

FORMULATING CRYPTOCURRENCIES DYNAMIC PORTFOLIO WITH CONSUMPTION SECTORS' STOCKS

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Abstract

This study was conducted to analyze the performance of the portfolio formed with different asset classes. The instrument used is the consumption sector index with 5 cryptocurrencies. Does the formed portfolio have a better performance than the portfolio that is only formed from the consumption sector index. The type of data in this study uses secondary data in the form of a daily frequency time series with a research period from January 2019 to January 2021. The data in this study used quantitative data. Portfolio performance measurement in this study was measured using the ratio of Sharpe, Treynor, Jensen, Sortino, and Omega. Based on the results of the study, it shows that the performance of the consumption sector index portfolio that is hedged with cryptocurrency produces a higher rate of return in the period during the pandemic than in the period before the pandemic. However, there is 1 crypto that produces negative values in each ratio and research period, namely Tether. Overall, the results of this study can be concluded that adding cryptocurrency to the formation of a portfolio will get a better portfolio performance.

Keywords: Portfolio; Hedging; Covid-19; DCC-GARCH; Cryptocurrency.

JEL Classification: G11, G14, G32

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INTRODUCTION

Investment is a short-term or long-term investment for realizing a profit. The purpose of investment is to protect assets from inflation and get high returns (Haryati, 2016). Eko (2008) research found that a good portfolio performance has a high asset return. The portfolio formation is based on a modern portfolio theory introduced by Markowitz (1952) and refined by Markowitz (1959).

The modern portfolio theory introduced by Markowitz (1952) is based on the assumption that generally distributed stock returns. However, this assumption contradicts real-world conditions, which often indicate that the data is not normally distributed (Adu et al. 2015; Brière et al. 2015; Ji et al. 2020; Urquhart & McGroarty, 2016). Furthermore, the modern portfolio formation used by Markowitz (1952) tends to use a static approach. The same thing was also done by Oktaviani & Wijayanto

(2016); Pratama (2019) in forming a portfolio using the single index model method. Unfortunately, the market tends to fluctuate, so the formation of a portfolio needs to use a dynamic approach so that portfolios using a dynamic approach are expected to produce better portfolio performance.

The formation of the dynamic portfolio can be done by different asset classes, one of which involves cryptocurrency instruments. Cryptocurrencies are emerging as a new asset class used to form dynamic portfolios (Nitha & Westra, 2020). The addition of multiple cryptocurrencies in the portfolio formation results in a higher rate of return (Ma et al. 2020). Since the emergence of the Covid-19 pandemic negatively impacted portfolio performance (Ben Khelifa et al. 2021). The Covid-19 virus also negatively impacts the global economy because many countries limit their activities with another country, for instance, limitation on the import and export activities, international flight limitation, and the implementation of lockdown (Burhanuddin & Abdi, 2020).

However, the research conducted by Mnif et al. (2020) shows that the Covid-19 has a positive impact on the efficiency of the cryptocurrency market. Cryptocurrencies are seen as hedging assets against other assets like stocks (Corbet et al. 2020, 2021; Mariana et al. 2021; Mnif et al. 2020; Vidal-Tomás, 2021). Vidal-Tomás (2021) and Mariana et al. (2021) found that incorporating cryptocurrency into a portfolio can significantly maximize performance during the pandemic. It is because cryptocurrency negatively correlates with stocks. Although, cryptocurrency has a poor performance when invested long-term because they have high volatility (Lahmiri & Bekiros, 2020).

Research that adds asset classes such as cryptocurrencies to portfolio formation is rare in Indonesia, especially those carried out using a dynamic approach. A study conducted by Avianti & Ratnasari (2021); Oktaviani & Wijayanto (2016);

Pratama (2019) still uses the traditional single index model portfolio formulation. There have been many studies on portfolio formation across asset classes, such as stocks with gold, stocks with property, and stocks with bonds (Robiyanto et al. (2018,2019); Stelk et al. (2017)). However, research is still rare that combines cryptocurrencies with stocks of the consumption sector in Indonesia.

The consumption sector price index represents the use of consumption sector stocks as part of the portfolio. Compared to other sector indexes, the stock movement has experienced a limited or defensive decline during the pandemic (Qolbi, 2020). This research was conducted to determine the performance of the consumption sector index portfolio before and during the pandemic and overall if cryptocurrency is added as a hedging asset. Therefore, combining other assets such as the five cryptocurrencies represented by Bitcoin, Ethereum, Tether, Binance Coin, and Cardano with the consumption sector index to form a good portfolio performance. This research is in line with Ma et al. (2020) stating that adding multiple cryptocurrencies in the formation of a portfolio can lead to higher returns. The formation of a dynamic portfolio using the DCC-GARCH technique was introduced by Engle (2002). This method has been widely used in research, including Susilo et al. (2020), Robiyanto (2017a) in Indonesia, Kumar (2014) in India, Arouri et al. (2015) in China. DCC-GARCH can accommodate data that is not normally distributed and provide dynamic correlation rather than static correlation.

