

Cryptocurrency Safe Haven Property against Indonesian Stock Market During COVID-19

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ABSTRACT

Safe-haven assets conserve their value or grow against another asset or portfolio during market turmoil. Indonesian stock market, represented by the Jakarta composite index (JKSE), plunged in price because of COVID-19, pushing investors to look for safe-havens. The cryptocurrency began to be perceived as a store of value as indicated by the transaction volume increase; hence it was expected to be a safe haven asset. However, cryptocurrency's high price volatility cast doubts on its store of value effectiveness, prompting inspection for its safe haven property as well. This research aimed to predict the assets' risk and return plus investigate whether cryptocurrency is safe haven assets against the Indonesian stock market during COVID-19. Daily closing prices of JKSE, Bitcoin, Ethereum, Litecoin, and Ripple were used, then the GARCH model was implemented in the forecasting. DCC-GARCH model, followed by dummy variable regression, will be applied to the return data to evaluate the safe haven property. The prediction projected Bitcoin as the most profitable asset and Ripple as the riskiest. The analysis and robustness test suggested that none of these cryptocurrencies were safe haven assets during the whole observation. This indicates that investors who intend to seek safe haven investments were advised against investing in these cryptocurrencies.

ABSTRAK

Aset safe haven memiliki nilai yang tetap atau tumbuh terhadap aset atau portofolio lain dalam keadaan pasar tertekan. Kinerja pasar modal Indonesia, yang direpresentasikan oleh Indeks Harga Saham Gabungan (IHSG), jatuh karena COVID-19, sehingga investor terdorong untuk mencari aset safe haven. Cryptocurrency mulai dilihat sebagai store of value yang ditandai dengan kenaikan volume transaksi, sehingga cryptocurrency diharapkan dapat menjadi safe haven. Namun, tingginya volatilitas harga cryptocurrency memunculkan keraguan terhadap kemampuannya sebagai store of value, sehingga sifat safe haven cryptocurrency juga perlu diperiksa lebih lanjut. Riset ini bertujuan memprediksi risiko serta imbal balik IHSG dan cryptocurrency, dan menentukan apakah cryptocurrency merupakan safe haven terhadap pasar modal Indonesia selama COVID-19. Data yang digunakan berupa harga harian dari IHSG, Bitcoin, Ethereum, Litecoin, dan Ripple, kemudian model GARCH digunakan untuk prediksi. Untuk menentukan sifat safe haven cryptocurrency, model DCC-GARCH diikuti regresi variabel dummy digunakan pada data imbal balik setiap aset. Bitcoin diprediksi memberikan imbal balik tertinggi, sementara Ripple diprediksi menjadi aset paling berisiko. Analisis dan tes kekokohan menunjukkan bahwa tidak ada cryptocurrency yang menjadi safe haven terhadap IHSG sepanjang observasi. Hal ini mengimplikasikan bahwa investor yang berniat mencari tempat berlindung yang aman disarankan untuk tidak berinvestasi dalam mata uang kripto

1. INTRODUCTION

Since the emergence of COVID-19 as a pandemic, stock markets had experienced a decrease in performance as a response. The reaction was quick

and significantly negative, as shown in each market's return. In particular, indices representing Asian stock markets reacted more quickly, despite the slight recovery later during the pandemic (Liu et

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al., 2020). Following restrictions imposed by the government in the United States (US) and voluntary social distancing, the US stock market reaction to the outbreak was seen as more forced than previous pandemics (Baker et al., 2020).

Indonesian stock market reacted quickly to the pandemic, as hinted by the Jakarta composite index (JKSE) price decline (Adekoya & Nti, 2020; Dani, Ainurrochmah, & Adrianingsih, 2021; Rabhi, 2020; Rahim et al., 2021; Shear, Ashraf, & Sadaqat, 2021). The JKSE performance was adversely affected by the daily growth of COVID-19 confirmed cases and the public unrest following deaths from COVID-19 news (Rabhi, 2020). Furthermore, stock market returns also plummeted due to investors' increased attention to the pandemic (Shear et al., 2021).

Since January 2020, investors had become wary of the COVID-19 development (Budiarso et al., 2020). Following the WHO declaration of COVID-19 as a pandemic on 11th March 2020. Komalasari, Manik, and Ganiarto (2021) stated that investors then pulled their capital from the stock market in response to the market instability. Bank Indonesia (2020: 3) also hinted that the uncertainty in the global market triggered capital outflow to safe havens during March 2020. A safe haven investment is defined as an asset that is uncorrelated (weak safe haven) or negatively correlated (strong safe haven) with another asset or portfolio during market turbulence (Baur & Lucey, 2009; Baur & McDermott, 2010).

Despite being one of the safe havens sought during the outbreak, gold lost its property as a safe-haven asset during March and April 2020 (Akhtaruzzaman et al., 2020). Investors were prompted to search for another alternative, one of them being a cryptocurrency. According to data from Coinmarketcap, transactions of cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP) took a high leap in volume since the pandemic announcement on 11th March 2020. On 15th April 2020, daily transaction volume had increased as many as 158%, 190%, 170%, and 723%, respectively, for BTC, ETH, LTC, and XRP compared to the daily transaction volume on 11th March 2020. The increased transaction volume implied that cryptocurrency began to garner attention as an investment alternative during the pandemic.

The Jakarta composite index (JKSE), representing the Indonesian stock market, dived price since 11th March 2020 after WHO officially announced COVID-19 as a pandemic. Meanwhile, cryptocurrencies experienced an increasing trend in

price. Compared to the price on 11th March 2020, the prices of BTC, ETH, LTC, and XRP had grown by 800%, 1293%, 591%, and 849% consecutively. According to Corbet et al. (2020), this was an indication that cryptocurrencies were perceived as a store of value, which was defined by the International Monetary Fund or IMF (2000: 58) as a means of holding wealth. Since the value of an asset or currency labeled as a store of value was retained or increase over time, including during market crashes, cryptocurrency may hold the potential to be a safe haven during the pandemic.

In contrast to the increase in transaction volume, Dark et al. (2019) and Perkins (2020) highlighted the doubts surrounding cryptocurrency's capabilities as a store of value due to high price volatility. Subsequently, demands for a more stable version of cryptocurrencies emerged. Although being perceived as a more durable alternative for cryptocurrency, collateralized stable coins will inherit the properties of their collaterals; that includes their volatilities (Bullmann, Klemm, and Pinna., 2019).

To the extent of the author's knowledge, only a few studies connected cryptocurrency to JKSE from the safe haven perspective; hence, the research gap emerged. One research studied the safe haven properties of several cryptocurrencies against global stock market indices, including JKSE, up to 2019 (Wang et al., 2019), and another investigated the relationship between Jakarta composite index, S&P500, gold, and cryptocurrency prices during COVID-19 (Gunawan et al., 2021). The former was conducted in 2019; therefore, it had not included the COVID-19 impact, and the latter used only BTC price data until 2020. Thus it did not address said properties in other cryptocurrencies.

For the novelty, this research will complement studies that tie cryptocurrencies to the Jakarta composite index by expanding the observation period to include data after the pandemic declaration of COVID-19 until April 2021 and involving non-BTC cryptocurrencies at the same time. The urgency for this research rose in response to the increase in cryptocurrency transactions including in Indonesia, and the difficulties in estimating the risks posed by cryptocurrencies. In addition, Tomić, Todorovic, and Čakajac (2020) argued that although cryptocurrency did not threaten the traditional monetary system in 2020, future estimates of its usage growth could erode central banks' ability to influence monetary policy, which further reinforces the urgency of the study.

This research aims to provide risk-and-return-based investment recommendations, determine which cryptocurrency has the most return and the least volatility and whether cryptocurrencies are safe havens against the Indonesian stock market during the COVID-19 pandemic. This study has three objectives: forecasting the risk and return of JKSE, BTC, ETH, LTC, and XRP, determining the volatilities of BTC, ETH, LTC, XRP, and JKSE returns before and during COVID-19, and whether BTC, ETH, LTC, and XRP are safe havens against JKSE before and during the COVID-19 pandemic.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

A virtual currency is defined by European Central Bank (2012, pp. 13-14) as an unregulated type of digital money developed and controlled by its creators, used, and accepted by members of a specific virtual community. With its decentralized transaction network and no need for third parties, digital currency, including cryptocurrency, began to garner attention as a payment alternative. These traits enable the users to be more time and cost-efficient during transactions compared to using the existing currencies. Virtual currencies are divided into three schemes: closed virtual money scheme, which has almost no relation to the economy, virtual money scheme with the unidirectional flow, which can be acquired using real money, but not vice versa, and virtual money scheme with the bidirectional flow, which can be exchanged according to each own rate, enabling both direct and online transactions.

