AFRE Accounting and Financial Review, 8(2): 94-108, 2025
https://jurnal.unmer.ac.id/index.php/afr

Cryptocurrency-stock portfolio formation using the ADCC-GARCH Method

Tutut Rina Hapsari, Robiyanto, Andrian Dolfriandra Huruta, Harijono

Department of Management, Faculty of Economics and Business,
Satya Wacana Christian University
Jl. Diponegoro No. 52-60 Salatiga, Central Java, 50711, Indonesia

Article Info:
Received: 2025-05-03
Revised: 2025-06-10
Accepted: 2025-07-12
Published: 2025-07-22

Abstract

The COVID-19 pandemic raised uncertainty in Indonesia's financial markets, subsequently highlighting the importance of evaluating portfolio diversification strategies. This study examined the performance of dynamic portfolios: combining cryptocurrencies with stocks included in the LQ45 Index and compares hedged and unhedged portfolio performance across different market periods. The analysis used secondary data comprising daily closing prices of the LQ45 Index and five cryptocurrencies with substantial global market capitalization from January 2019 to November 2021. Dynamic portfolio construction is conducted using the asymmetric dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (ADCC-GARCH) model. Portfolio performance is evaluated using the Sharpe Index, Treynor Index, Jensen Index, Sortino Ratio, and Omega Ratio. The findings indicate that differences in hedged and unhedged portfolio performance vary across evaluation periods and performance measures. During 2020, the difference in the Treynor Index is statistically significant at the 5% level, whereas the difference in the Jensen Index is significant at the 10% level. No statistically significant differences are observed for the Sharpe Index, Sortino Ratio, or Omega Ratio during the same period. These findings therefore suggest that the relative performance of cryptocurrency-equity portfolios depend on the market period and the performance measure employed. Accordingly, combining cryptocurrencies with the LQ45 Index does not necessarily yield consistently superior portfolio performance across all risk-adjusted measures.

Citation: Hapsari, T. R., Robiyanto., Huruta, A. D., & Harijono. (2026). Cryptocurrency-stock portfolio formation using the ADCC-GARCH Method. AFRe (Accounting and Financial Review), 8(3), 94-108.

Keywords:
ADCC-GARCH, Cryptocurrency, Hedge, LQ45 Index, Portfolio

ISSN (print): 2598-7763
ISSN (online): 2598-7771

✉*Corresponding Author:*
Name: Robiyanto
E-mail: robiyanto.robiyanto@uksw.edu

JEL Classification: G11, G17, C58
DOI: https://doi.org/10.26905/afr.v8i3.17079

1. Introduction

As the economy becomes increasingly modern, investment options continue to diversify. Investors can invest in capital and money markets to generate future returns. In making investment decisions, they must consider the relationship between risk and return to maximize potential gains and select portfolios that deliver superior performance (Pamilangan & Robiyanto, 2019). Markowitz's (1952) Portfolio Theory suggests that investment decisions should consider both expected returns and risk, as these factors jointly determine portfolio performance. A portfolio refers to a list of assets owned by investors to achieve certain economic goals, with the basic concept of allocating funds across various types of investments in expectation of generating optimal returns and minimizing risk (Eko, 2008). Therefore, investment is inherently associated with risk, which arises when actual returns differ from expected returns (Chandra & Hapsari, 2014).

Investors can minimize investment risk by diversification, based on the theory of risk and rate of return (Puspitasari & Pramesti, 2011). One way to mitigate investment risk is through portfolio formation, which helps balance risk and return across assets. Several studies conducted in Indonesia, including Eko (2008), Septyanto & Kertopati (2013), and Larasati et al. (2013), have examined portfolio formation using stocks included in the LQ45 Index. As it consists of stocks with relatively high liquidity and market capitalization, the LQ45 index offers a lower risk than other stocks that experience price fluctuations (Chandra & Hapsari, 2014). In line with study conducted by Chin et al. (2018), Darmawan & Purnawati (2015), and Puspitasari & Pramesti (2011) which shows that the use of the LQ45 index in portfolio formation can provide a high rate of return and has a low level of risk. Furthermore, Rini et al. (2013) evaluated the performance of portfolios formed from LQ45 Index stocks. Their findings indicated that these stocks offer high liquidity, but combining them with other asset classes may improve portfolio performance.

Beyond the LQ45 Index, portfolio formation can incorporate other asset classes. Studies by Warsito (2020) and Yuniarti (2010) have examined portfolios combining assets such as gold, stocks, and bonds. Previous studies have also reported the benefits of portfolio diversification across the LQ45 Index and other asset classes. To distinguish this study from earlier studies, the present study examines portfolio formation using the LQ45 Index and cryptocurrency. These assets have rather distinct risk and return characteristics, which investors can consider when diversifying their portfolios to mitigate potential risks (Pamilangan & Robiyanto, 2019).

Studies by Chin et al. (2018), Pamilangan & Robiyanto (2019), and Robiyanto et al. (2019) suggest that combining LQ45 Index stocks with cryptocurrency may improve portfolio returns and performance. Portfolio formation can be classified into simple and dynamic approaches. Simple portfolio formation has employed methods such as the Single Index Model and the Markowitz model (Darmawan & Purnawati, 2015; Priyatna & Sukono, 2003; Yuniarti, 2010). In contrast, dynamic portfolio formation has been examined using methods such as DCC-GARCH and ADCC-GARCH (Bhatia et al., 2018; Miralles-Quirós & Miralles-Quirós, 2017; Abdelkafi & Khoufib, 2019). These dynamic methods account for changes in conditional correlations over time, making them useful for analyzing assets whose relationships vary with market conditions.