Based on the description above, this study aims to assess the effectiveness of the combination of five cryptocurrencies represented by Bitcoin, Ethereum, Tether, Binance Coin, and Cardano with stocks (consumption sector) into dynamic portfolio performance. Does the portfolio performance between cryptocurrencies and consumption sector stocks have a better performance than the consumption sector

stock portfolio alone? This study used the period before the pandemic, from January 2019 to January 2021. The results of this study are expected to be a reference for the formation of a dynamic portfolio for stock investors using different asset classes such as cryptocurrencies. Thus, investors can decide on cryptocurrency as a hedge against other assets in the future.

LITERATURE REVIEW

Modern Portfolio Theory and Modern Hedging Theory

Keynes (1930) and Hart & Hicks (1939) proposed the hedging theory based on the assumption of hedging pressure, namely the risk premium earned by speculators in return for a transferable price risk tolerance. Then this theory is known as the traditional hedging theory. Through its development, the traditional hedging theory was presented by Working (1953). Working (1953) stated that hedging is an instrument in maximizing high returns.

Modern portfolio theory proposed by Markowitz (1952) and refined by Markowitz (1959) shows that hedging measures can minimize risk and obtain high returns. Utilization of assets in formulating an efficient portfolio is an essential means of minimizing risk and high returns (Grasse et al. 2016). This statement is in line with Dellano-Paz et al. (2017) research, which found that efforts to minimize risk and high returns are the main goals of portfolio formulation.

Formation of Dynamic Portfolio with Dynamic Conditional Correlation (DCC)

Research conducted by Engle (2002) explains that correlation is a critical input data for financial management. Asset allocation and risk estimates are entirely dependent on correlation. Formulating an optimal portfolio with a set of limitations requires estimating the return on the covariance matrix. Likewise, to estimate

the standard deviation of the portfolio, a covariance matrix of all assets in the portfolio is needed. Research conducted by Bouri et al. (2017) also uses the covariance matrix in portfolio formulation. These functions follow estimates from large covariance matrices with different assets (Robiyanto, 2017b).

Academics and capital market practitioners have conducted various studies on estimating correlations between financial variables. Research by Avianti & Ratnasari (2021), Oktaviani & Wijayanto (2016), Pratama (2019) has used a simple method of historical correlation and exponential smoothing. On the other hand, the use of more complex GARCH and stochastic volatility methods has been extensively studied in the econometric literature and adopted by many experts. One of them is Engle (2002), who has formulated Dynamic Conditional Correlation (DCC) with flexibility in univariate GARCH.

Previous Research on Developing Cryptocurrency Portfolios and Stocks Using DCC-GARCH

Several studies have been conducted studies on the formulation of dynamic portfolios of stocks and cryptocurrencies during the Covid-19 pandemic, such as Corbet et al. (2021), A. S. Kumar (2020), Mariana et al. (2021), Pamilangan & Robiyanto (2019). Mariana et al. (2021) and A. S. Kumar (2020) researched portfolio formulation using cryptocurrency as a hedging instrument for index portfolios in the American stock market. Research Mariana et al. (2021) and A. S. Kumar (2020) use cryptocurrency and stock returns as variables. They were connected using the analysis of various DCC-GARCH. Mariana et al. (2021) and A. S. Kumar (2020) research results proved that cryptocurrencies can be a good diversification tool for short-term portfolios and are capable of being an index hedge in the American stock market during the pandemic.

Corbet et al. (2021) found that cryptocurrencies can be hedged assets during a pandemic. The analysis used a variety of DCC-GARCH approaches. This study proves that cryptocurrencies have increased significantly during the pandemic. Hence, cryptocurrencies can be used as hedging assets during a pandemic. Pamilangan & Robiyanto (2019) researched the formation of a dynamic portfolio between cryptocurrencies and LQ45 stocks. The method used for portfolio formation is to use DCC-GARCH. Pamilangan & Robiyanto (2019) found that cryptocurrency and LQ45 stocks negatively correlate; thus, they can be used as hedging assets.

Hypothesis Development

Markowitz (1959) argues that asset allocation influences portfolio composition decisions. If portfolio managers take a proactive approach to invest, the allocation process can increase value over time (Pangestuti et al. 2017). However, when portfolio managers choose a passive approach, the asset allocation process will eliminate portfolio volatility (Robiyanto, 2018b). The formulation of the portfolio in this study uses a dynamic portfolio. Therefore, the risk-adjusted return of a hedged portfolio is much better than the risk-adjusted return of an unhedged portfolio.

The use of DCC can be expanded in terms of portfolio diversification and hedging efficiency. Some researchers who have implemented the DCC model to form portfolios with hedging instruments such as Corbet et al. (2021); Mariana et al. (2021); Pamilangan & Robiyanto (2019). They proved that formulating a hedging portfolio with cryptocurrencies combined with DCC could produce adjustable returns with lower risk. Based on this explanation, the following hypothesis is formulated:

H1: The portfolio formed from cryptocurrencies with consumption sector stocks performs better than the consumption sector stock portfolio.

