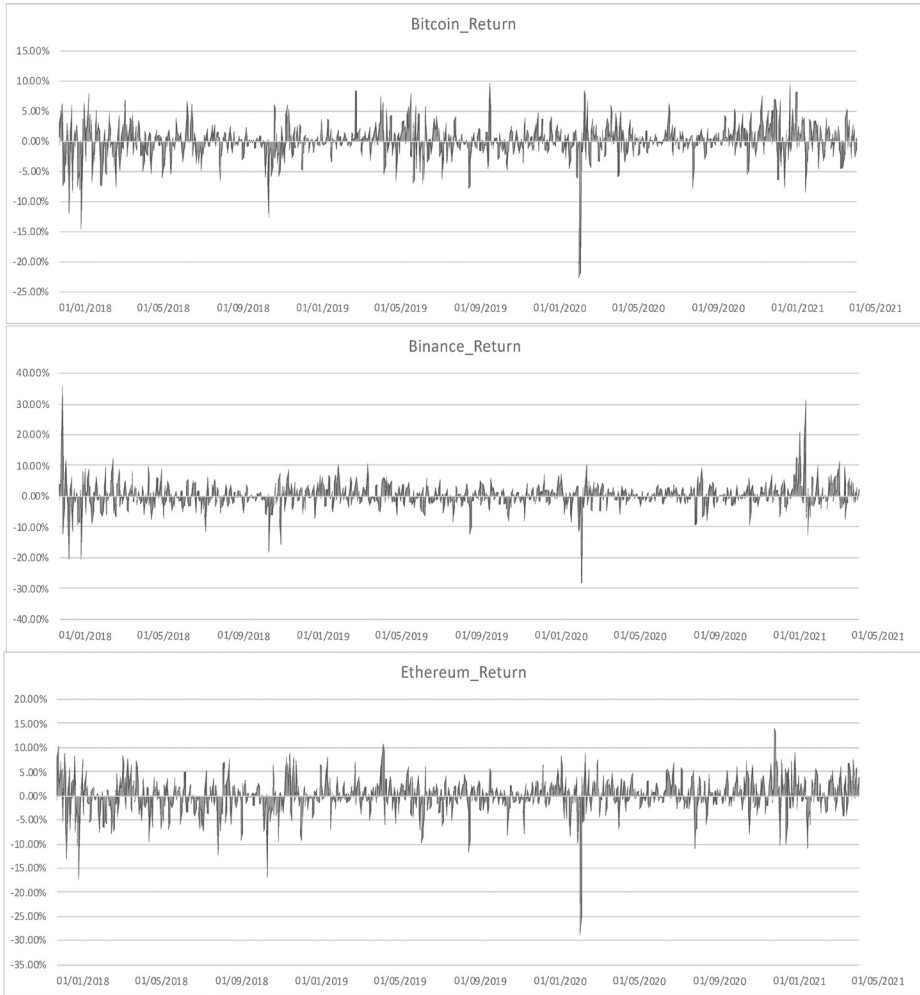


Figure 2. Historical return changes of Bitcoin, Binance, and Ethereum

Table 1. Summary Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
<i>Bitcoin_Price</i>	1,224	3,240.38	63,316.72	13,028.0626	13,355.68096
<i>Binance_Price</i>	1,224	4.55	665.86	44.9161	103.50531
<i>Ethereum_Price</i>	1,224	84.36	4,211.03	492.8935	575.85430
<i>Bitcoin_Return</i>	1,221	-22.80%	9.83%	0.0714%	2.80140%
<i>Binance_Return</i>	1,221	-28.36%	36.05%	0.2556%	4.19235%
<i>Ethereum_Return</i>	1,221	-28.84%	14.00%	0.0649%	3.59804%
<i>Valid N (listwise)</i>	1,221				

Table 2. Correlation Matrix of Major Cryptocurrencies Prices

		Bitcoin_ Price	Binance_ Price	Ethereum_ Price
<i>Bitcoin_Price</i>	<i>Pearson Correlation</i>	1	0.849*	0.900*
	<i>Sig. (2-tailed)</i>		0.000	0.000
<i>Binance_Price</i>	<i>Pearson Correlation</i>	0.849*	1	0.865*
	<i>Sig. (2-tailed)</i>	0.000		0.000
<i>Ethereum_Price</i>	<i>Pearson Correlation</i>	0.900*	0.865*	1
	<i>Sig. (2-tailed)</i>	0.000	0.000	

*Correlation is significant at the 0.01 level (2-tailed).