Third parties, usually a finance company, must validate payments in both online and direct transactions (Perkins, 2020: 6). One issue in these kinds of transactions lies in the extra time and cost which should be spent for every sales return. In cryptocurrency, this problem is addressed via replacing intermediaries with cryptographic proof (Chiu & Koepl, 2017). Blockchains and miners mainly support transactions using cryptocurrencies. Blockchains are illustrated as transaction ledgers, and the miner who manages to finish the payment validation first will update the corresponding blockchain.

It is possible for cryptocurrency, as a virtual currency, to display speculative behavior, as pointed out by ECB (2012, p. 33). Transactions using digital currencies are pseudonymous and decentralized by nature. Therefore they bear risks of criminality, such as money launderings, financial sanctions, and tax evasions, which lead to high price volatility

(Perkins, 2020). Another reason for its high volatility is cryptocurrency's having no intrinsic value, which caused doubts about its capability as a store of value (Carstens, 2018; Mersch, 2018). Although it did not threaten the traditional monetary system in 2020, future estimates of cryptocurrency usage growth could erode central banks' ability to influence monetary policy (Tomić et al., 2020).

Volatility is commonly known as a measure of risk. In finance, volatility is variance or standard deviation (Poon & Granger, 2003). Volatility is widely found as clusters in financial asset data. Hence the term volatility clustering is introduced, depending on the severity of the price swing (Brooks, 2008; Cont, 2001; Gregoriou, 2009). A possible cause of such clustering is the simultaneous, instead of separate, price change driving information at one time (Brooks, 2008). A volatility series experiences a higher rise after a price fall than a price rise is regarded as a leverage effect (Brooks, 2008; Cont, 2001). Mean reversion is also common in a volatility series, which refers to the tendency of the series to revert to its average level no matter how extreme the change is (Brooks, 2008; Poon & Granger, 2003). Volatility analysis is critical for decision-makers and traders because variability has generated issues in financial planning and international exchange markets. Gujarati (2003, p. 856) pointed out that increased volatility equates to a greater chance of making a significant profit or loss, as well as greater uncertainty.

Liu et al. (2020) highlighted that the Asian stock markets, including Indonesia, reacted more quickly to the outbreak than non-Asian markets. Several past studies concluded that the pandemic had affected the Indonesian stock market adversely (Goh, Henry, and Albert, 2021; Herwany et al., 2021; Liu et al., 2020), as evidenced by the fall in abnormal returns (Herwany et al., 2021; Liu et al., 2020). Investor fears sentiment was proven to intensify the COVID-19 effect on the stock market. However, Goh et al. (2021) provided a positive outlook, stating that the Indonesian economy will improve to survive the pandemic based on the estimation that the JKSE performance will climb over time.

An asset is defined as a safe haven if its value correlates negatively or is uncorrelated with another asset or portfolio during market turmoil (Baur & Lucey, 2009, p. 219). If the correlation is negative, a safe haven is regarded as strong. If it is zero, the safe haven is weak (Baur & McDermott, 2010). However, in normal or bullish market conditions, the correlation can be positive or negative because the safe haven property only applies during market

crashes (Baur & Lucey, 2009).

Before the pandemic, cryptocurrency may provide diversification benefits because its price has zero correlation with gold and S&P500 price. However, each cryptocurrency is positively correlated, creating risks that are tough to hedge against (Corbet et al., 2018). A study by Wang et al. (2019) on cryptocurrencies' safe haven properties against 30 global composite indices demonstrated that, from 2013 to 2018, cryptocurrencies were safe havens for most of them, including JKSE. However, the safe haven properties varied over time.

Corbet et al. (2020), which analyzed cryptocurrency behavior from the investor sentiment perspective, as reflected by social media keywords, in their study, had found that during the pandemic, cryptocurrency behaved as safe havens similar to precious metals during the crisis. Meanwhile, Mariana et al. (2021) argued that cryptocurrencies, BTC and ETH, in particular, were short-term safe havens against the S&P500 stock index. Contrary to these findings, another study suggested that cryptocurrency had become riskier than equity because its price became more unstable and irregular during the pandemic (Lahmiri & Bekiros, 2020). Moreover, based on Ji, Zhang, and Zhao (2020), the safe haven properties of cryptocurrencies became less effective over time because of the financial downturn triggered by the health crisis. Considering these studies and the nature of cryptocurrency, this study hypothesized that no cryptocurrency behaved as safe haven against JKSE.

As one of the phenomena discovered in a financial time series, volatility clustering can be captured by ARCH and GARCH models (Gujarati, 2003, p. 835). The ARCH was designed by Engle (1982), and the GARCH model was invented by Bollerslev (1986). GARCH model is superior to the ARCH model because it has higher parsimony, meaning it can capture the same phenomenon as the ARCH model with fewer parameters. Furthermore, Engle (2002) modified the GARCH model to observe the changing relationships between time series by incorporating dynamic conditional correlation (DCC) calculation; hence it was named the DCC-GARCH model.

3. RESEARCH METHOD

The research methodology was initiated by sourcing daily price data, then converting the data to daily return data. Price and return data will be tested using augmented Dickey-Fuller (ADF) and ARCH LM tests, followed by data modeling using the

GARCH(1,1) process. Forecast of risk and return will be made from the price GARCH model. Meanwhile, the DCC calculation will be carried out from the return GARCH model, and dummy variable regression on the DCC result will be employed to determine the safe haven properties.

Secondary data were sourced from Coinmarketcap (daily closing price of cryptocurrencies BTC, ETH, LTC, and XRP) and Thomson Reuters Eikon (Jakarta composite index / JKSE daily closing price), which were processed into return data. The observation period is from 1st January 2019 until 15th April 2021. There are 836 observations in total for each return data of cryptocurrency and JKSE. The robustness test for the safe-haven property was carried out by conducting the dummy variable regression for the two subperiods of the observation: pre-COVID-19 pandemic declaration (1st January 2019 - 11th March 2020) and post-COVID-19 pandemic declaration (12th March 2020 - 15th April 2021).

The calculation of asset return at t (r_t) is done in the same manner of computing price growth from period $t - 1$ to t as follows:

$$r_t = \frac{p_t - p_{t-1}}{p_{t-1}} \times 100\% \quad (1)$$

The annualized return (r) is calculated from the asset's future value at the n -th period (FV_n) and the asset's present value (PV) according to Gitman and Zutter (2015: 242), as shown below.

$$r = \left(\frac{FV_n}{PV} \right)^{\frac{1}{n}} - 1 \quad (2)$$

Before proceeding to the GARCH process, a financial time series will be tested for stationarity, using the augmented Dickey-Fuller (ADF) test, and heteroscedasticity, or having an unequal variance, in its set, using the Lagrange multiplier test as stated by Engle (1982). The DCC-GARCH method by Engle (2002) was adapted in this study to determine the volatility of each cryptocurrency and JKSE, as well as capture dynamic relationships between time series, as used by several studies (Akhtaruzzaman et al., 2020; Bouri et al., 2017; Mariana et al., 2021; Wang, Ma, and Wu, 2020). The process will be carried out in two steps: variance equation modeling using GARCH(1,1) and dynamic conditional correlation (DCC) calculation. For cryptocurrency i at time t , the model specification is:

$$\sigma_{i,t}^2 = c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \quad (3)$$

$$\eta_{i,t} = \frac{\varepsilon_{i,t}}{\sigma_{i,t}} \tag{4}$$

where $\varepsilon_{i,t}$ is residual term, with $\varepsilon_{i,t} | \Omega_{i,t-1} \sim N(0, \sigma_{i,t})$, $\sigma_{i,t}^2$ is conditional variance, α_i and β_i are ARCH and GARCH parameters respectively, and $\eta_{i,t}$ is standardized residual term.

