Cryptocurrency Risk Analysis During the Covid-19 Pandemic: Value at Risk (VaR) Approach

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ABSTRACT

The COVID-19 outbreak had a severe impact on almost all countries in the world. One aspect of concern during the pandemic is an investment. In this study, the GARCH model used to estimate Value at Risk (VaR) on cryptocurrency investments as a tolerable loss during the COVID-19 pandemic. Data in this study are ten cryptocurrencies with the largest capitalization. The observation period when WHO declared COVID-19 as a pandemic, namely on March 11, 2020 - June 11, 2020. From this study, the highest cryptocurrency VaR value is Crypto.com with an amount of 0,18214. It means that the maximum loss that an investor can tolerate with an investment of $500.000.000 for a 95 percent confidence level is $ 91.070.392.

Keywords: COVID-19, cryptocurrency, GARCH, Value-at-Risk (VaR).

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INTRODUCTION

Today the world is struggling against COVID-19 outbreak, also known as a coronavirus pandemic. The virus outbreak, which began in Wuhan, China in December 2019, then on January 30, 2020, The Public Health Emergency of International Concern (PHEIC) is a formal declaration by the World Health Organization (WHO) about extraordinary events determined as public health risks for other countries through the spread of international diseases and need a coordinated international response (Zhahrina, 2020). World Health Organization (WHO) officially announced the outbreak COVID-19 as a global pandemic on March 11, 2020. In less than 3 months, COVID-19 has infected more than 126.000 people in 123 countries, from Asia, Europe, the US, to South Africa (Putri, 2020).

Besides having severe implications for human health, COVID-19 also has a significant impact on business and the economy. The COVID-19 pandemic has caused an unprecedented human and health crisis. The measures necessary to contain the virus have triggered an economic downturn. At this point, there is great uncertainty about its severity and length. The latest Global Financial Stability Report shows that the financial system has already felt a dramatic impact (Adrian and Natalucci, 2020). Financial and economic researchers such as Corbet *et al.*, (2020), Goodell, (2020), Yarovaya *et al.*, (2020a), and Sharif *et al*., (2020) responded quickly to the pressing needs of the various financial impacts of this pandemic that have affected global financial markets in almost all dimensions, from traditional financial assets such as equities, bonds and precious metals to more contemporary asset classes such as cryptocurrency. COVID-19 is considered a black swan event, given that it is difficult to predict and unprecedented so that the existing risk management model fails to mitigate risk adequately (Yarovaya *et.al.*, 2020b) Facing unprecedented risks, people have an increasingly greater need to find assets as safe-haven investments. The motivation for safe-haven investment is the unwillingness of investors to lose money (Tversky and Kahneman, 1991). A safe-haven is an investment that is useful to secure assets value during times of financial crisis (Sholohah and Sulistyawati, 2018). Return is one of the factors that motivates investors to invest and is also a reward for the courage of investors to risk the investment they make (Hartono, 2013). In this case, the investor faces a trade-off between the risk and the expected level of return.

The growing popularity of cryptocurrency makes it a candidate for safe-haven investment. As can be seen in Figure 1, about the development of the cryptocurrency market capitalization value from 2013-2019.