The DCC-GARCH method was initially developed by Engle (2002) to formulate portfolio formation. The model was subsequently extended by Cappiello et al. (2006) by incorporating asymmetric effects, resulting in the Asymmetric Dynamic Conditional Correlation (ADCC) model. When asymmetry shows a negative residual, it has a smaller effect than a positive residual. Miralles-Quirós & Miralles-Quirós (2017) demonstrated that the ADCC-GARCH model can be used to estimate investment returns and volatility in European stock markets. Similarly, Fur et al. (2016) showed that the ADCC-GARCH model can capture volatility and asymmetric effects across different types of investments.

Taken together, this study aims to determine whether a portfolio combining LQ45 Index stocks and cryptocurrencies outperforms a portfolio consisting solely of LQ45 stocks. The findings are expected to provide a reference for dynamic portfolio formation and enhance investors' understanding of LQ45 stocks and cryptocurrencies when making investment decisions. They may also help investors assess portfolio diversification as a strategy for mitigating investment risk.

2. Literature Review and Hypotheses Development

Optimal Portfolio Theory and Dynamic Portfolio

The formation of portfolio theory, introduced by Markowitz (1952), provides a framework for investors to choose a low-risk level with a high return by creating a portfolio to spread the risk among assets. Investors can therefore minimize risk without reducing expected returns by creating an optimal portfolio (Zahra, 2017). Pracanda & Abundanti (2017) and Ermis et al. (2020) found that stocks selected for an optimal portfolio can offer favorable returns at relatively low risk. In contrast, Puspitasari & Pramesti (2011) reported no clear relationship between portfolio risk and return, suggesting that an optimal portfolio does not necessarily guarantee high returns and low risk. This may be attributed to systematic and firm-specific risk factors that investors cannot fully control.

Portfolio theory assumes that data is normally distributed and correlation tends to be constant,

which inversely related to rapidly changing market conditions. Therefore, a portfolio formation approach that can be particularly relevant in volatile markets is needed. The formulation of portfolio formation is based on dynamic conditional correlation (DCC). Therefore, dynamic portfolio formation can adapt to volatile market conditions without requiring a normal distribution (Pamilangan & Robiyanto, 2019).

Cryptocurrency

Cryptocurrency is a digital currency that utilizes cryptographic technology to conduct virtual transactions (Robiyanto et al., 2019). Cryptocurrencies are decentralized meaning there are no intermediaries, while also transparent since all transactions are monitored by the cryptocurrency's system. Conventional currencies, on the other hand, have intermediaries, such as banks or credit card companies. Moreover, cryptocurrencies offer secure digital transactions over the internet by utilizing cryptographic techniques and blockchain technology. Over the past 10 years, its global recognition and price continue to increase (CNBC, 2020). This study particularly highlights Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Tether (USDT), and Binance Coin (BNB) because these five cryptocurrencies have the largest market capitalization.

Bitcoin (BTC), introduced by Satoshi Nakamoto in 2009, pioneered the cryptocurrency market and contributed to the development of the broader digital currency ecosystem (Farell, 2015). The advantages of low transaction costs, security, and transaction speed make Bitcoin widely used for peer-to-peer electronic money transfers.

Ethereum (ETH), according to Warsito (2020), is generally similar to Bitcoin by having a peer-to-peer network. However, it has different functions and purposes, since Ethereum can be used as an application for transferring Ether electronic money or transferring other forms of Ethereum.

Seijas et al. (2020) said that Cardano is also a popular cryptocurrency and is known as a third-generation decentralized smart contract platform. Cardano offers a solution to the problem of hindering the adoption of blockchain technology through its Poor of Stake consensus mechanism, using the programming languages Plutus and Haskell.

USDT, or Tether, is a cryptocurrency whose value is pegged to the US dollar. USDT was created to protect its users from the high volatility of other cryptocurrencies. Tether coins in crypto transactions enable users to price cryptocurrencies in USD without having a USD bank account, and Tether can be used to convert other electronic currency exchanges from one cryptocurrency to another (Wei, 2018). Sun & Yu (2020) analyzing the security issues of blockchain technology using the Binance Coin.

LQ45 Index

The LQ45 Index is an active stock index consisting of 45 company shares that meet certain criteria set by the Indonesia Stock Exchange (IDX), including high liquidity and market capitalization. LQ45 stocks fluctuate based on the issuer's liquidity and are used as a proxy for calculating stock market returns (Darmawan & Purnawati, 2015). Mahadwartha & Gunawan (2018) stated that the LQ45 Index has an optimal level of price liquidity, enabling it to generate favorable returns for shareholders. Similarly, Maf'ula et al. (2018) selected the LQ45 Index for their study because its constituent stocks tend to exhibit price stability and offer promising returns.

Studies using the performance of portfolios formed from LQ45 stocks has been conducted by Septyanto & Kertopati (2013), Suryani & Herianti (2015), Zahra (2017), and Ermis et al. (2020). The results show that portfolios comprising LQ45 stocks can generate higher returns at relatively low risk, supported by the index's strong liquidity and the profitability of its constituent stocks compared with those in other indices. Most studies in Indonesia have used the Markowitz and Single Index Models to analyze the performance of portfolios formed from LQ45 stocks.