Table 3 represents that there is a positive and significant correlation among the three major cryptocurrencies' daily returns. BTC return is highly correlated with BNB and ETH returns. In other words, when BTC return goes up by 1 unit, BNB and ETH return increase by 0.644 and 0.799 units, respectively. In addition to this, ETH and BNB returns are highly correlated with each other (0.636).

As a summary of the correlation matrix, there are positive and significant correlations among variables. Therefore, there could be a problem in this model, which is known as multicollinearity. The extent to which other explanatory variables can explain a variable is multicollinearity (Aparecido Maciel da Silva et al., 2020). According to Aparecido Maciel da Silva et al. (2020), another method for testing the presence of multicollinearity is to use the variance inflation factor (VIF) test, in which variables with values of more than 10 should be excluded from the model. VIFs have no upper limit and

Table 3. Correlation Matrix of Major Cryptocurrencies Daily Returns

		Bitcoin_ Return	Binance_ Return	Ethereum_ Return
<i>Bitcoin_Return</i>	<i>Pearson Correlation</i>	1	0.644*	0.799*
	<i>Sig. (2-tailed)</i>		0.000	0.000
<i>Binance_Return</i>	<i>Pearson Correlation</i>	0.644*	1	0.636*
	<i>Sig. (2-tailed)</i>	0.000		0.000
<i>Ethereum_Return</i>	<i>Pearson Correlation</i>	0.799*	0.636*	1
	<i>Sig. (2-tailed)</i>	0.000	0.000	

*Correlation is significant at the 0.01 level (2-tailed).

begin at 1. A value of 1 implies that there is no relationship between this independent variable and any other variables. VIFs between 1 and 5 indicate a moderate association, although it is not severe enough to necessitate corrective measures. VIFs higher than 5 indicate significant levels of multicollinearity in which the coefficients are poorly estimated, and the *p*-values are questionable. Table 4 indicates the result of the multicollinearity test.

According to Table 4, VIF values of BNB (3.979) and ETH (3.979) are between 1 and 5. This means a moderate association between these two variables, and the model is appropriate to explain the price relationship among major cryptocurrencies.

According to Table 5, *p*-values, which are associated with each series, are higher than 0.05 at the level. Therefore, the null hypothesis is a unit root, and

Table 4. Multicollinearity

Variables	VIF
BNB	3.979
ETH	3.979

Note: The dependent variable is the BTC Bitcoin. The independent variables are BNB and ETH.

Table 5. All Unit Root Test Results – Augmented Dickey-Fuller Test (ADF)

All Unit Root Test Results – Augmented Dickey-Fuller Test (ADF)										
At Level		Tabular Value	Bitcoin		Binance		Ethereum			
			t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.		
				2.112054	1	6.054976	1	5.053064	1	
	With Constant	1% level	3.43555							
		5% level	2.863724							
		10% level	2.567983							
				Bitcoin		Binance		Ethereum		
				t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.	
	With Constant & Trend			0.416017	0.999	6.105235	1	4.394912	1	
		1% level	3.965661							
5% level		3.413536								
			10% level	3.128817						

Table 5. (Continued)

All Unit Root Test Results – Augmented Dickey-Fuller Test (ADF)									
At Level				Bitcoin		Binance		Ethereum	
				<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.
	<i>Without Constant & Trend</i>			2.762988	0.999	6.280475	1	4.53517	1
		<i>1% level</i>	2.566878						
		<i>5% level</i>	1.941086						
<i>10% level</i>	1.616523								
At First Difference				Bitcoin		Binance		Ethereum	
		<i>Tabular Value</i>	<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	
	<i>With Constant</i>			10.81038	0	5.660196	0	6.280445	0
		<i>1% level</i>	3.43523						
		<i>5% level</i>	2.863712						
		<i>10% level</i>	2.567977						
				Bitcoin		Binance		Ethereum	
				<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.
	<i>With Constant & Trend</i>			9.974542	0	6.321792	0	7.258008	0
		<i>1% level</i>	3.965661						
		<i>5% level</i>	3.413536						
		<i>10% level</i>	3.128817						
				Bitcoin		Binance		Ethereum	
			<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	<i>t</i> -statistic	Prob.	
<i>Without Constant & Trend</i>			10.70156	0	5.432389	0	6.160324	0	
	<i>1% level</i>	2.566868							
	<i>5% level</i>	1.941084							
	<i>10% level</i>	1.616524							

the null hypothesis should be rejected at all significance levels. In particular, the test has been done under the first differences. As a result of this, there are no unit roots in first differences (p -values < 0.05), and so each of the series must be either $I(0)(0)$ or $I(1)(1)$.