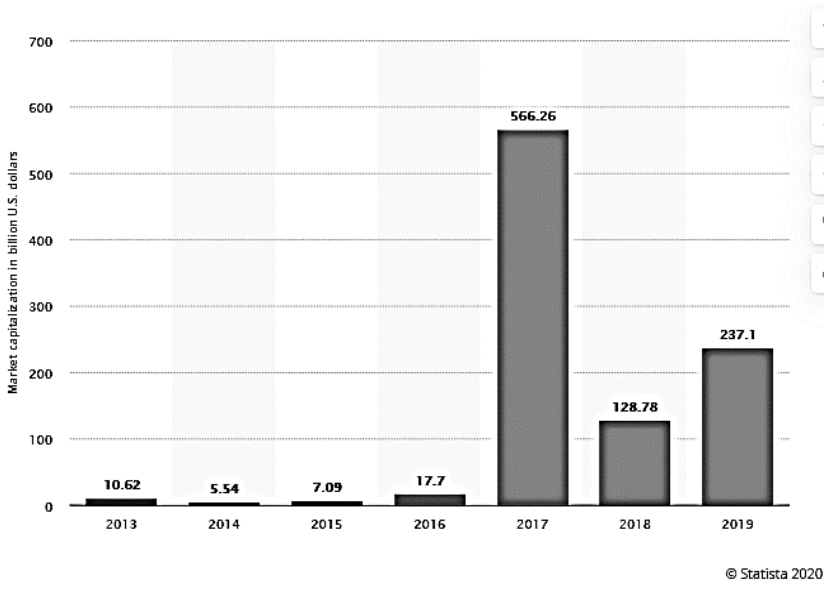

Figure 1. Cryptocurrency Market Capitalization (Statista, 2020)

2017 is the year where the cryptocurrency market experienced a significant increase compared to the previous four years. The market cap of all cryptocurrency was around $ 566 billion in 2017, then dropped to $ 128,78 billion in 2018 and then slightly increased to $ 237,1 billion in 2019. The development of cryptocurrency capitalization makes it as a candidate for safe-haven investment, several studies in the past year also stated about the benefits of this investment. The research of Bouri *et al.*, (2017) and Urquhart and Zhang, (2019) stated Bitcoin as a safe-haven investment during times of financial turmoil. Shahzad *et al.*, (2019) revealed that the role of safe-haven Bitcoin, gold, and commodities varied over time and differed across the stock market indices studied. Guesmi *et al.*, (2019) found that the addition of Bitcoin in portfolios consisting of gold, oil, and emerging market shares reduced portfolio risk.

At the first time launched Cryptocurrency is not an investment asset, but because of its popularity, many investors use it (Inci & Lagasse, 2019). The interest of investors and analysts in cryptocurrency in recent years, especially after 2008 has become widespread and growing since the popularity of Bitcoin was introduced by Nakamoto, (2008) as a decentralized digital currency, so cryptocurrency takes an important role in life throughout the world (Hileman and Rauchs, 2017). The particular nature of making Bitcoin does not depend on specific governments or central banks, the formation of Bitcoin prices related to supply and demand (Bouoiyour *et al*., 2015; Buchholz *et al*., 2012). The next question is whether Bitcoin's ability is the same for other cryptocurrencies in this pandemic situation. It is important to note that on July 15, 2020, there were 5,735 cryptocurrencies registered on the coinmarketcap website (CoinMarketCap, 2020). Therefore, research is needed to calculate the potential risk of cryptocurrency investments during the COVID-19 pandemic. Significant changes in cryptocurrency prices can be said to contain an element of uncertainty so that it carries not only large profits but also substantial risks. Risk is the uncertainty that something will happen at a certain time (Van Horne & Wachowicz Jr, 2012), or the possibility of events and their consequences about what is desired or undesirable (Griffin, 2011). In the investment, the risk is the possibility that an investor will receive a return that is different from the expected return (Damodaran, 2007), because there is a deviation between the expected rate of return and the actual rate of return (Saham *et al.*, 2017).

The next problem faced by investors is in determining which assets should be purchased, in this case, which is the cryptocurrency to invest? So that risk management is needed in making investment decisions. Nowadays, there are many developing calculations in investments so that investors can find out the value of risk early to reduce potential losses. Because of the financial crisis, risk management is increasingly attractive to investors and uses Value-at-Risk, which is part of widely accepted risk management. According to Best, (1998) the Value at Risk (VaR) method is a risk assessment method for estimating potential losses that might occur based on a portfolio at a certain level and confidence. Value at Risk (VaR) is one of the most important measures of market risk that has been used for financial risk management by institutions, including banks, regulators, and portfolio managers.

Researchers do not always use the causal method in analyzing a phenomenon, as used in the correlation regression method. In the correlation regression method, researchers use two or more variables and look for the influence of one or several variables on other variables. In the economic world, also known as time-series data, which have specific characteristics, so that its value fluctuates. For an example, is the price of an index in the capital market. The ARIMA (Autoregressive Integrated Moving Average) method is one method of time series analysis, ARIMA is a method developed and studied by George Box and Gwilym Jenkins, Therefore their name is often associated with the ARIMA process and applied to data analysis and forecasting time series data. ARIMA is an attempt to find the most suitable data pattern from a group of data, so the ARIMA method requires full historical and current data to produce short-term forecasts. In general, the Box Jenkins model formulated with the ARIMA notation (p, d, q). In this case: p = Order or degree of AR (Autoregressive), d = Order or degree of differentiation (Differencing), and q = Order or degree of MA (Moving Average) (Sugiarto & Harijono, 2000).