Asymmetric - Dynamic Conditional Correlation (ADCC-GARCH) Application

The DCC-GARCH approach was initially introduced by Engle (2002), subsequently extended by Cappiello et al. (2006) by adding an asymmetric term to the DCC model. The negative asymmetric term indicates that positive residuals have no significant impact on the variance of negative residuals. This approach is designed to capture asymmetric effects in financial asset volatility, as price declines tend to have different effects from price increases. Miralles-Quirós & Miralles-Quirós (2017) used the ADCC-GARCH approach because it can estimate investment returns in the stock market over time. Their results indicate that the ADCC-GARCH approach can improve the Sharpe ratio compared with other approaches, such as the DCC model.

Bhatia et al. (2018) further analyzed the dynamic relationship between oil and precious metals using the DCC-GARCH and ADCC-GARCH methods. The results concluded that both methods have a dynamic conditional relationship. Baumöhl (2013) using stock prices in the CEE region, including Czech Republic, Poland, Hungary, and Slovakia, with the G7 developed markets including Germany and the US. Baumöhl (2013) applied the ADCC-GARCH method to estimate time-varying conditional correlation. The results of this study concluded that the ADCC-GARCH method was able to provide increased profits and had better performance. Using the ADCC-GARCH approach, Gupta & Basu (2009) examined portfolio diversification as a strategy for reducing risk in the Indian stock market. Their findings suggest that stocks in the Indian industrial sector can serve as effective diversification instruments, as they can generate above-average returns.

Several studies illustrate portfolio market risk in the BRICS (Brazil, Russia, India, China, and South Africa) economies. Bonga-Bonga & Nleya (2016) used several multivariate risk models to compare portfolio value-at-risk. Their results show that portfolio formation can reduce the risk of losses in BRICS stock markets. The studies conducted by Bonga-Bonga & Nleya (2016) and Abdelkafi & Khoufib (2019) both employed the ADCC-GARCH within the model to analyze portfolio formation. Their findings suggest that this approach can produce more optimal returns and improve portfolio performance while maintaining relatively low risk.

Furthermore, Zhang et al. (2021) shows that when Bitcoin added with other assets in a portfolio will provide more optimal performance. Supported by Trimborn et al. (2017), which shows that combining cryptocurrency with 3 different financial assets into a portfolio can reduce complex risks and thus increase returns. Ćosić & Časni (2019) combine Bitcoin with the European Union (EU) emerging market index. The results of this study demonstrate that a portfolio incorporating the EU index and Bitcoin offers lower risk and higher returns than a portfolio without Bitcoin. In line with Majdoub et al. (2021), which combines Bitcoin with EUR, JPY, and GBP currencies into a portfolio formation. Majdoub et al. (2021) revealed that forming a cryptocurrency portfolio with other assets can generate better returns. Forming an LQ45 index portfolio using the ADCC-GARCH analysis method is expected to generate better risk-adjusted returns. Therefore, the following hypotheses can be formulated:

H_1: A cryptocurrency portfolio with the LQ45 index outperforms a portfolio with the LQ45 index alone.
H_2: A Bitcoin portfolio with the LQ45 index outperforms a portfolio with the LQ45 index alone.
H_3: An Ethereum portfolio with the LQ45 index outperforms a portfolio with the LQ45 index alone.
H_4: A Cardano portfolio with the LQ45 index outperforms a portfolio with the LQ45 index alone.
H_5: A Tether portfolio with the LQ45 index outperforms a portfolio with the LQ45 index alone.
H_6: Binance Coin portfolio with LQ45 index outperforms portfolio with LQ45 index alone.

3. Methodology

Data

The instruments used in this study are the LQ45 index and cryptocurrencies with the largest market capitalization. The required data are the daily closing prices of the LQ45 index obtained from Yahoo Finance and cryptocurrencies obtained from investing websites from January 2019 to November 2021. The study period was chosen considering that the COVID-19 virus, including in Indonesia, rocked the world in early 2020, causing economic turmoil. This study also compares portfolios formed in the period before the COVID-19 pandemic with those formed during the COVID-19 pandemic. The research sample used purposive sampling, with the criteria being the five cryptocurrencies with the largest market capitalization. The five cryptocurrencies used are Bitcoin (BTC), Ethereum (ETH), Cardano (ADA), Tether (USDT), and Binance Coin (BNB).

The data in this study consist of returns from each variable. The calculation of the rate of return is formulated as Equation 1-6 (Eq. 1-6).

$$Return\ LQ45_t = \frac{LQ45_t - \text{-}LQ45_{t-1}}{LQ45_{t-1}} \quad \text{(Eq. 1)}$$

$$\Delta BTC_t = \frac{BTC_t - BTC_{t-1}}{BTC_{t-1}} \quad \text{(Eq. 2)}$$

$$\Delta ETH_t = \frac{ETH_t - ETH_{t-1}}{ETH_{t-1}} \quad \text{(Eq. 3)}$$

$$\Delta ADA_t = \frac{ADA_t - ADA_{t-1}}{ADA_{t-1}} \quad \text{(Eq. 4)}$$

$$\Delta USDT_t = \frac{USDT_t - USDT_{t-1}}{USDT_{t-1}} \quad \text{(Eq. 5)}$$

$$\Delta BNB_t = \frac{BNB_t - BNB_{t-1}}{BNB_{t-1}} \quad \text{(Eq. 6)}$$

Analysis Technique

The analysis technique used to form a portfolio formed between the LQ45 index and cryptocurrency is Asymmetric Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (ADCC-GARCH) model, which is used to see whether there is a dynamic correlation between one variable and another in order to measure the optimal hedging ratio performance from various GARCH estimates, it is necessary to calculate Hedging Effectiveness (HE) and Hedging Ratio.