RESEARCH METHODS

The type of data in this study uses secondary data with a quantitative approach. The data source comes from time-series data on the daily frequency of closing prices for cryptocurrencies (Bitcoin, Ethereum, Tether, Binance Coin, and Cardano) obtained from the www.coinmarketcap.com website. The closing price of the consumption sector index is obtained from www.finance.yahoo.com during the research period before the pandemic in January 2019 to January 2021. The population in this study is cryptocurrency. The sampling uses purposive sampling with the criteria of 5 cryptocurrencies that have a large market capitalization, such as Bitcoin, Ethereum, Tether, Binance Coin and Cardano can be seen in Table 1. In the following sections, the operational definitions used in this study are explained.

Changes in the Consumer Goods Industry Sector Index (JKCONS)

$$\Delta JKCONS_t = \frac{JKCONS_t - JKCONS_{t-1}}{JKCONS_{t-1}}$$

Where:

$\Delta JKCONS_t$: Changes in the index of the consumer goods industry sector at time t

$JKCONS_t$: Consumer goods industrial sector index at time t

$JKCONS_{t-1}$: Consumer goods industrial sector index at time t-1

Bitcoin Price Change

$$\Delta Bitcoin_t = \frac{Bitcoin_t - Bitcoin_{t-1}}{Bitcoin_{t-1}}$$

Where:

$\Delta Bitcoin_t$: Bitcoin price change at time t

$Bitcoin_t$: Bitcoin price at time t

$Bitcoin_{t-1}$: Bitcoin price at time t-1

Ethereum Price Change

$$\Delta Ethereum_t = \frac{Ethereum_t - Ethereum_{t-1}}{Ethereum_{t-1}}$$

Where:

$\Delta Ethereum_t$: Ethereum price change at time t

$Ethereum_t$: Ethereum price at time t

$Ethereum_{t-1}$: Ethereum price at time t-1

Tether Price Change

$$\Delta Tether_t = \frac{Tether_t - Tether_{t-1}}{Tether_{t-1}}$$

Where:

$\Delta Tether_t$: Tether price change at time t

$Tether_t$: Tether price at time t

$Tether_{t-1}$: Tether price at time t-1

Binance Coin Price Change

$$\Delta Binance\ Coin_t = \frac{Binance\ Coin_t - Binance\ Coin_{t-1}}{Binance\ Coin_{t-1}}$$

Where:

$\Delta Binance\ Coin_t$: Binance Coin price change at time t

$Binance\ Coin_t$: Binance Coin price at time t

$Binance\ Coin_{t-1}$: Binance Coin price at time t-1

Cardano Price Change

$$\Delta Cardano_t = \frac{Cardano_t - Cardano_{t-1}}{Cardano_{t-1}}$$

Where:

$\Delta Cardano_t$: Cardano price change at time t

$Cardano_t$: Cardano price at time t

$Cardano_{t-1}$: Cardano price at time t-1

The analysis of the Bitcoin, Ethereum, Tether, Binance Coin, and Cardano portfolios and the consumption sector stock index uses DCC-GARCH (Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroscedasticity). DCC-GARCH was first introduced by Engle (2002). Further, the researcher uses the time-series data method to check whether there is a dynamic correlation between one variable and another. DCC-

GARCH calculation using Eviews 9 Software with the following formula:

$$r_t | =_{t-1} \sim N(0, D_t R_t D_t) \dots\dots\dots(1)$$

$$D_t^2 = diag\{\omega_i\} + diag\{k_i\} \circ r_{t-1} r_{t-1}' + diag\{\lambda_i\} \circ D_{t-1}^2,$$

$$\varepsilon_t = D_t^{-1} r_t,$$

$$Q_t = S^{\circ}(I' - A - B) + A^{\circ} \varepsilon_{t-1} \varepsilon_{t-1}' + B^{\circ} Q_{t-1}$$

$$R_t = diag\{Q_i\}^{-1} Q_t diag\{Q_i\}^{-1}.$$

The logarithm of the estimator or the Likelihood Log is as follows:

$$Lr_t =_{t-1} \sim N(0, H_t) \dots\dots\dots(2)$$

$$L = -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) +$$

$$\log |H_t| + r_t' H_t^{-1} r_t)$$

$$= -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) +$$

$$\log |D_t R_t D_t| + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t)$$

$$= -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) + 2 \log |D_t| +$$

$$\log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t)$$

$$= -\frac{1}{2} \sum_{t=1}^T (n \log(2\pi) + 2 \log |D_t| +$$

$$r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t' \varepsilon_t + \log |R_t| + \varepsilon_t' R_t^{-1} \varepsilon_t),$$

This model maximizes the model parameters to facilitate a prediction through a vast co-variance matrix. The formulation of the model is carried out into consistency and normality asymptotic of the qualified parameters. These will happen if both of the parameter D and additional parameters of R are recorded (Newey & McFadden, 1994). The log-likelihood can be expressed as follows:

$$L(\theta, \phi) = Lv(\theta) +$$

$$Lc(\theta, \phi) \dots\dots\dots(3)$$

The formula for volatility is as follows:

$$Lv(\theta) = -\frac{1}{2} \sum_t (n \log(2\pi) + \log |D_t|^2 +$$

$$r_t' D_t^{-2} r_t) \dots\dots\dots(4)$$

The components of the correlation are as follows:

$$Lv(\theta, \phi) = -\frac{1}{2} \sum_t (\log |R_t| + \epsilon'_t R_t^{-1} \epsilon_t - \epsilon'_t \epsilon_t) \dots\dots\dots(5)$$