The time-series data usually has a variant that is not constant (heterokedastisitas). The Autoregressive Conditional Heteroscedastic (ARCH) model introduced by Engle is one of the

earliest time series models to enable heteroscedasticity (Engle, 1982). Bollerslev (1986) extended this idea into Generalized Autoregressive Conditional Heteroscedastic (GARCH) models. The ARCH / GARCH model has become a widely used model for predicting volatility for VaR risk calculation. Dwipa (2016) used the ARCH / GARCH model in his research to find out the best forecasting model of JSX composite, stock return data is a type of data series, which has high volatility, and different variants at each point sought. Furthermore, this GARCH model is used to estimate the VaR value as the maximum value to be obtained over a specified period at a certain level of confidence.

This study aims to estimate the value of Value at Risk (VaR) with volatility modelling using the ARCH / GARCH model so that it can measure investment risk on ten cryptocurrencies with the largest capitalization value and find out how much the maximum loss that can be tolerated by investors during the COVID-19 pandemic, so the application of the VAR method can help investors in making cryptocurrency investment decisions

Review of Literature

Many have tried to explore the advantages of such modern e-currency technologies since Bitcoin has emerged as the most important digital currency. Bonneau *et al*., (2015) defined the main characteristics of Bitcoin and suggested improvements to achieve its potential stability. In addition, they discussed the problem of anonymity in such transactions and introduced steps to remove intermediaries. Corbet *et al.*, (2018) is another research report that illustrates the beneficial elements of cryptocurrencies. They include reasons in favor of a stable and safe investment asset for cryptocurrencies. On the other side, there are research papers that illustrate the negative aspects of cryptocurrencies, such as research undertaken by Bucko *et al*., (2015) they examine the high volatility of cryptocurrency values, the potential for hacking, and the ability to finance anonymous illegal activity, security, transportation, and trust issues.

It is imperative to follow an econometric model to examine cryptocurrency volatility in detail as cryptocurrency investors increase. Thus, several researchers favour traditional ARCH and GARCH as an effective model for studying cryptocurrencies. They are intended to measure heteroscedasticity in times of great shifts in the market for cryptocurrencies. Based on the approach used, the results of previous study are collected to explain and see the theoretical research framework, either to improve testing or to change. Compared with previous studies that were limited to volatility analysis. Katsiampa (2017) performed one of the first studies analyzing volatility in digital currencies, estimating Bitcoin's volatility by comparing different GARCH models and concluding that AR-CGARCH is the model that better represents the volatility of Bitcoin.

GARCH was used by Warsito and Robiyanto (2020) to analyze cryptocurrency volatility, gold volatility, dollar volatility, and JSX Composite volatility. Bitcoin and Ethereum are the cryptocurrency objects in this study because they have the highest market capitalization value. This study shows that the volatility of Bitcoin and Ethereum depends on the price of Bitcoin and Ethereum, respectively, not on other variables. Miglietti *et al.*, (2019) in his research investigates the volatility of Bitcoin, Litecoin and Euro. The statistical methods used, including standard deviation and annual volatility based on the currency chosen, show that Litecoin is more volatile than Bitcoin and Euro. At the same time, Bitcoin is more volatile than the Euro. Al-Yahyaee *et al*., (2019) analyzed Bitcoin's downside risk and diversification advantages through the application of bivariate DCC-GARCH models and reported that Bitcoin portfolios could provide better results.

The GARCH model was used by Dyhrberg (2016) to explore the potential of Bitcoin as a financial commodity. In his analysis, the GARCH model actually proves that this asset can be used in portfolio management since it is suitable for risk-averse investors. In order to investigate whether Bitcoin exhibits hedging capabilities and acts as an exchange medium comparable to gold and the US dollar from July 2010 to May 2015, Dyhrberg (2016) employs an asymmetric GARCH methodology. Results show that Bitcoin can be considered between the US dollar and

the gold for these functions. There is also evidence that Bitcoin not only can lead to benefit as an investment but also as a tool for risk management.