The DCC equation is defined for positive definite matrix Q_t as conditional covariance, which is (R. Engle, 2002, p. 341):

$$Q_t = (1 - a - b) \bar{Q} + aQ_{t-1} + b\eta_{t-1} \eta'_{t-1} \tag{5}$$

where a, b are both nonnegative parameters satisfying $a + b < 1$, \bar{Q} is nonconditional covariance matrix of η_t , and $\eta_t = (\eta_{1t} \ \eta_{2t})$ standardized residual vector. The equation for DCC matrix calculation ρ_t is

$$\rho_t = D_t Q_t D_t \tag{6}$$

where $D_t = \text{diag} \left\{ q_{11,t}^{-\frac{1}{2}}, q_{22,t}^{-\frac{1}{2}} \right\}$ is normalized matrix such that ρ_t is a correlation matrix. The DCC of cryptocurrency i and the composite index j at time t is:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{7}$$

The dummy variable regression will be applied to the DCC results to determine the safe-haven property of each cryptocurrency versus the

composite index, which equation was adapted from past studies (Baur & McDermott, 2010; Ratner & Chiu, 2013; Wang et al., 2020):

$$\rho_{i,t} = c_0 + c_1 D(r_{CI} q_{10}) + c_2 D(r_{CI} q_5) + c_3 D(r_{CI} q_1) \tag{8}$$

where $\rho_{i,t}$ is the conditional correlation of cryptocurrency i and composite index at time t , while $r_{CI} q_n$ represents the n -th quantile of composite index return, $D(x)$ is dummy variable representing the event x , c_0 as the constant term, and c_k as dummy variable coefficients ($k = 1,2,3$). The 10th, 5th, and 1st quantile of JKSE returns will represent the market turmoil event. The null hypothesis is all coefficients and constant terms are equal to zero. The magnitude of the safe-haven property will be determined from two cases: nonrejection of null hypothesis for c_1, c_2 , and c_3 means cryptocurrency i is a weak safe-haven against the composite index, and if c_1, c_2 , and c_3 are negative, then cryptocurrency i is a strong safe-haven against the composite index.

4. DATA ANALYSIS AND DISCUSSION

To identify the stationarity, the ADF test was applied to every asset price and return data. Table 1 summarized the results of the tests. All price data were determined to be stationary in the first differential form at a 1% significance level, except for XRP price, which was shown to be stationary at a 5% significance level. Meanwhile, at a 1% significance level, all return data were stable at level form.

Table 1. ADF Test Result

Data	ADF Test Statistic	Order of Stationarity
JKSE Price	-23.83559703***	First difference form
BTC Price	-29.36733078***	First difference form
ETH Price	-7.429379558***	First difference form
LTC Price	-12.26527331***	First difference form
XRP Price	-2.936910552**	First difference form
JKSE Return	-23.83775341***	Level form
BTC Return	-31.02218591***	Level form
ETH Return	-31.26256577***	Level form
LTC Return	-29.66409337***	Level form
XRP Return	-28.42949127***	Level form

** and *** denotes a 5% and 1% significance level, respectively

Consecutively, the ARCH LM test was run on the same data to see if the ARCH effect existed, with the findings reported in Table 2. Except for the BTC return series, which was then assumed to be

heteroscedastic, every asset price and return time series was affected by the ARCH effect. The GARCH(1,1) model will be applied to the data after passing the ADF and ARCH LM tests.

Table 2. ARCH LM Test Result

Data	F-Statistic	Observation $\times R^2$
JKSE Price	91.31092**	82.47851**
BTC Price	22.92650**	22.36592**
ETH Price	64.96867**	60.40777**
LTC Price	35.59368**	34.21548**
XRP Price	22.57835**	22.03466**
JKSE Return	137.7845**	118.4926**
BTC Return	1.631077	1.631798
ETH Return	4.827146**	4.810838**
LTC Return	15.13665**	14.90192**
XRP Return	15.75422**	15.49862**

** denotes rejection of null hypothesis at 5% significance level

Table 3 shows the estimated coefficients and constant for the conditional variance equation modeled using the GARCH process. Because all of the price data in Table 3 contained significant ARCH and

GARCH parameters, the conditional variance equations of the price data could be utilized as forecasting models.

Table 3. GARCH(1,1) Output for Conditional Variance Equation

Data	C	α	β
JKSE Price	195.3891**	0.229101**	0.687019**
BTC Price	2746.283**	0.199620**	0.834561**
ETH Price	2.878220**	0.186105**	0.834484**
LTC Price	0.196489**	0.088843**	0.908000**
XRP Price	1.83×10^{-5} **	0.879542**	0.456837**
JKSE Return	3.94×10^{-6} **	0.198984**	0.752332**
BTC Return	0.000136**	0.095272	0.817279**
ETH Return	0.000180	0.078801	0.843745**
LTC Return	0.000412	0.072999	0.771468
XRP Return	0.000385**	0.675677**	0.456357**

** denotes rejection of null hypothesis at 5% significance level

The price model was subjected to both dynamic and static forecasting. According to the dynamic forecasting, BTC, ETH, and XRP were more volatile as their variance rose gradually towards the end of the prediction. LTC's variance rose at a slower rate than its cryptocurrency rivals. Meanwhile, when the variance prediction converged to a single number, the price of JKSE grew steadier, as shown in Figure 1.

On the other hand, the static forecasting result in Figure 2 revealed volatility clusters for each crypto-

currency and JKSE. For JKSE, the clusters peaked on 13th March 2020, following the pandemic declaration, and on 11th September 2020, following the implementation of Jakarta's second large-scale social restriction, both of which prompted investors to abandon their holdings, fearing an economic slump due to business closures. The volatility clusters for cryptocurrencies peaked in the first quarter of 2021, following increased investor interest and Elon Musk's endorsement of cryptocurrencies.