Partial volatility is the sum of each individual's GARCH likelihood:

$$Lv = -\frac{1}{2} \sum_t \sum_{i=1}^n (\log(2\pi) + \log(h_{i,t}) + \frac{r_{i,t}^2}{h_{i,t}}) \dots\dots\dots(6)$$

To get maximum results, you can combine the formula above. Both sections are to estimate the correlation parameters. Parameters do not bind this quadratic residual, so it cannot participate in the first-order condition and must be ignored. DCC LL INT results from an estimator because it uses an integrated model. Through a two-step approach to obtain optimal results, you can use the following formula:

$$(\hat{\theta}) = \arg \max(Lv(\theta)) | \dots\dots\dots(7)$$

The value goes to the second step:

$$\max_{\phi} \{L_c(\hat{\theta}, \phi)\} \dots\dots\dots(8)$$

To measure the hedging effectiveness of the formed portfolio, Hedging Effective (HE) has been used in the research of Arouri et al. (2012); Basher & Sadorsky (2015); Pamilangan & Robiyanto (2019); Putra et al. (2018) with the following formula:

$$HE = \frac{Var_{Unhedged} - Var_{Hedged}}{Var_{Hedged}} \dots\dots\dots(9)$$

Where:

$Var_{Unhedged}$: Consumption stock index variance

Var_{Hedged} : Variance of cryptocurrency portfolio and consumption stock index

The Hedge Ratio formula is formulated as follows:

$$\beta_t^{CS} = \frac{h_t^{SC}}{h_t^C} \dots\dots\dots(10)$$

Where:

β_t^{CS} : *Optimal Hedge Ratio*

h_t^{SC} : Conditional covariance between cryptocurrency returns and consumption sector stock returns at time t

h_t^C : Conditional variance of cryptocurrency return at time t

Measuring dynamic portfolio performance is calculated using ratios such as the Sharpe Index introduced by Sharpe in 1996, which can be used to find the Risk-Adjusted Return of hedge portfolios and unhedged portfolios with the following formula:

$$Risk\ Adjusted\ Return = \frac{Average\ of\ Portfolio\ Return - Risk - Free\ Rate}{Portfolio\ Standard\ Deviation} \dots\dots\dots(11)$$

The standard deviation of the portfolio is formulated:

$$Standar\ Deviasi(\sigma_i) = \sqrt{\frac{\sum [(R_{i,t} - E(R_{i,t}))]^2}{N}} \dots\dots\dots(12)$$

Portfolio performance measured using the Jensen Index ratio can be formulated as follows:

$$Jensen\ Index = R_p - [R_f + \beta_p(R_m - R_f)] \dots\dots\dots(13)$$

Where:

R_p : portfolio return at time t

R_f : return on risk-free investment at time t

β_p : portfolio beta coefficient

R_m : market returns

Jensen Index is used to measure whether a portfolio is performing well or vice versa. The higher the positive value of the

Jensen Index, the better the portfolio performance.

Portfolio performance measurement using the Adjusted Sharpe Index ratio can be formulated as follows:

$$\text{Adjusted Sharpe Index (ASI)} = \text{Sharpe Index} \times \frac{\text{Number of Observations (N)}}{\text{Number of Observations (N)} + 0,75} \dots\dots\dots(14)$$

Portfolio performance measurement using the Sortino Ratio can be formulated as follows:

$$\text{Sortino Ratio (SoM)} = \frac{R_i - RFR_t}{\sigma} \dots\dots\dots(15)$$

Where σ is the downside deviation which can be calculated using the following formula:

$$\sigma = \sqrt{\frac{\sum (\min Rp - MARO)^2}{N-1}} \dots\dots\dots(16)$$

Where:

σ : Downside deviation

Rp : Return portfolio

MAR : Acceptable return or risk-free rate

N : Number of observations

The higher the Sortino Ratio value, the lower the loss rate (Lakaba & Robiyanto, 2018).

Portfolio performance measurement using the Treynor Index ratio can be formulated as follows:

$$\text{Treynor's Index} = \frac{\text{Average of Portfolio Return} - \text{Risk Free Rate}}{\beta_i} \dots(17)$$

Where :

β_i : market beta coefficient

If the Treynor Index value is positive and higher, it indicates that the portfolio performance is better.

Portfolio performance measurement using the Omega ratio can be formulated as follows:

$$\text{Omega Ratio } \Omega(r) = \frac{\int_r^b (1-F(x)) dx}{\int_a^r F(x) dx} \dots\dots(18)$$

Where:

$\Omega(r)$: Probability weighted ratio between profit and loss

a and b : Return interval

$F(x)$: Cumulative return distribution

r : Rate of return

Omega Ratio is a cumulative probability ratio with a specified lower and upper threshold. If the average return is the threshold, the Omega value will be 1. The greater the threshold level, the smaller the Omega value.