From December 2010 to June 2015, Bouoiyour and Selmi (2015) analyzed the price of Bitcoin using regular data samples. Among the models they adopted, GARCH was the most fitting and showed that volatility decreased dramatically even though the demand for cryptocurrencies was still fresh. Gronwald (2014) compared the market for gold and bitcoin and analyzed the price of bitcoin using GARCH models. He realized that its price had changed enormously and the market where it was selling was not mature. Therefore, several researchers support ARCH and GARCH as the correct model for the cryptocurrency analysis since they are designed to test heteroscedasticity during times of valuable cryptocurrency changes (Kyriazis *et al*., 2019).

RESEARCH METHOD

In this study, the authors chose cryptocurrency index data to conduct research. The data used in this study is quantitative, that is, data expressed in numerical form (Supranto, 2008). From the time dimension, this research belongs to the time series data group, which is a set of observations about a specific time (Widarjono, 2009). This study is a type of empirical research with the data used is secondary data that is the daily closing price cryptocurrency from the site coindesk.com. The population in this study is all cryptocurrency obtained on coinmarketcap.com site, the sample selection in this study is using a purposive sampling method. The purposive sampling method is the determination of the sample by taking specific data that is considered appropriate and related to the research conducted. Sample in this study is ten cryptocurrencies with the largest capitalization value. The reason for choosing the sample criteria is because market capitalization is one of the benchmarks commonly used by both investors and fund managers in the decision to purchase a company's shares. The amount of market capitalization itself is a company-owned value, the better a company performs its business, the higher the value of market capitalization (Darmawan, 2017). From the purposive data, the cryptocurrency in this study are Bitcoin, Ethereum, Ripple XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, Binance Coin, Cardano, and Crypto.com. The observation period was the date when COVID-19 was declared a pandemic by the WHO.

In this study, data processing uses Microsoft Excel 2019, Minitab 18, and Eviews 8 software. This research begins with the first step in collecting the required data related to the return of cryptocurrencies using clean prices. The next step is performing the calculation of return. After knowing the valued, then the data stationarity test is performed using the Augmented Dickey-Fuller (ADF), if the data is stationary, then the process can continue without problems, But if the data turns out not to be stationary in the level then do the Differencing until it reaches stationary then ARIMA modelling is done by entering the AR or MA variables involving the model. Before doing ARCH/ GARCH modelling, it is necessary to check whether there is an ARCH Effect in the model with ARCH-LM testing. If there is an ARCH Effect in the model, the research can proceed to the ARCH/ GARCH modeling stage then the selection of the best model and finally the conclusion drawing. The variable in this study is the clean price of ten cryptocurrencies which is then calculated return.

RESULT AND DISCUSSION

Descriptive statistics

Descriptive statistics are statistics used to analyze data by figure out or describing collected data without intending to make conclusions that apply to the public (Sugiyono, 2017). This study uses daily data on cryptocurrency prices during the observation period from March 11, 2020 to June 11, 2020 or for 93 days. Furthermore, the data will be used in the formation of data returns for the estimation of volatility and VaR value to determine the investment risk. To see the results of the descriptive statistics can be seen in Table 1 as follows.

Table 1. Descriptive Research Variable

Cryptocurrency	Mean	Std. Dev	Median	Maximum	Minimum
Bitcoin	0,002370	0,052474	0,000685	0,161040	-0,315950
Ethereum	0,002140	0,066753	0,003025	0,188640	-0,423570
Tether	0,000013	0,010031	0,000000	0,049980	-0,049160
XRP	-0,000574	0,049122	0,000945	0,144140	-0,289040
Bitcoincash	-0,000724	0,065612	0,001755	0,232290	-0,428980
Bitcoinsv	-0,000342	0,075357	0,000005	0,323570	-0,462290
Litecoin	-0,000880	0058677	0,002215	0,160630	-0,377040
Binancecoin	-0,000139	0,073248	0,004320	0,193460	-0,542810
Cardano	0,006952	0,068461	0,003305	0,203460	-0,348720
Crypto.com Coin	0,008275	0,068579	0,010655	0,141280	-0,490430