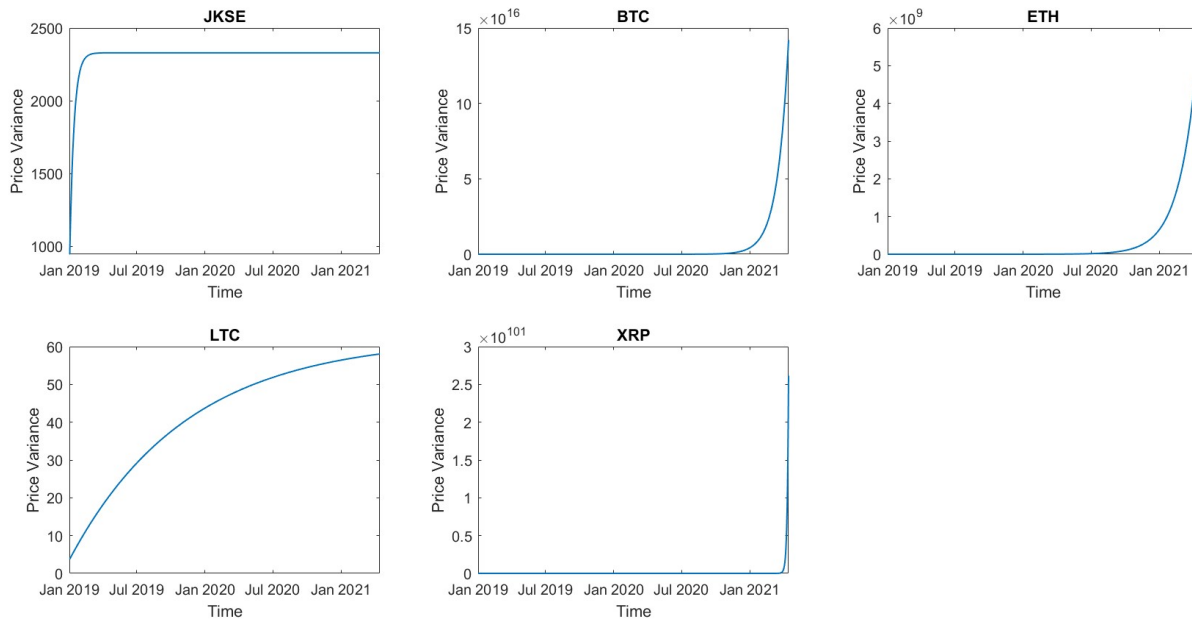


Figure 1. Dynamic Forecasting Result of Price Variance

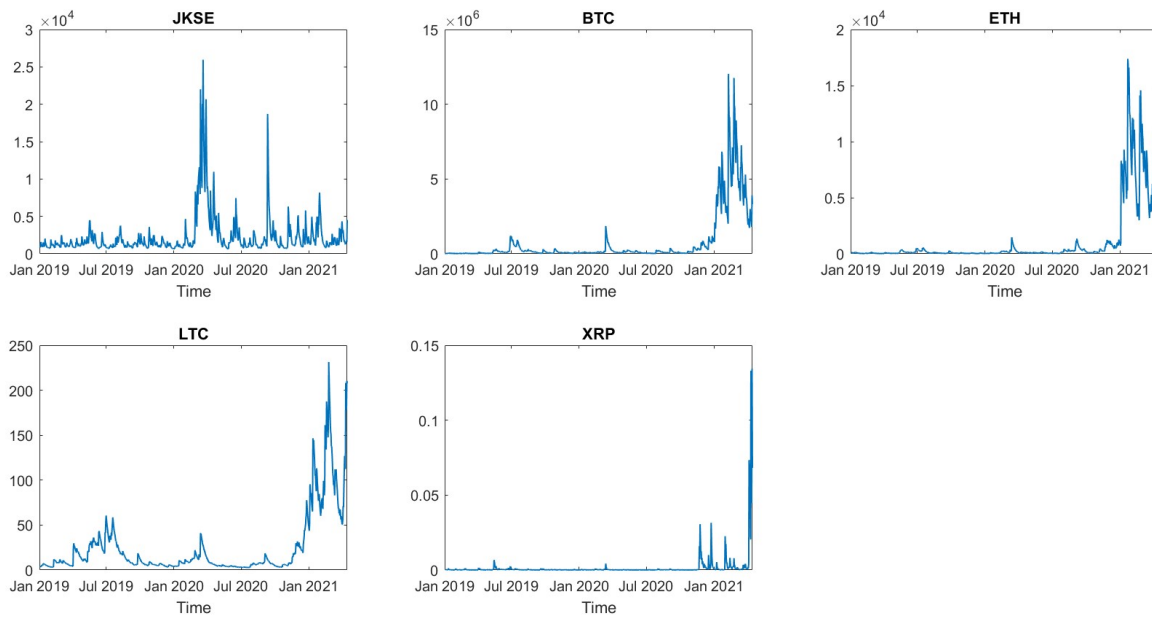


Figure 2. Static Forecasting Result of Price Variance

The accuracy of each forecasting model was evaluated using the Mean Absolute Percent Error (MAPE), which was reported in Table 4. Dynamic forecasting has a higher error rate than static forecasting. Regardless of their flaws, both forms of forecasts will be utilized to estimate the price and volatility of each asset. Static forecasting will be used to predict the price since it is more accurate than

dynamic forecasting, while dynamic forecasting will be used to predict the volatility because it captures more possible price variance. Predictions of asset prices and volatility were produced in order to provide investment recommendations. Because the model relies entirely on historical data, the forecast will only be provided from 16th April to 30th April 2021.

Table 4. MAPE of Price Forecasting from 1st January 2019 to 15th April 2021

Price Data	Dynamic Forecasting	Static Forecasting
JKSE Price	12.15787%	0.572863%
BTC Price	27.44565%	2.439042%
ETH Price	44.26066%	3.242189%
LTC Price	38.83120%	3.502904%
XRP Price	22.75249%	3.318505%

From 1st January 2021 to 30th April 2021, Figure 3 depicted the predicted price of JKSE and the cryptocurrencies. Despite price changes since January 2021, the JKSE price was expected to rise through 30th April 2021, according to Figure 3. On 30th April 2021, the price estimate was between IDR 5,708 and IDR 6,518. The annualized forecasted return from the prediction if on 15th April 2021 investment was made would be 0.03 percent, and the predicted variance on 30th April 2021 would be 17.91 percent.

Meanwhile, BTC's price increased since 1st January 2021, which lasted until the end of April 2021. Investors who bought BTC on 15th April 2021 may anticipate a 0.22 percent return on 30th April 2021, with a price range of USD 50,006 to USD 81,122. The annualized variance arising from the forecast, on the other hand, would be 22.75 percent. The projection predicted that the price of ETH would continue to rise until the end of April 2021, although to a lower extent. The annualized variance from prediction was 21.27

percent, and the return on investments placed on 15th April 2021 was projected to be 0.01 percent on 30th April 2021. Furthermore, on 30th April 2021, the price estimate ranged from USD 1,634 to USD 3,407. In contrast to previous cryptocurrencies, the forecast indicated that the price of LTC would fall until 30th April 2021. On 15th April 2021, investments were expected to provide a negative return of -0.36 percent. Furthermore, on 30th April 2021, the price is anticipated to range between USD 163 and USD 376, with an annualized variance of 19.49 percent. Similar to LTC, XRP price was also predicted to fall until 30th April 2021 based on the prediction. If investments were placed on XRP on 15th April 2021, a 2.15% loss would be incurred on 30th April 2021, with an annualized variance of 42.25 percent. Moreover, the XRP price variance also increased exponentially over time, meaning that XRP price would become increasingly volatile in the future.

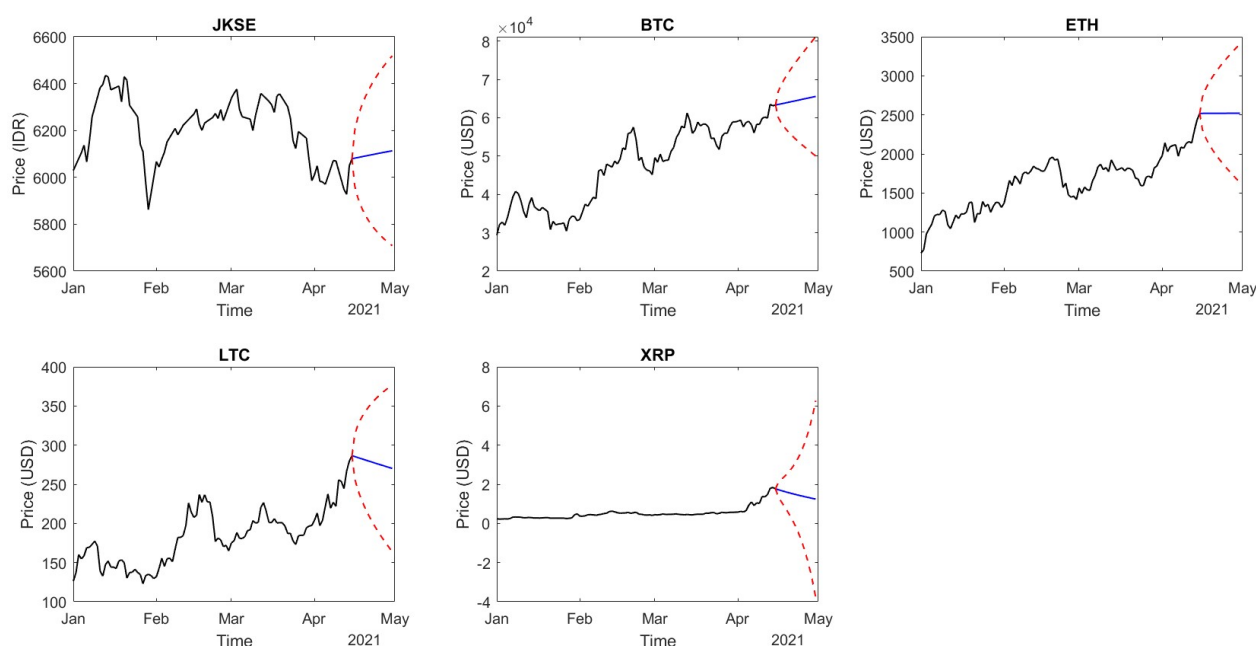


Figure 3. Price Prediction

JKSE, BTC, ETH, and LTC return volatilities from the GARCH(1,1) process are presented in Figure 4. After the pandemic declaration on 11th March 2020, investors were pressured to sell their assets due to fear of economic fall triggered by the pandemic. As a result, the assets surged in volatility during March 2020. BTC, ETH, and LTC volatilities peaked on 13th March 2020, while JKSE was on 28th March 2020. Frequent spikes in volatilities were seen from November 2020 until March 2021. This might be caused by the increasing concerns for the economic outlook caused by new strains and renewed waves of COVID-19 despite the increased hope for recovery

since vaccines were approved worldwide, as International Monetary Funds (2021) pointed out in January 2021. The volatility of XRP also surged after the official WHO declaration, as shown in Figure 5, for the same reasons. However, the surge in XRP volatility was more severe because of legal issues. The US Securities and Exchange Commission (SEC) had been pushing charges against Ripple on allegations of using unregistered securities offering to sell XRP tokens in December 2020. On 31st January 2021, XRP volatility peaked as WallStreetBets retail traders conspired to buy and sell tokens at once.