$$\text{HE} = \frac{\text{Var}_{\text{Unhedged}} - \text{Var}_{\text{hedged}}}{\text{Var}_{\text{hedged}}} \quad \text{(Eq. 7)}$$

$$\beta_t^{CS} = \frac{h_t^{SC}}{h_t^{C}} \quad \text{(Eq. 8)}$$

A high HE value can reduce portfolio risk, improving the effectiveness of the hedge. Portfolio performance can be measured using the Sharpe Index, Jensen Index, Treynor's Index, Omega Ratio, and Sortino Ratio (Hidayat, 2017; Iskandar et al., 2020; Manurung, 2019; Pamilangan & Robiyanto, 2019).

4. Results

Descriptive Statistics

Table 1 shows the results of descriptive statistical analysis of cryptocurrency returns, including the minimum, maximum, average return, and standard deviation values of each cryptocurrency.

The highest average return before and during the COVID-19 outbreak was found in Binance Coin (BNB) with an average of 0.009 percent, while the lowest return was found in Tether (USDT) with an average of 0.002 percent. BTC and BNB are the cryptocurrencies with the highest risk levels, with a standard deviation of 0.070, while ADA has the lowest risk level, with a standard deviation of 0.016. Standard deviation calculations are used to predict the level of risk and return on investments in the future. The standard deviation reflects the predicted risk, while the average return on investments helps determine the potential profit.

ADCC-GARCH Statistics between LQ45 Index and Cryptocurrency

The average ADCC values between the LQ45 Index and the five cryptocurrencies tend to be low, ranging from -0.006 to 0.074. Diversification can be used to reduce risk when asset returns exhibit low correlations.

Before the COVID-19 pandemic in 2019, the highest average ADCC value was 0.021 for the USDT-LQ45 pair, while the lowest ADCC value was -0.159

Table 1. Descriptive statistics of cryptocurrency returns

Cryptocurrencies	N	Minimum (%)	Maximum (%)	Mean (%)	Std. Dev.
BTC	694	-0.372	0.225	0.005	0.070
ETH	694	-0.423	0.384	0.007	0.048
ADA	694	-0.396	0.322	0.008	0.016
USDT	694	-0.051	0.055	0.000	0.061
BNB	694	-0.419	0.698	0.009	0.070

Table 2. ADCC summary between LQ45 index and cryptocurrencies

Periods	BTC-LQ45	ETH-LQ45	ADA-LQ45	USDT-LQ45	BNB-LQ45
Before COVID-19 Pandemic (2019)	-0.144	-0.159	-0.076	0.021	-0.093
1st year of COVID-19 Pandemic (2020)	0.070	0.065	0.153	0.021	0.109
2nd year of COVID-19 Pandemic (2021)	0.111	0.026	0.075	0.015	0.066
All Period	0.038	0.015	0.074	-0.006	0.051

for the ETH-LQ45 pair. While during the first year of pandemic in 2020, the ADCC value of USDT-LQ45 was the lowest among the five cryptocurrencies at 0.021 and the highest average was found in ADA-LQ45 at 0.153. In the second year of pandemic in 2021, the USDT-LQ45 again had the lowest average value at 0.015, with the highest average value of 0.111 found in BTC-LQ45.

ADCC-GARCH Analysis and Portfolio Weight Ratio

The results of the ADCC-GARCH analysis between the LQ45 index and cryptocurrency are shown in Figure 1. In conclusion, the ADCC-GARCH graph between the LQ45 index and cryptocurrency tends to be stable from 2019 to the end of 2021, indicating a constant correlation between cryptocurrency and the LQ45 index. The use of constant correlation coefficients for the five types of crypto can therefore be used as hedging assets against other assets. Furthermore, the time-varying portfolio weights between the LQ45 index and cryptocurrency are presented, which are used to form dynamic portfolios. Overall, the average portfolio weight is 0.04 percent for the LQ45 and the highest average is 0.9 percent for cryptocurrency.

Figure 1 shows that portfolio weights exhibited little correlation over time. The lowest correlation between the LQ45 index and cryptocurrency ranged from -0.168 to 0.141. Meanwhile, the average portfolio weight was 0.001 percent for the LQ45 index, and the highest average was 0.005 percent for cryptocurrency.

Figure 2 shows a graph during the pandemic (2020-2021). In the first year, the highest average correlation between the LQ45 index and cryptocurrency was found in BNB-LQ45, at 0.060. The highest average correlation value in the second year was found in BNB-LQ45, at 0.017. Therefore, it can be concluded that BNB-LQ45 had the highest correlation value among the five cryptocurrencies over the two years. The average LQ45 index value in the first year was -0.001 percent and in the second year was 0.004 percent.