From Table 1, we can see that XRP, Bitcoin Cash, Bitcoin SV, Litecoin, and Binancecoin have return-value with a negative mean value. It means that these cryptocurrencies during the COVID-19 pandemic tend to have high losses and risks. When viewed from the standard deviation values that reflect volatility, a cryptocurrency that has the highest volatility during the observation period is Crypto.com Coin and Cardano , which means that they have a high risk and high return during the COVID-19 pandemic. Maximum value means the maximum profit return level that can get while the minimum value is the maximum loss level that can get. Bitcoin, the maximum profit level that can get is 16 percent with a maximum loss rate of 31 percent.

The Data Stationarity Test

The data stationarity testing method used in this study uses the Augmented Dickey-Fuller Test. If the statistical value is higher than the McKinnon critical level, at a predetermined critical value of 1 percent, 5 percent, or 10 percent, then H0 is accepted which means the data contains unit roots or not stationary. Conversely, if the statistical value is smaller than the McKinnon critical value, H0 is rejected, which indicates that the data is stationary. Time series economic data are generally stochastic or have non-stationary trends. It means that the data contain root units. To estimate a model, the first step to take is the stationarity test, if the data used is not stationary then it will be difficult to determine a model using the data because the data trends tend to fluctuate and are not around the average value. Then it can be concluded that the stationary data will tend to approach the average value and fluctuate around the average value (Gujarati, 2003).

Procedure to determine whether the data is stationary or not by comparing the Augmented Dickey-Fuller statistical value (ADF) with its critical value, namely the statistical distribution (critical value), the ADF statistical value is indicated by the t-statistic value. If the ADF statistical value is smaller than the critical value, then H0 is rejected, so the observed data shows that the data is stationary. Conversely, the data is not stationary if the ADF statistical value is greater than the critical value of the statistical distribution. The stationarity test results can be seen in Table 2 as follows.

Table 2. Descriptive Research Variable

Cryptocurrency	t-Statistic	Prob	Explanation
Bitcoin	-9,663931	0,0000	Stationer
Ethereum	-10,86490	0,0000	Stationer
Tether	-10,44622	0,0000	Stationer
XRP	-8,404239	0,0000	Stationer
Bitcoincash	-11,40288	0,0001	Stationer
Bitcoinsv	-10,80013	0,0000	Stationer
Litecoin	-12,23708	0,0001	Stationer
Binancecoin	-19,9754	0,0001	Stationer
Cardano	-14,12928	0,0001	Stationer
Crypto.com Coin	-18,03454	0,0001	Stationer

The McKinnon critical value in the calculation of this study at α = 1 percent; α = 5 pecent; α = 10 percent; each one is -3.503879; -2.893589; -2.583931. In table 2 above shows, the results of the ADF test for each cryptocurrency has a t-statistic value that is smaller than the McKinnon critical value for the level of 1 percent, 5 percent, or 10 percent, so the probability value becomes less than α 5 percent even zero. With this value, all stationary cryptocurrency data or data return do not have a root unit and can say that the data is stationary.

Identifying ARIMA Model

This stage is estimating the best ARIMA model that can read data return patterns. The best model indicator from the calculation results is the model that has significance to all parameters; the model that has the lowest error value and passes the Fit model test. More about the best ARIMA forecasting model in this study can be seen in Table 3 as follows.