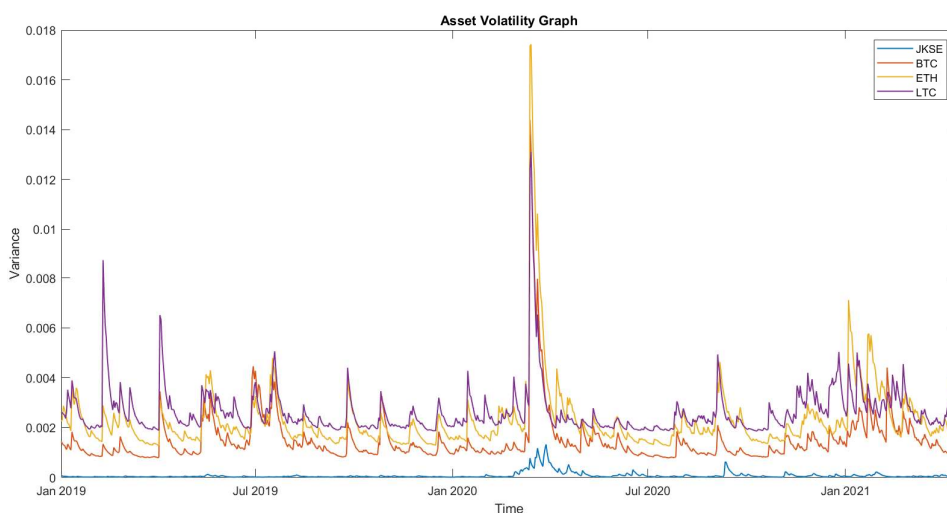


Figure 4. Return Volatility of JKSE, BTC, ETH, and LTC

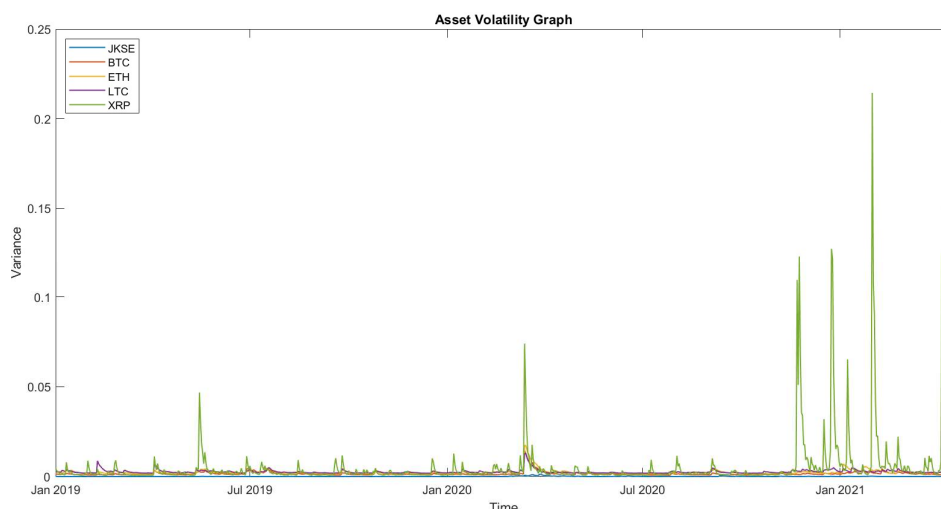


Figure 5. Return Volatility of JKSE, BTC, ETH, LTC, and XRP

Figure 6 compared the movements of the return and volatility of JKSE during the whole observation. After the WHO announcement on 11th March 2020,

the JKSE price decreased by 5.01% on 12th March 2020 as the economy fell due to COVID-19, especially in the tourism and transportation sectors. JKSE

rebounded from 23rd to 26th March 2020 as the return increased from -4.90% to 10.19% after banking sectors received foreign capital inflow and health sectors and enterprises received global stimulus. The JKSE volatility peaked on 28th March 2020 following the growth in COVID-19 infection rate and fear of economic downturn triggered by the passing of the social restriction law on 31st March 2020. After DKI Jakarta implemented large-scale social restriction (PSBB), the volatility went up on 11th September 2020, fearing another economic fall. Since November 2020, Indonesia fell into recession. Until January 2021, there were still concerns regarding the uncertainty of economic recovery from COVID-19, which was reflected from the frequent peaks during November 2020 to January 2021.

On 12th March 2020, according to Figure 7, BTC entered its riskiest time as an investment after its price plunged by 37.17%, followed by a sudden escalation in volatility to its peak on the next day. However, in April 2020, the volatility reverted to the same average level as before 11th March 2020. In January 2021, however, a longer price swing occurred, supposedly because of market corrections, Elon Musk's Bitcoin endorsement, and the warning of BTC use in illicit financing by Janet Yellen, the US Treasury Secretary.

After WHO declared COVID-19 as a pandemic, ETH's volatility peaked on 13th March 2020, after its price fell 42.35% on 12th March 2020, indicating that ETH's return was the most uncertain in the period

covered by this volatility cluster. Since April 2020, uncertainty has subsided, but it began to climb again on 4th January 2021, following a 25.95% price increase the day before. ETH's daily return and volatility graphs are shown in Figure 8.

Following a price drop of 42.35% on 12th March 2020, the return volatility of LTC surged sixfold on 13th March 2020. Despite a brief spike on 4th September 2020, the LTC return volatility has recovered to its typical level since April 2020. However, from 17th November 2020, volatility clusters have formed in shorter time intervals and gradually risen, implying a more extended period of uncertainty and a more prolonged price fluctuation, as seen by the return series. LTC's daily return and volatility were displayed in Figure 9.

According to Figure 10, the volatility clusters in XRP return stood out in the observation after the WHO declaration was formed starting 24th November 2020. On 12th March 2020, after the COVID-19 pandemic was declared, the XRP price decreased by 32.90%, causing a spike in volatility on 13th March 2020. The volatility series has been reverting to its average level since April 2020. However, since 24th November 2020, XRP has experienced a price change of 38.38% on 23rd November 2020, -42.33% on 23rd December 2020, and 56.06% on 30th January 2021, resulting in a burst of volatility on the following day of each price swing due to price uncertainty.