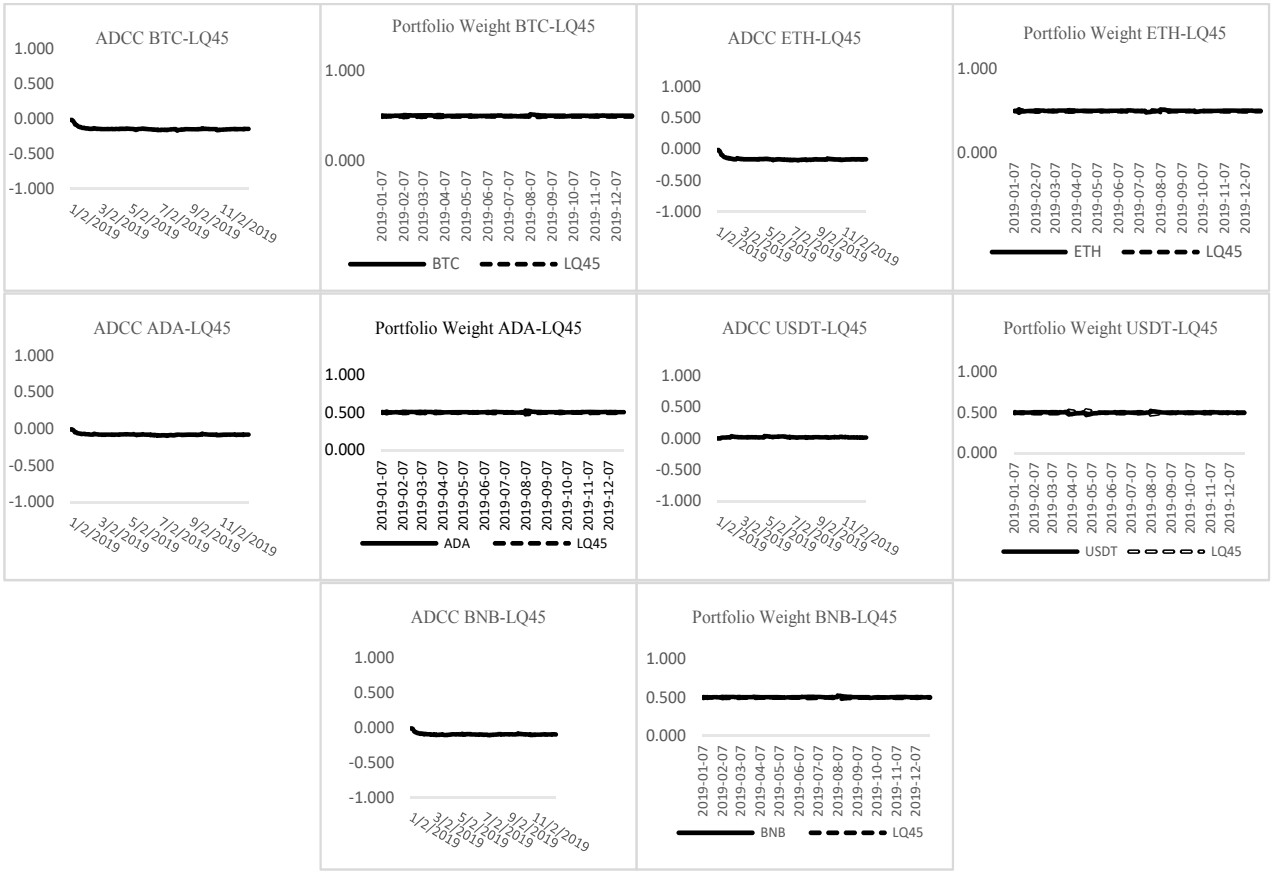


Figure 1. ADCC between the LQ45-cryptocurrency index and portfolio weights over time before the COVID-19 pandemic

Figure 3 shows the correlation between the LQ45 index and cryptocurrencies as a whole before and during the COVID-19 pandemic. The average portfolio weight for the LQ45 index was 0.004 percent, with a lowest average of -0.423 and a highest average of 0.698 for cryptocurrencies.

Optimal Hedging Ratio, Hedging Effectiveness, and Sharpe Ratio of Individual Stocks with the LQ45 Index

The optimal hedge ratio calculation is presented in Table 3, which includes the optimal hedge ratio, hedge effectiveness, Sharpe Index,