Table 3. The Best ARIMA Model Estimation Results

Cryptocurrency	Parameter	Test		Residual Sums of Square		Box-Pierce		
		Coef	P-Value	SS	MS	Chi-Square	DF	P-Value
Bitcoin	AR 1	-0,9986	0,0000**	0,23034	0,00259	10,39	9	0,320
	MA 1	-0,9009	0,0000**					
	Constant	0,0042	0,6790					
Ethereum	AR 1	-0,9971	0,0000**	0,35490	0,00399	8,87	9	0,449
	MA 1	-0,8937	0,0000**					
	Constant	0,0036	0,7760					
Tether	AR 1	-1,4575	0,0000**	0,00536	0,00006	26,67	20	0,145
	AR 2	-0,5643	0,0000**					
	MA 1	-0,9917	0,0000**					
	Constant	-0,0003	0,8470	0,18537	0,00208	7,98	9	0,536
XRP	AR 1	-0,9974	0,0000**					
	MA 1	-0,8787	0,0000**					
	Constant	-0,0018	0,8410					
Bitcoincash	AR 1	-0,9974	0,0000**	0,32720	0,00368	11,14	9	0,267
	MA 1	-0,8668	0,0000**					
	Constant	-0,0024	0,8390					
Bitcoinsv	AR 1	-0,9978	0,0000**	0,45984	0,00517	11,75	9	0,228
	MA 1	-0,9078	0,0000**					
	Constant	-0,0015	0,9170					
Litecoin	AR 1	-0,9972	0,0000**	0,26135	0,00294	12,72	9	0,176
	MA 1	-0,8494	0,0000**					
	Constant	-0,0027	0,7990					
Binancecoin	AR 1	-0,9963	0,0000**	0,38718	0,00435	7,37	9	0,599
	MA 1	-0,6565	0,0000**					
	Constant	0,0026	0,8230					
Cardano	AR 1	-0,9961	0,0000**	034448	0,00387	5,25	9	0,812
	MA 1	-0,7681	0,0000**					
	Constant	0,0156	0,1770					
Crypto.com	AR 1	-0,9052	0,0000**	0,35083	0,00394	9,63	9	0,381
	MA 1	-0,5650	0,0000**					
	Constant	0,0182	0,0790					

Note: Prob value. <α 5%, so that it is significant

The best ARIMA model results for ten cryptocurrency shows all the parameters of the model are significant because it has a probability value smaller than alpha 5%. For Fit Test, the model with Box-Pierce (Ljung-Box) produces a probability value higher than alpha 5 percent, meaning that the ARIMA model (p, d, q) is fit (excellent).

ARCH Effect Test

A Lagrange-Multiplier test will perform to determine the ARCH of the selected ARIMA model. If there is an ARCH effect or heteroscedasticity data, then the estimation model can be done with the ARCH / GARCH model, but if there is no ARCH effect or homoskedasticity data then it cannot be continued with the ARCH / GARCH model. The probability value that is smaller than 5 percent, so that H0 rejected, it means that there is heteroscedasticity and the estimation will do with the ARCH / GARCH. Still, if the probability value is higher than 5%, then the data is homokedastisitas and cannot to continue with the ARCH / GARCH model. Based On The Information In Table 4 we can see the ARCH Effect test in this study.

Table 4. ARCH Effect Test

Cryptocurrency	F-Statistic	Prob F
Bitcoin	9,74E+24	0,0000
Ethereum	9,90E+24	0,0000
Tether	2,60E+23	0,0000
XRP	1,47E+25	0,0000
Bitcoincash	9,93E+24	0,0000
Bitcoinsv	1,93E+22	0,0000
Litecoin	1,44E+25	0,0000
Binancecoin	3,94E+24	0,0000
Cardano	4,11E+24	0,0000
Crypto.com Coin	1,23E+25	0,0000

The ARCH effect test results show that all cryptocurrencies has a probability value smaller than alpha 5 percent, which means that the ARIMA estimation model has an ARCH effect, so it needs to be estimated the best ARCH / GARCH model.

The Best ARCH / GARCH Model Results

The estimation of the ARCH / GARCH model must perform to calculate the value of volatility so that the risk value can predict with the VaR calculation on the selected ARCH / GARCH model. The best ARCH / GARCH model requirements are that the model has significant parameters both in the main model and its volatility model. And the results of the best ARCH / GARCH model must be free from heteroscedasticity. After knowing the existence of a significant ARCH effect, then an estimate is made using the order from the ARIMA model as input to the ARCH / GARCH estimate. The best model acquire by looking at the value of Log-Likelihood and the criteria of AIC and SIC