Table 1. Market Capitalization Cryptocurrency

<i>Cryptocurrency</i>	<i>Market Capitalization</i>
Bitcoin	\$ 639,546,075,506
Ethereum	\$ 270,289,329,857
Tether	\$ 62,336,753,254
Binance Coin	\$ 49,057,862,803
Cardano	\$ 45,186,262,522

Source: www.coinmarketcap.com

RESULT AND DISCUSSION

Result

The results of descriptive statistics on the return of 5 cryptocurrencies used as samples in the research period before and during the Covid-19 pandemic and overall can be seen in table 2. While DCC-GARCH analysis technique for each consumption sector index and cryptocurrency in the research period before and during the Covid-19 pandemic and as a whole can be seen in Table 3. Next, calculation of the optimal hedge ratio, hedge effectiveness, Sharpe, Treynor, Jensen, Sortino, Omega ratio between the consumption sector index and cryptocurrency is carried out to determine how

effective the consumption sector index portfolio hedged with cryptocurrency is. The results of calculating the optimal hedge ratio, hedging effectiveness, and Sharpe, Treynor, Jensen, Sortino, Omega ratios for the consumption sector index portfolio with cryptocurrency research periods before and during the Covid-19 pandemic and as a whole have been summarized and can be seen in Table 4. Based on the results, the different test results of the consumption sector index portfolios which hedged and not hedged with cryptocurrencies, the research period before and during the Covid-19 pandemic, and as a whole has been summarized and can be seen in Table 5.

Table 2. Descriptive Statistics Return of 5 Cryptocurrency Before and During The Covid-19 Pandemic and Overall

BEFORE THE COVID-19 PANDEMIC					
Name	N	Minimum (%)	Maximum (%)	Average (%)	Dev. Std.
Bitcoin	287	-14.703	22.513	0.364	0.042
Ethereum	287	-16.831	19.654	0.291	0.049
Tether	287	-1.269	1.514	-0.008	0.004
Binance Coin	287	-17.540	21.497	0.530	0.052
Cardano	287	-18.786	18.163	0.191	0.053
DURING THE COVID-19 PANDEMIC					
Name	N	Minimum (%)	Maximum (%)	Average (%)	Dev. Std.
Bitcoin	220	-37.170	18.188	0.768	0.051
Ethereum	220	-42.347	38.399	1.085	0.071
Tether	220	-5.121	5.484	0.004	0.007
Binance Coin	220	-41.905	22.503	0.571	0.060
Cardno	220	-39.567	29.845	1.227	0.081
OVERALL					
Name	N	Minimum (%)	Maximum (%)	Average (%)	Dev. Std.
Bitcoin	507	-37.170	22.513	0.539	0.046
Ethereum	507	-42.347	38.399	0.636	0.060
Tether	507	-5.121	5.484	-0.003	0.005
Binance Coin	507	-41.905	22.503	0.547	0.055
Cardano	507	-39.567	29.845	0.640	0.067

Source: processed data.

Table 3. DCC-GARCH Summary Between Cryptocurrency and Consumption Sector Indices Before and During The Covid-19 Pandemic and Overall

BEFORE THE COVID-19 PANDEMIC			
Portfolio	Minimum	Maximum	Average
Bitcoin-JKCONS	-0.262	0.166	-0.031
Ethereum-JKCONS	-0.642	0.970	-0.098
Tether-JKCONS	-0.124	0.289	0.055
Binance Coin-JKCONS	-0.130	0.002	-0.067
Cardano-JKCONS	-0.117	0.026	-0.043
DURING THE COVID-19 PANDEMIC			
Portfolio	Minimum	Maximum	Average
Bitcoin-JKCONS	-0.182	0.392	0.055
Ethereum-JKCONS	0.003	0.279	0.093
Tether-JKCONS	-0.112	0.017	-0.074
Binance Coin-JKCONS	-0.157	0.571	0.133
Cardano-JKCONS	-0.339	0.735	0.132
OVERALL			
Portfolio	Minimum	Maximum	Average
Bitcoin-JKCONS	-0.178	0.322	0.016
Ethereum-JKCONS	-0.188	0.202	-0.016
Tether-JKCONS	-0.280	0.284	-0.003
Binance Coin-JKCONS	-0.100	0.339	0.024
Cardano-JKCONS	-0.177	0.448	0.045

Source: processed data.