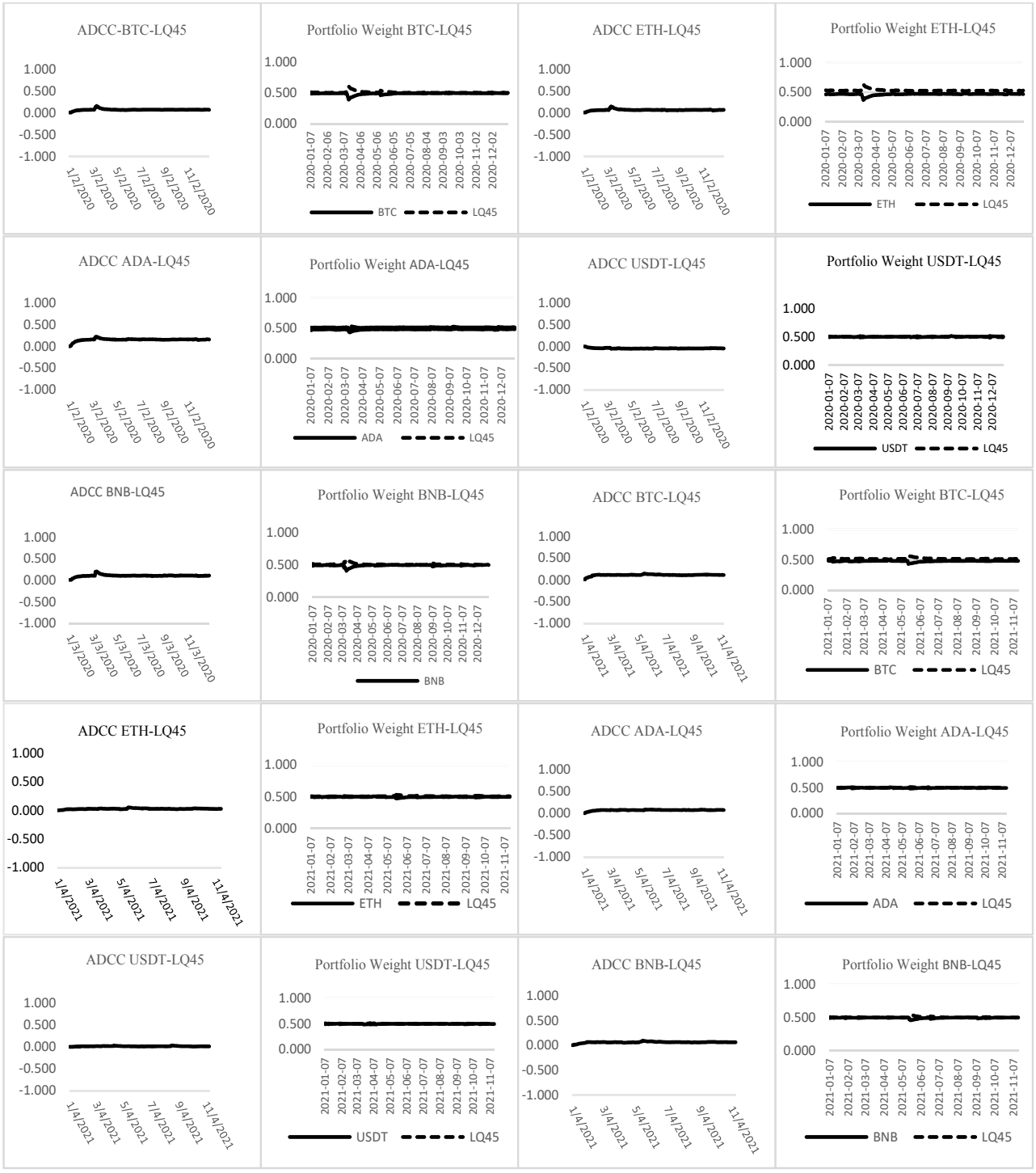


Figure 2. ADCC between the LQ45-cryptocurrency index and portfolio weights over time during the COVID-19 pandemic (2020-2021)

Jensen Index, Treynor's Index, Omega Ratio, and Sortino Ratio, which are used to determine portfolio performance. The average calculation results in order to determine the optimal hedge ratio for each study periods before and during the pandemic were 0.091 percent, 0.072 percent, 0.054 percent, and 0.034 percent, respectively. The lowest average hedge ratio during the pre-pandemic period was observed for the ETH-LQ45 portfolio at -0.161 percent, whereas the highest optimal hedge ratio during the pandemic was recorded for the ADA-LQ45 portfolio at 0.157 percent. These findings suggest that investors holding ETH may consider investing in LQ45 stocks to hedge their cryptocurrency exposure.

For example, an investor who purchases IDR 1 worth of Ethereum should hedge the position by investing IDR 0.002 in LQ45 index stocks. Conversely, investors holding Cardano can hedge their positions by selling LQ45 index stocks. For every IDR 1 worth of Cardano purchased, they should sell IDR 0.001 worth of LQ45 index stocks.

Hedging Effectiveness

Table 3 shows that the lowest hedging effectiveness value in both before and during the pandemic was found in the USDT-LQ45 portfolio at -82.919 percent. Adding USDT to a portfolio involving the LQ45 index was therefore ineffective since it resulted in a negative value. The hedging effectiveness with Tether, which also had a negative value, was unable to provide a hedge. Meanwhile, the highest hedging effectiveness value was found in the ETH-LQ45 portfolio at 0.751 percent in the period before the pandemic. Therefore, adding ETH shares to the LQ45 index portfolio could reduce the risk of LQ45 index shares by 0.751 percent. The average hedging effectiveness values overall were 0.472 percent, 0.124 percent, -15.989 percent, and -171.208 percent. Taken together, the periods before and during the pandemic showed negative hedge ratios for USDT, indicating that it may not be effective as a hedge against the LQ45 Index for reducing portfolio risk.