According to Table 6, the Durbin-Watson stat value is in an acceptable range of 1.50 to 2.00. 99% of the variance of the Bitcoin daily price can be

Table 6. ARDL Method

Dependent Variable:	BITCOIN_PRICE			
Method:	ARDL			
Included observations:	1,220 after adjustments			
Maximum dependent lags:	4			
Model Selection Method:	Akaike info criterion (AIC)			
Dynamic Regressors (4 lags, automatic):	BINANCE_PRICE ETHEREUM_PRICE			
Fixed Regressors:	C @TREND			
Selected Model:	ARDL(4,3,4)			
Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BITCOIN_PRICE(-1)	1.663612	0.028362	58.65716	0.0000
BITCOIN_PRICE(-2)	-1.100765	0.052918	-20.80148	0.0000
BITCOIN_PRICE(-3)	0.599613	0.052089	11.51132	0.0000
BITCOIN_PRICE(-4)	-0.155843	0.027736	-5.618844	0.0000
BINANCE_PRICE	18.26033	2.001306	9.124211	0.0000
BINANCE_PRICE(-1)	-20.16861	3.535940	-5.703889	0.0000
BINANCE_PRICE(-2)	5.567194	3.616790	1.539264	0.1240
BINANCE_PRICE(-3)	-5.195829	2.122553	-2.447916	0.0145
ETHEREUM_PRICE	11.39573	0.422048	27.00099	0.0000
ETHEREUM_PRICE(-1)	-20.71009	0.864971	-23.94311	0.0000
ETHEREUM_PRICE(-2)	15.13888	1.082556	13.98439	0.0000
ETHEREUM_PRICE(-3)	-6.930314	1.028207	-6.740192	0.0000
ETHEREUM_PRICE(-4)	1.054932	0.544417	1.937729	0.0529
C	-19.54376	23.33890	-0.837390	0.0325
TREND	0.027843	0.042751	0.651295	0.0150
<i>R-squared</i>	0.999463	<i>Mean dependent var</i>		13022.65
<i>Adjusted R-squared</i>	0.999457	<i>S.D. dependent var</i>		13377.19
<i>S.E. of regression</i>	311.7998	<i>Akaike info criterion</i>		14.33482
<i>Sum squared residual</i>	1.17E + 08	<i>Schwarz criterion</i>		14.39760
<i>Log-likelihood</i>	-8729.239	<i>Hannan-Quinn criterion</i>		14.35845
<i>F-statistic</i>	16,0184.6	<i>Durbin-Watson stat</i>		1.944419
<i>Prob(F-statistic)</i>	0.000000			

*Note: p -values and any subsequent tests do not account for model selection.

Table 7. ADRL Long-Run Bound Test

Levels Equation				
Case 1: Unrestricted Constant and Unrestricted Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
<i>BINANCE_PRICE</i>	232.2420	89.84912	2.584800	0.0099
<i>ETHEREUM_PRICE</i>	7.687552	6.157590	1.248468	0.0121
$EC = BITCOIN_PRICE - (232.2420 \times BINANCE_PRICE + 7.687552 \times ETHEREUM_PRICE)$				
F-Bounds Test		Null Hypothesis: No levels of relationship		
Test Statistic	Value	Sig.	I(0)	I(1)
<i>F-Statistic</i>	29.875952	Asymptotic: $n = 1,000$		
		10%	4.19	5.06
		5%	4.87	5.85
		2.50%	5.79	6.59
		1%	6.34	7.52

explained by ETH and BNB prices. The model fits to explain the price relationship among cryptocurrencies as the p -value is less than 5%. Subsequently, ARDL (4,3,4) has been reached in Table 7.

ARDL long-run bound test or error correction test checks the long-run relationship between dependent and independent variables in Table 7. F -statistic value is generated as 29.875952 within the F -Bound test. This value is greater than the lower and upper bound; therefore, there is a long-term relationship between dependent and independent variables. Subsequently, the long-run formulation is as follows:

$$EC = BITCOIN_PRICE - (232.2420 \times BINANCE_PRICE + 7.687552 \times ETHEREUM_PRICE)$$

5 CONCLUSIONS

This study aimed to investigate the price relationship between Bitcoin and major cryptocurrencies. The results showed that the version and association of major cryptocurrencies price at market value with Bitcoin, which is the best known and also with the highest market value. As ETH and BNB prices increase, so does Bitcoin. In the absence of research within the scope of finance in the literature applied to Bitcoin, this study provides an important discussion to the literature. For future research, this study can have its gaps filled and advance the theme of finance applied to Bitcoin and other cryptocurrencies involving aspects of volatility.

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