Table 4. Optimal Hedging Ratio, Hedging Effectiveness, and Sharpe, Treynor, Jensen, Sortino, Omega Ratio for Cryptocurrency with Consumption Sector Indices

BEFORE THE COVID-19 PANDEMIC									
Portfolio	Optimal Hedge Ratio (%)	Hedging Effectiveness (%)	Average Return (%)	Standard Deviation	Sharpe Ratio	Treynor Ratio	Jensen Ratio	Sortino Ratio	Omega Ratio
Bitcoin	-	-	0.364	0.042	0.082	-0.005	0.003	0.155	1.291
Ethereum	-	-	0.291	0.049	0.057	-0.003	0.003	0.099	1.181
Tether	-	-	-0.008	0.004	-0.059	-0.006	0.000	-0.100	0.853
Binance Coin	-	-	0.530	0.052	0.100	-0.012	0.005	0.191	1.311
Cardano JKCONS	-	-	0.191	0.053	0.033	-0.003	0.002	0.058	1.095
BTC-JKCONS	-3.557	66.697	-0.130	0.010	-0.144	-0.001	-0.001	-0.208	0.678
ETH-JKCONS	-	-	0.124	0.024	0.051	0.007	0.001	0.088	1.171
USDT-JKCONS	-7.782	73.986	0.055	0.025	0.022	-0.025	0.001	0.037	1.067
BNB-JKCONS	5.404	-97.358	-0.084	0.006	-0.150	-0.002	-0.001	-0.220	0.669
ADA-JKCONS	-6.708	74.953	0.180	0.026	0.070	0.006	0.002	0.130	1.202
Average	-4.334	74.800	0.014	0.026	0.005	0.001	0.000	0.009	1.014
	-3.395	38.615			0.006	-0.003	0.001	0.021	1.048

Table 5. Continue ...

DURING THE COVID-19 PANDEMIC									
Portfolio	Optimal Hedge Ratio (%)	Hedging Effectiveness (%)	Average Return (%)	Standard Deviation	Sharpe Ratio	Treynor Ratio	Jensen Ratio	Sortino Ratio	Omega Ratio
Bitcoin	-	-	0.768	0.051	0.147	0.034	0.007	0.223	1.636
Ethereum	-	-	1.085	0.071	0.151	0.027	0.011	0.259	1.626
Tether	-	-	0.004	0.007	-0.011	0.001	0.000	-0.017	0.947
Binance Coin	-	-	0.571	0.060	0.093	0.010	0.005	0.134	1.345
Cardano	-	-	1.227	0.081	0.150	0.020	0.012	0.281	1.572
JKCONS	-	-	0.008	0.020	-0.002	0.000	0.000	-0.003	0.994
BTC-JKCONS	5.954	72.479	0.320	0.027	0.119	0.005	0.003	0.173	1.460
ETH-JKCONS	9.497	74.057	0.503	0.036	0.139	0.008	0.005	0.225	1.543
USDT-JKCONS	-7.355	-127.075	-0.004	0.010	-0.004	0.000	0.000	-0.007	0.988
BNB-JKCONS	14.230	72.224	0.254	0.032	0.080	0.003	0.002	0.115	1.292
ADA-JKCONS	15.131	78.610	0.433	0.038	0.115	0.006	0.004	0.199	1.403
Average	7.491	34.059			0.088	0.010	0.004	0.143	1.346
OVERALL									
Portfolio	Optimal Hedge Ratio (%)	Hedging Effectiveness (%)	Average Return (%)	Standard Deviation	Sharpe Ratio	Treynor Ratio	Jensen Ratio	Sortino Ratio	Omega Ratio
Bitcoin	-	-	0.539	0.046	0.113	0.053	0.005	0.188	1.440
Ethereum	-	-	0.636	0.060	0.104	0.035	0.006	0.181	1.387
Tether	-	-	-0.003	0.005	-0.031	0.005	0.000	-0.049	0.891
Binance Coin	-	-	0.547	0.055	0.096	0.013	0.005	0.157	1.325
Cardano	-	-	0.640	0.067	0.094	0.015	0.006	0.171	1.318
JKCONS	-	-	-0.070	0.015	-0.055	-0.001	-0.001	-0.090	0.845
BTC-JKCONS	1.660	72.567	0.208	0.024	0.086	0.004	0.002	0.137	1.303
ETH-JKCONS	-1.517	73.868	0.260	0.030	0.085	0.005	0.003	0.142	1.301
USDT-JKCONS	-0.382	-118.266	-0.056	0.008	-0.071	-0.001	0.000	-0.110	0.806
BNB-JKCONS	2.401	72.649	0.224	0.029	0.077	0.003	0.002	0.124	1.250
ADA-JKCONS	4.627	74.331	0.247	0.034	0.073	0.004	0.003	0.128	1.235
Average	1.357	35.029			0.051	0.012	0.002	0.089	1.191

Source: processed data.