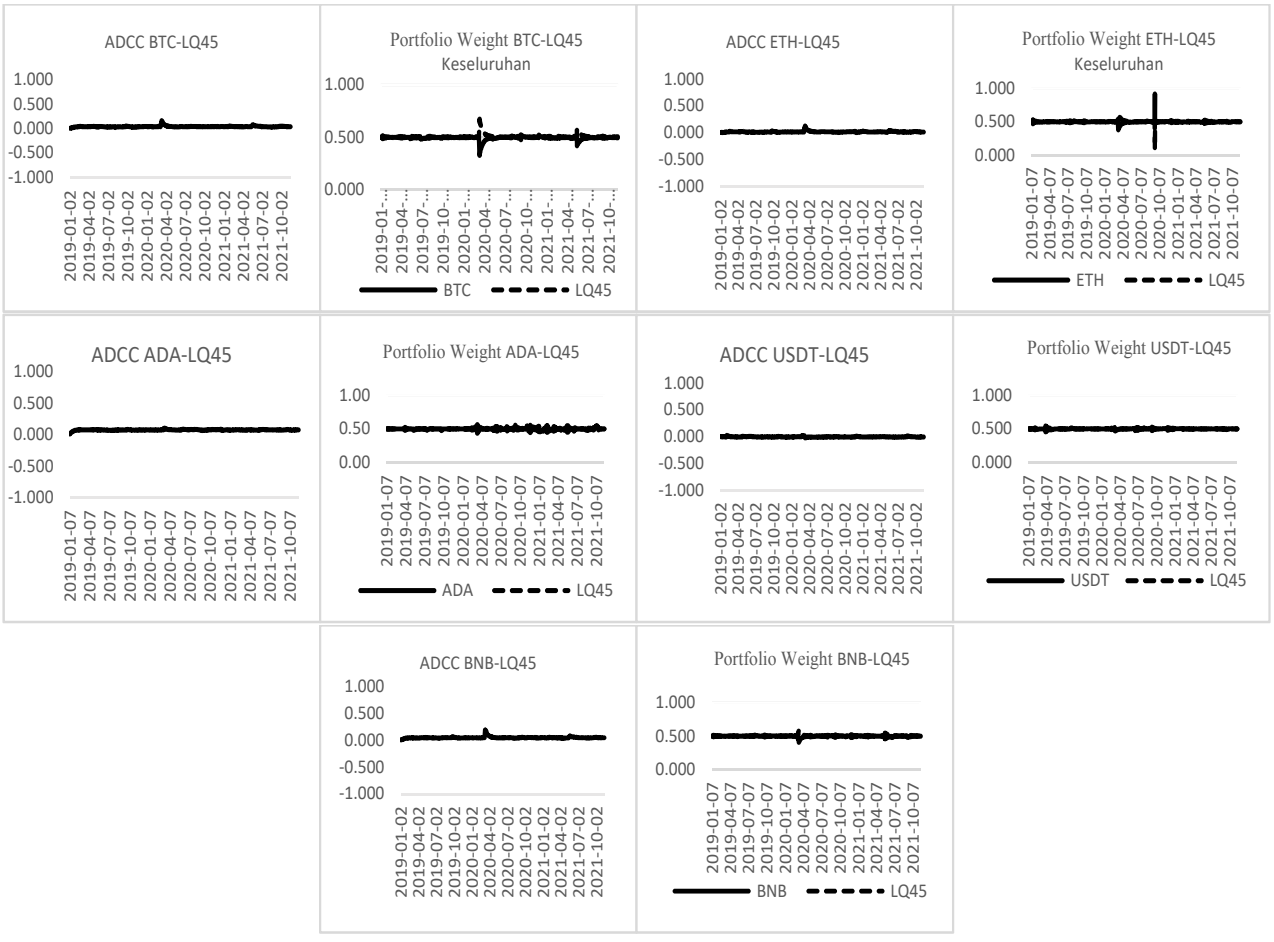


Figure 3. ADCC between the LQ45-cryptocurrency index and portfolio weights over time before and during the COVID-19 pandemic

Table 3. Optimal hedging ratio, hedging effectiveness, and sharpe ratio of individual stocks with the LQ45 index