Table 5. The Best ARCH / GARCH Model Results

Model	Variable	Estimasi		ARCH test	
		Coef	Prob	F-statistics	Prob (F)
Bitcoin	C	0,0056	0,1597	0,0099	0,9211
GARCH(1,1)	AR(1)	-0,9555	0,0000		
	MA(1)	0,9401	0,0000		
		Variance Equation			
	C	0,0002	0,0000		
	RESID(-1)^2	-0,0728	0,0077		
	GARCH(-1)	0,9159	0,0000		
Ethereum	@SQRT(GARCH)	-0,3988	0,0000	0,7706	0,3824
M-GARCH(1,1)	C	0,0234	0,0000		
	AR(1)	-0,8700	0,0000		
	MA(1)	0,7534	0,0000		
		Variance Equation			
	C	0,0005	0,0000		
	RESID(-1)^2	-0,1222	0,0000		
	GARCH(-1)	0,8412	0,0000		

Model	Variable	Estimasi		ARCH test	
		Coef	Prob	F-statistics	Prob (F)
Tether	C	0,0000	0,0089	0,7872	0,3774
GARCH(1,1)	AR(1)	0,0523	0,0001		
	AR(2)	0,0892	0,0006		
	MA(1)	-0,7054	0,0000		
		Variance Equation			
	C	0,0000	0,3867		
	RESID(-1)^2	0,9775	0,3160		
	GARCH(-1)	0,5245	0,0011		
XRP	@SQRT(GARCH)	0,1082	0,8744	0,3125	0,5776
M-GARCH(1,0)	C	-0,0004	0,9897		
	AR(1)	0,5793	0,0000		
	MA(1)	-0,7672	0,0000		
		Variance Equation			
	C	0,0011	0,0000		
	RESID(-1)^2	0,3272	0,0287		
Bitcoincash	@SQRT(GARCH)	-1,0349	0,0794	0,3390	0,5619
M-GARCH(1,0)	C	0,0598	0,0626		
	AR(1)	-1,0000	0,0000		
	MA(1)	0,7887	0,0000		
		Variance Equation			
	C	0,0018	0,0000		
	RESID(-1)^2	0,7094	0,0405		
Bitcoinsv	@SQRT(GARCH)	-0,2154	0,0593	0,0095	0,9226
M-GARCH(1,1)	C	0,0065	0,1831		
	AR(1)	-0,9928	0,0000		
	MA(1)	0,9842	0,0000		
		Variance Equation			
	C	0,0001	0,0000		
	RESID(-1)^2	-0,0847	0,0000		
	GARCH(-1)	0,9866	0,0000		
Litecoin	@SQRT(GARCH)	-0,6561	0,1249	0,5717	0,4516
M-GARCH(1,0)	C	0,0266	0,1475		
	AR(1)	-0,8511	0,0000		
	MA(1)	1,0000	0,0000		
		Variance Equation			
	C	0,0012	0,0000		
	RESID(-1)^2	0,2324	0,0074		
Binancecoin	@SQRT(GARCH)	0,0847	0,8616	1,3367	0,2507
M-GARCH(1,0)	C	0,0017	0,9336		
	AR(1)	-0,8920	0,0000		
	MA(1)	0,7820	0,0000		
		Variance Equation			
	C	0,0013	0,0000		
	RESID(-1)^2	0,5070	0,0071		
Cardano	@SQRT(GARCH)	-0,6058	0,0000	0,7706	0,3824
M-GARCH(2,1)	C	0,0410	0,0000		
	AR(1)	-0,8219	0,0000		
	MA(1)	0,5545	0,0056		
		Variance Equation			
	C	0,0007	0,0089		
	RESID(-1)^2	-0,1070	0,0000		
	RESID(-2)^2	0,0896	0,0853		
	GARCH(-1)	0,7174	0,0000		

Model	Variable	Estimasi		ARCH test	
		Coef	Prob	F-statistics	Prob (F)
Crypto.com	C	0,0187	0,0000	1,9016	0,1714
M-GARCH(1,0)	AR(1)	-0,9365	0,0000		
	MA(1)	0,8907	0,0000		
		Variance Equation			
	C	0,0011	0,0000		
	RESID(-1)^2	0,6799	0,0048		

From Table 5 above, the estimated results of the model chosen in Bitcoin are the GARCH model (1,1). The best model criteria are to have significant parameter values and the smallest AIC and SIC values. GARCH (1,1) is the best model for forecasting Bitcoin based on the value of Akaike Info Criterion (AIC) -3,566132, Schwarz Criterion (SIC) -3,401667 and a Log-Likelihood value of 170.0421 obtained from the Eviews output compared to other ARCH / GARCH Models. The reason for being the best model is because of the smallest AIC and SIC values and the largest Log-Likelihood value, and this applies to nine other cryptocurrencies.