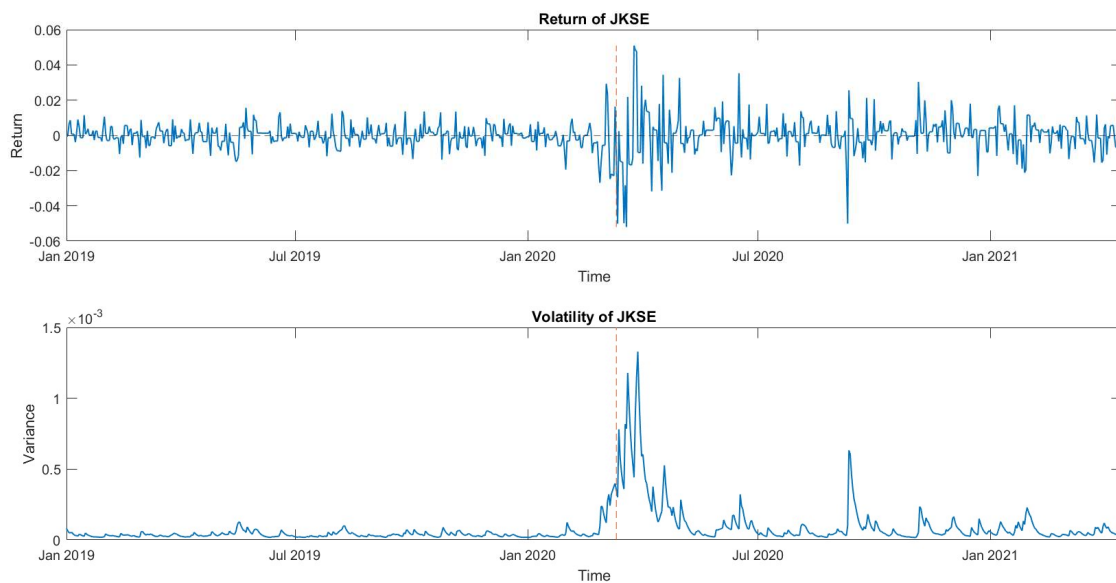


Figure 6. Return and Return Volatility of JKSE

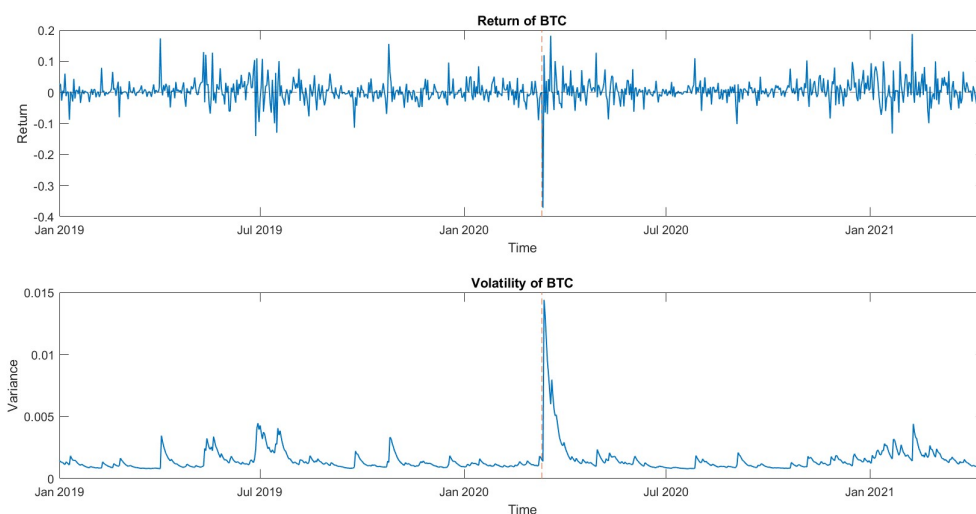


Figure 7. Return and Return Volatility of BTC

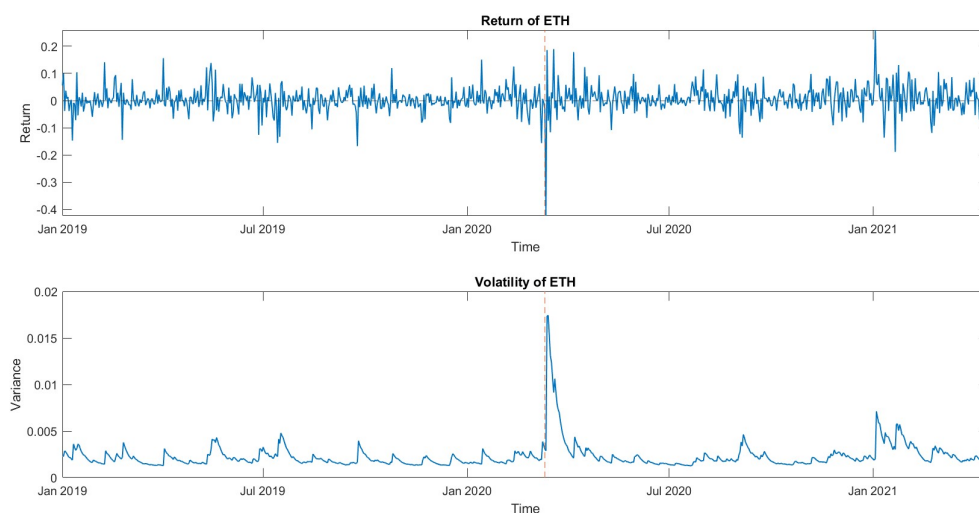


Figure 8. Return and Return Volatility of ETH

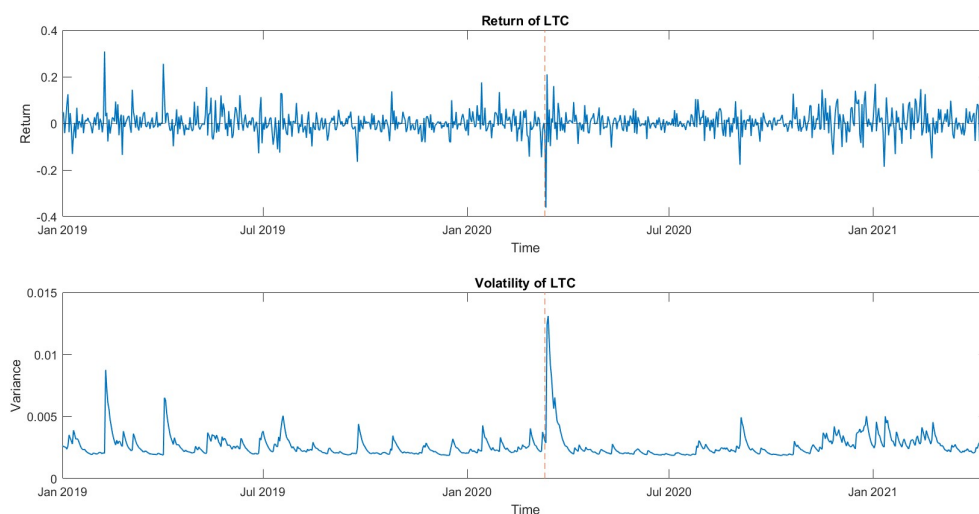


Figure 9. Return and Return Volatility of LTC

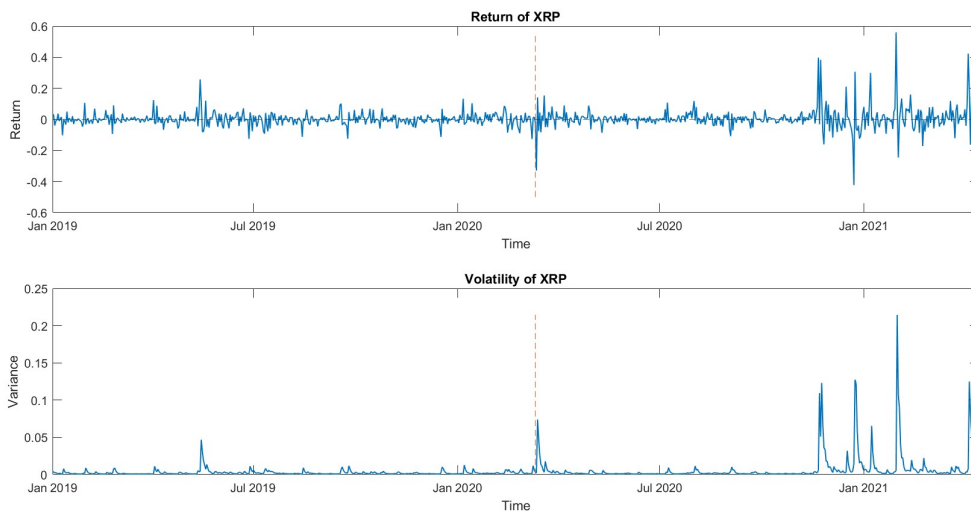


Figure 10. Return and Return Volatility of XRP

Figure 11 illustrates the DCC of each cryptocurrency and JKSE. In general, both before and during the pandemic, the DCCs of the four cryptocurrencies against JKSE were seen to fluctuate between positive and negative. On 13th March 2020, two days after WHO proclaimed COVID-19 a pandemic, all four correlations achieved extreme values.

The dummy variable regression results of the DCC against JKSE returns are displayed in Table 5. Analysis of the whole observation revealed that no cryptocurrencies in this study were safe havens against JKSE. This was implied from the positive correlation with the 1st quantile of JKSE return shown

by the cryptocurrency returns.

The robustness test showed that despite the changes that occurred after the observation period was split, their inability to behave as safe havens persisted. Based on Table 5, all cryptocurrencies were not safe havens for JKSE before the pandemic announcement on 11th March 2020 because they had positive correlations with the 1st quantile of JKSE return. Meanwhile, during the COVID-19 pandemic, all cryptocurrencies showed a positive connection in return with the 10th quantile of JKSE return, implying that cryptocurrencies still did not act as safe havens against the JKSE persisted.