Table 6. Test of Hedging and Unhedged Portfolio Difference

BEFORE THE COVID-19 PANDEMIC				
Description	Mean Difference	t	Significance	Conclusion
Sharpe Unhedged – Hedged by Crypto	0.143	3.677	0.021	Difference
Treynor Unhedged – Hedged by Crypto	-0.001	-0.274	0.798	No Difference
Jensen Unhedged – Hedged by Crypto	0.001	3.138	0.035	Difference
Sortino Unhedged – Hedged by Crypto	0.216	3.562	0.024	Difference
Omega Unhedged – Hedged by Crypto	0.346	3.641	0.022	Difference
DURING THE COVID-19 PANDEMIC				
Description	Mean Difference	t	Significance	Conclusion
Sharpe Unhedged – Hedged by Crypto	0.091	3.628	0.022	Difference
Treynor Unhedged – Hedged by Crypto	0.004	3.226	0.032	Difference
Jensen Unhedged – Hedged by Crypto	0.002	3.255	0.031	Difference
Sortino Unhedged – Hedged by Crypto	0.144	3.491	0.025	Difference
Omega Unhedged – Hedged by Crypto	0.343	3.561	0.024	Difference
OVERALL				
Description	Mean Difference	t	Significance	Conclusion
Sharpe Unhedged – Hedged by Crypto	0.105	3.460	0.026	Difference
Treynor Unhedged – Hedged by Crypto	0.004	3.814	0.019	Difference
Jensen Unhedged – Hedged by Crypto	0.003	5.477	0.005	Difference
Sortino Unhedged – Hedged by Crypto	0.174	3.580	0.023	Difference
Omega Unhedged – Hedged by Crypto	0.334	3.545	0.024	Difference

Source: processed data.

Discussion

Descriptive Statistical Analysis

The results of the descriptive statistical calculations are in table 2. The highest average cryptocurrency returns before and during the Covid-19 pandemic is Binance Coin. Cardano occupies the highest position during the pandemic with an average return of 0.530%, 1.227%, and 0.640%, while the lowest average returns are all owned by Tether with returns -0.008%, 0.004%, and -0.003%. The cryptocurrency with the highest risk level is Cardano in each study period with standard deviation values of 0.053, 0.081, and 0.067. At the same time, Tether has the lowest risk level in each study period with standard deviation values of 0.004, 0.007, and 0.005.

DCC-GARCH Analysis and Portfolio Weight Ratio

DCC average between the consumption sector index and cryptocurrency is in a low category. So, the portfolio formulation between the consumption sector index and cryptocurrency is appropriate. DCC ranging from -0.642 to 0.970 was found before the Covid-19 pandemic. Based on

research by Markowitz (1952), diversification can eliminate risk if the return on assets is not correlated. The highest average DCC was found during the Covid-19 pandemic on Binance Coin-JKCONS with a value of 0.133, while the lowest was found before the Covid-19 pandemic Ethereum-JKCONS with a value of -0.098.

Optimal Hedging Ratio, Hedging Effectiveness and Sharpe, Treynor, Jensen, Sortino, Omega Cryptocurrency Ratio with Consumption Sector Index Portfolio

The average results of the optimal hedging ratio for the consumption sector index hedging with cryptocurrency instruments per research period before and during the Covid-19 pandemic are -3.395%, 7.491%, and 1.357%. The ETH-JKCONS portfolio before the Covid-19 pandemic period had the lowest optimal hedging ratio value than other instruments (with a value of -7.782%). The highest value was in the ADA-JKCONS portfolio in the research period during the Covid-19 pandemic with 15.131%. Investors who own consumption sector index stocks must also buy Ethereum crypto to hedge their

portfolios. The comparison is that if you buy an index share of the consumption sector for IDR 1, it must be balanced with buying crypto Ethereum for IDR 0.077 (also applies as a futures contract, both mini contracts, and regular contracts). Meanwhile, investors holding consumption sector index stocks must also sell Cardano crypto to hedge their portfolios. The comparison used is that if you buy a consumption sector index share of Rp. 1, it must be balanced by selling a crypto Cardano of IDR 0.151 (only valid as a futures contract, both mini and regular contracts).

Based on Table 4, the results of hedging effectiveness which have the lowest value, are the USDT-JKCONS portfolio during the Covid-19 pandemic (with a value of -127.075%). It means that adding crypto Tether to a portfolio consisting of consumption sector index stocks is not good because it shows poor results, negative. Overall, during the research period, the effectiveness of hedging with crypto Tether showed negative results so that he could not be hedged. Meanwhile, the highest hedging effectiveness value is found in the ADA-JKCONS portfolio, with a value of 78.610% during the Covid-19 pandemic. Adding Cardano crypto to a portfolio consisting of consumption sector index stocks can reduce the risk of consumption sector index stocks by 78.610%. Crypto Tether showed negative results during the study period, so it could not be added to each study period's consumption sector index stock. It could not reduce portfolio risk. Overall, the average value of hedging effectiveness for the respective consumption sector indexes that were hedged with cryptocurrencies before and after the Covid-19 pandemic was 38.615%, 34.059%, and 35.019%. These findings overall support the research of Arouri et al. (2015), D. Kumar (2014), Robiyanto (2018a).

The measurement of portfolio performance with the Sharpe Index can also be seen in Table 4. The lowest consumption

sector index value occurred in the research period before the pandemic, with a value of -0.144. In contrast, the highest occurred during the period during the pandemic with a value of -0.002. The consumption sector index portfolio with the lowest cryptocurrency was on Tether in the research period before the pandemic with a value of -0.150. The highest was on Ethereum, with a value of 0.139 in the research period during the pandemic. Portfolio performance can improve when the Sharpe Index results have a fair or favorable value. The overall research results show that Tether generated negative scores in each study period, thus showing a poorer performance than other cryptocurrencies.