Value at Risk Analysis

In calculating VaR, the first step is to assume the funds allocated for investment. It found for the next one day period from June 12, 2020, predicted by the GARCH model, that the maximum loss that an investor could tolerate with an investment of $ 500,000,000 for a 95 percent confidence level. The results of the Value at Risk ten cryptocurrencies are shown in table 6.

Table 6. Value at Risk

Cryptocurrency	Mean Return	δ	Zα	Risk	Day	Value At Risk	
Bitcoin	0,002370	0,04079	1,65	0,06731	1	-0,06494	$32.470.719
Ethereum	0,002140	0,05053		0,08337		-0,08123	$40.616.658
Tether	0,000013	0,00176		0,00291		-0,00290	$1.448.740
XRP	-0,000574	0,03330		0,05495		-0,05552	$27.761.217
Bitcoincash	-0,000724	0,04562		0,07528		-0,07600	$38.002.010
Bitcoinsv	-0,000342	0,04383		0,07231		-0,07265	$36.326.910
Litecoin	-0,000880	0,03470		0,05726		-0,05814	$29.067.884
Binancecoin	-0,000139	0,03565		0,05882		-0,05896	$29.478.953
Cardano	0,006952	0,04868		0,08032		-0,07337	$36.683.701
Crypto.com Coin	0,008275	0,11540		0,19042		-0,18214	$91.070.392

Based on Table 6, it means with a 95 percent confidence level and a one-day holding period. The cryptocurrency with the highest value at risk is Crypto.com with an amount of -0,18214, which means that the maximum loss that an investor can tolerate is IDR 91.070.392. VAR is one of the instruments for risk management, but besides that, investors also need to know the most dominant risk factors. Thus, investors will be safer in investing.

CONCLUSION

Based on the analysis in this paper, the conclusions that can acquire are as follows: the cryptocurrency with an average value of positive return from high to low is Crypto.com Coin, Cardano, Ethereum, Bitcoin, and Tether. It means that the five cryptocurrencies give good profit for investors. The standard deviation values that reflect volatility, it shows that the cryptocurrency that has the highest volatility in this group is Crypto.com Coin and Cardano which means that both of them has high risk and high return during a pandemic COVID-19.

The average value of negative returns from high to low is Binancecoin, Bitcoin SV, XRP, Bitcoin Cash, and Litecoin, so it means that the five cryptocurrencies during the COVID-19 pandemic tend to have high losses and risks. In this group, the cryptocurrency that has the highest potential risk is Bitcoin SV and Binance because of the high standard deviation so that it can be said to be High-Risk Low Return.

Value at Risk calculation in this study found that for the next one day period from June 12, 2020, predicted by the GARCH model, that the maximum losses that can be tolerated by investors with an investment value of $ 500.000.000 for a 95 percent confidence level are as follows.

- Bitcoin with a VaR value of -0,06494 the amount is $ 32.470.719
- Ethereum with a VaR value of -0,08123 the amount is $40.616.658
- Tether with a VaR value of -0,000290 the amount is $ 1.448.740
- XRP with a VaR value of -0,05552 the amount is $ 27.761.217
- Bitcoincash with a VaR value of -0,07600 the amount is $ 38.002.010
- Bitcoinsv with a VaR value of -0,07265 the amount is $ 36.326.910
- Litecoin with a VaR value of -0,05814 the amount is $ 29.067.884
- Binancecoin with a VaR value of -0,05896 the amount is $ 29.478.953
- Cardano with a VaR value of -0,07337 the amount is $ 36.683.701
- Crypto.com Coin with a VaR value of -0,18214 the amount is $ 91.070.392

The conclusion from the results obtained that the highest risk cryptocurrency is Crypto.com Coin.

Acknowledgments

The author would like to thank the Saintek Scholarship-Education and Training Center of the Ministry of Research and Technology / National Research and Innovation Agency, for supporting the authors with scholarships to continue their studies and conduct this research.

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