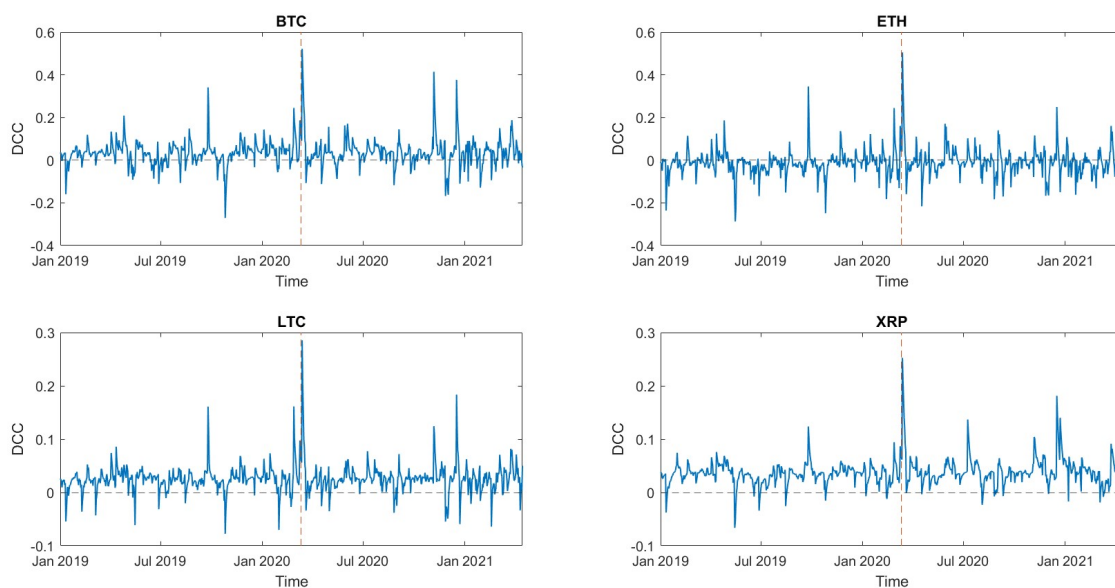


Figure 11. DCC Calculation Result of Each Cryptocurrency Against JKSE

Table 5. Dummy Variable Regression Result

Parameter	BTC			ETH		
	Full	Before	After	Full	Before	After
Constant (c_0)	0.034**	0.033**	0.034**	-0.011**	-0.013**	-0.009**
1% Quantile (c_1)	0.057**	0.092**	0.062	0.062**	0.132**	0.027
5% Quantile (c_2)	0.033**	0.022	-0.048**	0.015	-0.027	-0.047**
10% Quantile (c_3)	-0.012	-0.022	0.046**	-0.008	-0.010	0.046**

Parameter	LTC			XRP		
	Full	Before	After	Full	Before	After
Constant (c_0)	0.025**	0.024**	0.026**	0.037**	0.034**	0.040**
1% Quantile (c_1)	0.030**	0.061**	0.024	0.029**	0.037**	0.032**
5% Quantile (c_2)	0.013**	-0.008	-0.018	0.005	-0.006	-0.017
10% Quantile (c_3)	-0.006	-0.002	0.018**	0.001	-0.004	0.017**

Full: entire period (1st January 2019 – 15th April 2021)

Before: Before COVID-19 pandemic declaration (1st January 2019 – 11th March 2020)

After: After COVID-19 pandemic declaration (12th March 2020 – 15th April 2021)

**denotes rejection of null hypothesis under 5% significance level

The findings of this study suggested that cryptocurrencies were not a safe-haven against JKSE, which was in line with the hypothesis. This implied that with the addition of data during COVID-19 in the analysis, this study contradicted Wang et al. (2019), therefore agreeing with the claims made by Ji et al. (2020) regarding the deterioration of the safe-haven property of cryptocurrency during the pandemic. Furthermore, the result of this research contradicts findings from Gunawan et al. (2021), possibly because this research used a different method and approached the safe-haven property from the return data perspective instead of price data in the analysis.

5. CONCLUSION, IMPLICATION, SUGGESTION, AND LIMITATIONS

If investments were made on 15th April 2021, BTC gave the best return compared to JKSE, ETH, LTC, and XRP, according to price forecasts through 30th April 2021. Meanwhile, LTC and XRP prices were expected to decrease, with XRP falling the most. The forecast, on the other hand, revealed that the price of XRP had the highest fluctuation, making it the most volatile cryptocurrency when compared to BTC, ETH, and LTC, while JKSE was the least volatile asset among the five assets examined in the study. BTC was recommended for risk-averse investors who seek short-term capital gain and risk-taker investors, while investors who seek long-term capital gain but have low-risk tolerance can invest in JKSE.

The Dummy regression variable concluded that all cryptocurrencies were not qualified as safe havens against JKSE during the whole observation

period. Despite the change in behavior after splitting the observation period, all cryptocurrencies still did not show any safe haven property against JKSE before and during the COVID-19 pandemic. Therefore, it is not recommended for investors looking for safe havens against the Indonesian stock market to invest in cryptocurrencies.

Practical implications for this study cover the perspectives of investors and policymakers. By taking into account the cryptocurrency's nature and its inaptitude as safe havens against the Indonesian stock market, policymakers could regard this study as additional feedback during the making of policies to sustain the central bank's influence over the monetary policy. For instance, by restricting the cryptocurrency trading volume, policymakers might have the chance to offset its adverse effect on the Indonesian economy by maintaining its national money supply.

On the other hand, the practical implications on investors would vary, depending on the investor's behaviors. This research has concluded that none of the cryptocurrencies studied behaved as safe-haven against the Indonesian stock market. Consequently, investors who intend to seek the safe-havens were advised against investing in these cryptocurrencies. However, several recommendations were also made if the investors decided to invest in cryptocurrencies, regardless of their incompatibility as safe havens. A risk-taker investor may choose BTC to invest because of its high volatility among the assets with positive returns. Meanwhile, a risk-averse investor is encouraged to pick JKSE for long-term capital gain because of its low volatility. They can also choose

BTC for short-term capital gain because of its high return using swing trading, which is also applicable for risk-takers. Because both LTC and XRP are projected to provide negative returns, this study discourages investors from choosing them as an investment.

Limitations set in this research were: no other factors than the historical data was considered in the forecast, Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Ripple (XRP) were the only cryptocurrencies employed in this research, the observation time window is 1st January 2019 – 15th April 2021, which was split into two periods: before COVID-19 (1st January 2019 – 11th March 2020) and during COVID-19 (12th March 2020 – 15th April 2021).

There are numerous avenues for developments that may be pursued in this work. The data may be expanded to encompass a longer time frame or more types of cryptocurrencies. Because the approach is based on historical data, this study may be further developed by incorporating methodologies that capture the impact of external influences on price data. Conducting a comparable analysis versus stock markets in nations that have legalized the usage of cryptocurrencies in transactions is another viable path for additional research.