The results of calculations with the Treynor Index show a better portfolio performance if it has a positive result. The portfolio hedged with cryptocurrencies with the lowest value is Ethereum, with a value of -0.025 occurring in the research period before the Covid-19 pandemic. In contrast, the highest value is owned by Ethereum (with a value of 0.008) Covid-19 pandemic research period. In general, the Treynor Index measurement shows positive results based on the value of cryptocurrencies during the research period.

Jensen Index portfolio measurement has the lowest consumption sector index value experienced in the research period before the pandemic. Overall, it has a value of -0.001 and the highest in the period during the pandemic with a value of 0.000. In Table 4, the value of portfolio performance measurement with the Jensen Index on the consumption sector index portfolio with the lowest cryptocurrency yield -0.001 research period before the pandemic on crypto Tether, while the highest with a value of 0.005 research period during the pandemic on crypto Ethereum. If the Jensen Index value produces a positive value, it indicates a good portfolio performance. Thus, Tether has the worst portfolio performance with the Jensen Index, among other cryptos, because it has nega-

tive results in the research period before the pandemic.

Calculation of portfolio performance with the Sortino Ratio with the lowest yield occurred in Tether with a value of -0.220 in the research period before the Covid-19 pandemic. The highest occurred in Ethereum with a value of 0.225 for the research period during the Covid-19 pandemic. The Sortino Ratio is an excellent risk-focused ratio based on a risk-free rate. If the Sortino Ratio has a positive value and the higher the portfolio performance, the better. In calculating portfolio performance, the results show that when combined with cryptocurrencies, it produces negative performance such as Tether in each research period showing a negative value.

Omega Ratio is a cumulative probability ratio with a defined lower and upper threshold. The lowest Omega Ratio portfolio performance is in Tether (with a value of 0.669), which happens before the Covid-19 pandemic research period. In contrast, the highest occurred in Ethereum during the research period during the Covid-19 pandemic with 1.543. The higher the Omega Ratio value, the better the portfolio performance formed. If the value is 1, it is the same as the reference return, while if it is more than 1, it is greater than the reference return and vice versa.

Hedging and Unhedged Portfolio Tests

The different tests using a significance level of 5% or 0.05 overall showed significant results or a difference with a significance value of less than 5% or 0.05. Before the Covid-19 pandemic, some results showed no difference, namely the Treynor ratio with a significance value of more than 5% or 0.05 of 0.798. Based on the results of the Treynor ratio, the consumption sector index is not good if it is hedged with the mean difference value is -0.001 and the t-value is -0.274. At the same time, the best performance results before the Covid-19 pandemic found in the Omega ratio with a mean difference value

of 0.346 and an at-value of 3.641. Meanwhile, the results of different tests carried out during the research period during the Covid-19 pandemic and overall showed significant results. There was a difference with a significance value of less than 5% or 0.05. The lowest value in the study before the Covid-19 pandemic and its overall was in the Jensen ratio with a mean difference of 0.002 and 0.003 and t values of 3.255 and 5.477. The best value occurs in the Omega ratio with a mean difference of 0.343 and 0.334 and 3.561 and 3.545.

Thus, the results of the different tests in this study show that hedged portfolios with cryptocurrencies have a better ratio performance than those not hedged. However, in the performance ratio in the research period before the Covid-19 pandemic, one ratio showed poor results when used for hedging, namely the Treynor ratio, because the significance value was above 5% or 0.05. Meanwhile, based on the Omega ratio, it produces the best value in each research period. This finding supports Trabelsi et al. (2021) and D. Kumar (2014) empirical results that adding another asset class (gold) to the stock portfolio can improve its performance.

CONCLUSION AND RECOMMENDATION

Conclusion

This study aimed to analyze the performance of the consumption sector index portfolio before and during the pandemic and as a whole if cryptocurrencies were added as a hedging asset. The overall results show that the consumption sector index portfolio's performance during the pandemic that was hedged with cryptocurrencies resulted in higher returns than those in the pre-pandemic period. However, one crypto, namely Tether, cannot be used to hedge because it produces negative values in all study ratios and each period. In the results of the different tests, there is one ratio, namely

Treynor, in the research period before the pandemic, which has a negative value. Based on this ratio, the consumption sector index is not good if hedging. Based on the description above, this research can be concluded that cryptocurrency can be used as a hedging asset against the consumption sector index during the pandemic.

Recommendation

This study aimed to analyze the performance of the consumption sector index portfolio before and during the pandemic and as a whole if cryptocurrencies were added as a hedging asset. The overall results show that the consumption sector index portfolio's performance during the pandemic that was hedged with cryptocurrencies resulted in higher returns than those in the pre-pandemic period. However, one crypto, namely Tether, cannot be used to hedge because it produces negative values in all study ratios and each period. In the results of the different tests, there is one ratio, namely Treynor, in the research period before the pandemic, which has a negative value. Based on this ratio, the consumption sector index is not good if hedging. Based on the description above, this research can be concluded that cryptocurrency can be used as a hedging asset against the consumption sector index during the pandemic.

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