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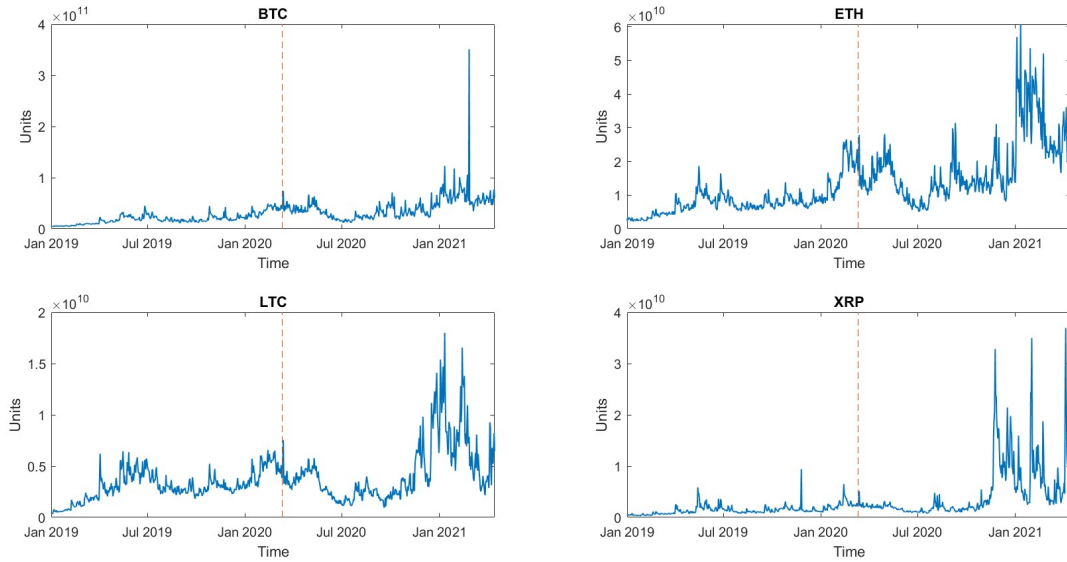
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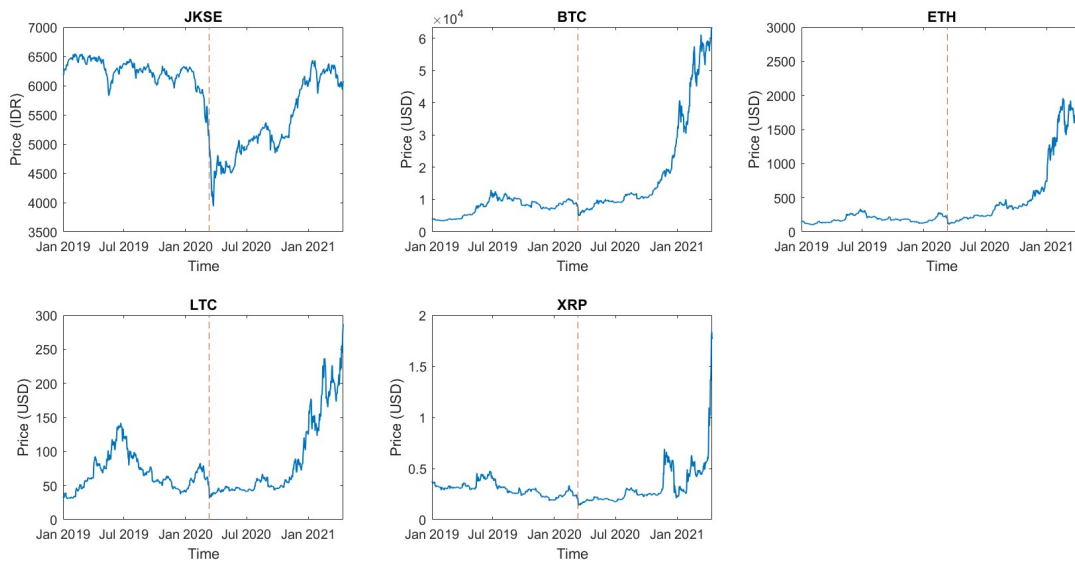
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APPENDICES



Cryptocurrency Daily Transaction Volume from 1st January 2019 – 15th April 2021
 (Source: Coinmarketcap; note: the pandemic declaration by WHO was marked by dotted lines on 11th March 2020)



All Asset Daily Price per Unit From 1st January 2019 – 15th April 2021
 (Source: Thomson Reuters Eikon and Coinmarketcap; note: the pandemic declaration by WHO was marked by dotted lines on 11th March 2020)

Descriptive Statistics Of Asset Prices

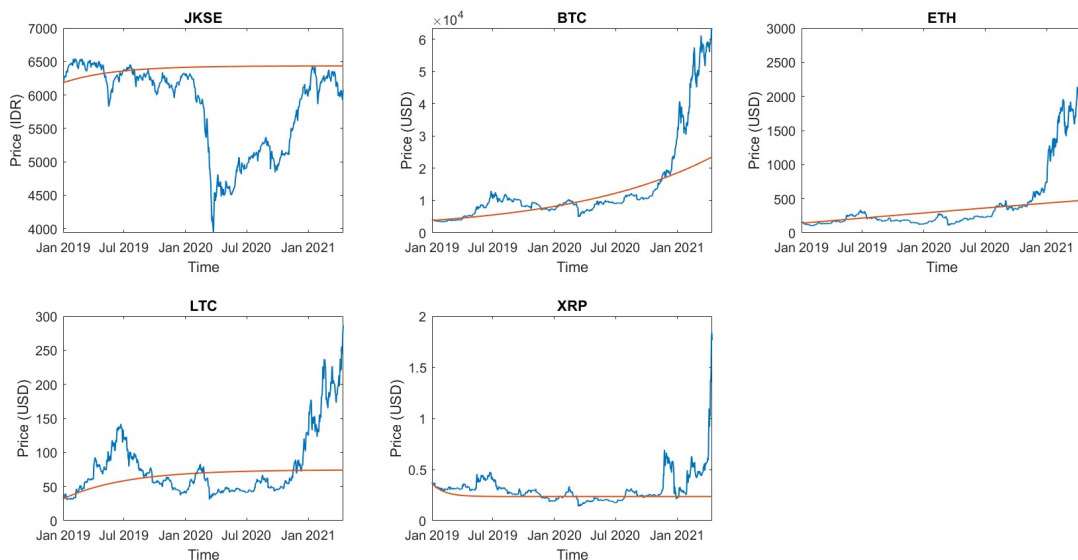
	JKSE	BTC	ETH	LTC	XRP
Mean	5823.0950	14044.8900	418.5505	78.1152	0.3141
Median	6133.5520	9412.2260	222.5800	59.3711	0.2822
Maximum	6547.8770	63503.4600	2519.1160	286.5906	1.8392
Minimum	3937.6320	3399.4720	104.5353	30.3329	0.1396
Standard Deviation	639.8859	13669.9900	489.1585	47.7668	0.1606
Skewness	-0.8590	2.2385	2.2892	1.7585	4.6931
Kurtosis	2.3474	6.9475	7.1022	5.6342	36.8212
Jarque-Bera	117.64***	1240.96***	1316.37***	672.55***	42913.68***

***denotes null hypothesis rejection at 1% significance level

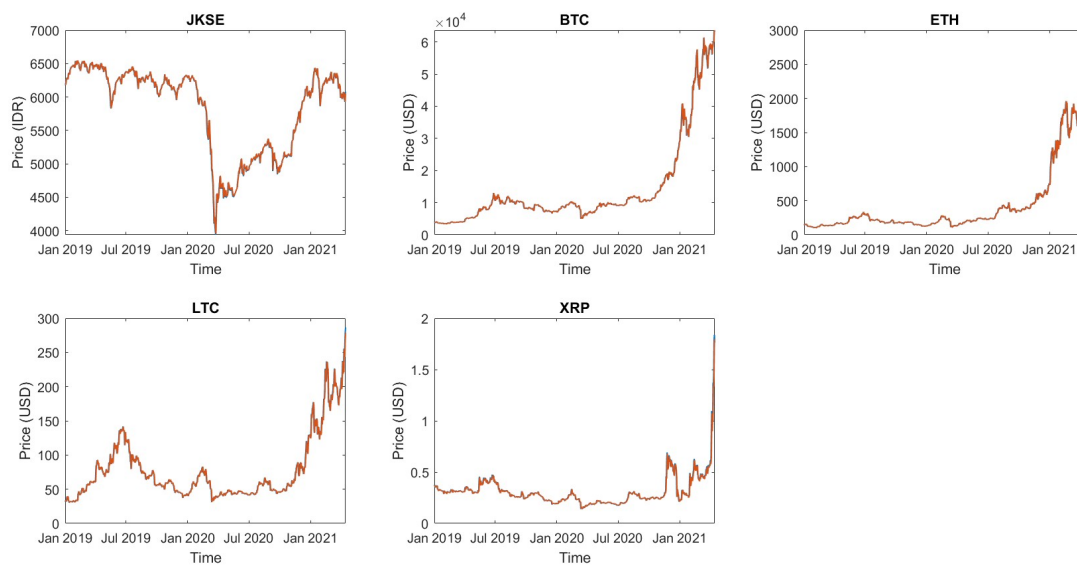
Descriptive Statistics Of Asset Returns

	JKSE	BTC	ETH	LTC	XRP
Mean	0.000019	0.004127	0.004689	0.004001	0.003661
Median	0.000255	0.001953	0.002384	0.001655	0.000092
Maximum	0.050953	0.187465	0.259475	0.308294	0.560112
Minimum	-0.052013	-0.371695	-0.423472	-0.361773	-0.423341
Standard Deviation	0.008972	0.037938	0.047558	0.051248	0.060209
Skewness	-0.174725	-0.626969	-0.652545	0.127989	1.965251
Kurtosis	11.4748	17.0249	13.0467	9.1462	24.9475
Jarque-Bera	2506.06***	6906.44***	3575.30***	1318.15***	17317.06***

***denotes null hypothesis rejection at 1% significance level



Dynamic Forecast of Price Data From 1st January 2019 to 15th April 2021
(Blue line: actual data, red line: forecasted data)



Static Forecast of Price Data From 1st January 2019 to 15th April 2021
 (Blue line: actual data, red line: forecasted data)