Before COVID-19 Pandemic (2019)									
Portfolio	**Hedge Optimal Ratio (%)**	**Hedging Effectiveness (%)**	**Average Return (%)**	**Std. Dev.**	**Sharpe Ratio**	**Treynor Ratio**	**Jensen Ratio**	**Sortino Ratio**	**Omega Ratio**
BTC	-	-	0.505	0.044	0.078	-0.005	0.003	0.145	1.279
ETH	-	-	0.502	0.048	0.007	0.000	0.000	0.012	1.022
ADA	-	-	0.504	0.052	0.002	0.000	0.000	0.004	1.006
USDT	-	-	0.502	0.004	-0.046	-0.005	0.000	-0.077	0.884
BNB	-	-	0.504	0.052	0.089	-0.011	0.005	0.171	1.277
LQ45	-	-	0.498	0.009	-0.006	0.000	0.000	-0.010	0.985
BTC-LQ45	-0.146	0.746	0.002	0.022	0.077	0.006	0.002	0.143	1.263
ETH-LQ45	-0.161	0.751	0.000	0.024	0.006	0.001	0.000	0.011	1.019
ADA-LQ45	-0.077	0.742	0.000	0.027	0.001	0.000	0.000	0.002	1.003
USDT-LQ45	0.021	-0.622	0.000	0.005	-0.025	0.000	0.000	-0.041	0.939
BNB-LQ45	-0.094	0.744	0.002	0.052	0.089	-0.011	0.002	0.168	1.262
Average	-0.091	0.472	0.274	0.031	0.025	-0.002	0.001	0.048	1.085
During COVID-19 Pandemic (2020)									
Portfolio	**Hedge Optimal Ratio (%)**	**Hedging Effectiveness (%)**	**Average Return (%)**	**Std. Dev.**	**Sharpe Ratio**	**Treynor Ratio**	**Jensen Ratio**	**Sortino Ratio**	**Omega Ratio**
BTC	-	-	0.491	0.047	0.138	0.023	0.007	0.370	1.603
ETH	-	-	0.467	0.064	0.143	0.021	0.009	0.318	1.569
ADA	-	-	0.498	0.074	0.131	0.017	0.010	0.266	1.482
USDT	-	-	0.501	0.007	-0.016	0.002	0.000	-0.051	0.930
BNB	-	-	0.492	0.060	0.097	0.009	0.006	0.173	1.355
LQ45	-	-	0.502	0.023	-0.008	0.000	0.000	-0.012	0.978
BTC-LQ45	0.072	0.674	0.003	0.027	0.110	0.003	0.003	0.161	1.437
ETH-LQ45	0.066	0.725	0.004	0.033	0.121	0.004	0.004	0.183	1.455
ADA-LQ45	0.157	0.706	0.005	0.040	0.116	0.005	0.005	0.197	1.410
USDT-LQ45	-0.047	-2.179	0.000	0.012	-0.130	0.000	0.000	-0.021	0.963
BNB-LQ45	0.111	0.694	0.003	0.033	0.081	0.003	0.003	0.118	1.285
Average	0.072	0.124	0.269	0.038	0.071	0.008	0.004	0.155	1.315
During COVID-19 Pandemic (2021)									
Portfolio	**Hedge Optimal Ratio (%)**	**Hedging Effectiveness (%)**	**Average Return (%)**	**Std. Dev.**	**Sharpe Ratio**	**Treynor Ratio**	**Jensen Ratio**	**Sortino Ratio**	**Omega Ratio**
BTC	-	-	0.004	0.053	0.082	0.004	0.004	0.212	1.247
ETH	-	-	0.009	0.066	0.130	0.032	0.008	0.320	1.419
ADA	-	-	0.013	0.081	0.160	0.017	0.013	0.481	1.596
USDT	-	-	0.000	0.001	-0.156	-0.018	0.000	-0.369	0.645
BNB	-	-	0.017	0.096	0.180	0.021	0.017	0.631	1.766
LQ45	-	-	0.000	0.011	-0.005	0.000	0.000	-0.009	0.988
BTC-LQ45	0.115	0.744	0.002	0.027	0.078	0.002	0.002	0.128	1.236
ETH-LQ45	0.027	0.745	0.004	0.033	0.127	0.006	0.004	0.205	1.413
ADA-LQ45	0.077	0.739	0.007	0.042	0.156	0.007	0.006	0.319	1.579
USDT-LQ45	-0.016	-82.919	0.000	0.006	-0.014	0.000	0.000	-0.026	0.963
BNB-LQ45	0.068	0.746	0.009	0.048	0.178	0.009	0.008	0.384	1.750
Average	0.054	-15.989	0.006	0.042	0.083	0.007	0.006	0.207	1.327
Combining Periods Before and During COVID-19 Pandemic (2019-2021)									
Portfolio	**Hedge Optimal Ratio (%)**	**Hedging Effectiveness (%)**	**Average Return (%)**	**Std. Dev.**	**Sharpe Ratio**	**Treynor Ratio**	**Jensen Ratio**	**Sortino Ratio**	**Omega Ratio**
BTC	-	-	0.494	0.048	0.017	0.018	0.005	0.250	1.385
ETH	-	-	0.497	0.061	0.110	0.024	0.007	0.252	1.389
ADA	-	-	0.498	0.070	0.112	0.017	0.008	0.291	1.390
USDT	-	-	0.500	0.005	-0.030	-0.019	0.000	-0.517	0.885
BNB	-	-	0.497	0.071	0.128	0.017	0.009	0.333	1.495
LQ45	-	-	0.503	0.016	-0.005	0.000	0.000	-0.009	1.315
BTC-LQ45	0.038	-311.761	0.003	0.025	0.095	0.003	0.002	0.153	1.332
ETH-LQ45	0.015	-180.894	0.003	0.032	0.101	0.004	0.003	0.168	1.356
ADA-LQ45	0.074	-162.894	0.004	0.036	0.013	0.004	0.004	0.188	1.352
USDT-LQ45	-0.006	-23.034	0.000	0.008	-0.014	0.003	0.000	-0.024	0.958
BNB-LQ45	0.050	-177.457	0.005	0.036	0.122	0.005	0.004	0.244	1.455
Average	0.034	-171.208	0.273	0.037	0.059	0.007	0.004	0.121	1.301

The Sharpe Index is employed to determine portfolio performance. A higher Sharpe value indicates a greater reduction in portfolio risk, subsequently increases the effectiveness of the hedge. Table 3 shows that USDT had the lowest Sharpe Index values in both periods, at -0.046 before the pandemic and -0.156 during the pandemic. In contrast, BNB recorded the highest Sharpe Index values, at 0.089 before the pandemic and 0.180 during the pandemic. The Sharpe Index calculation results during the study period indicate that Tether crypto has a negative value. Therefore, it does not perform well compared to other cryptocurrencies.

The lowest Treynor Index value in the pre-pandemic period was recorded for BNB at -0.011, whereas the highest value during the pandemic was recorded for ETH at 0.032. A positive Treynor Index indicates better risk-adjusted portfolio performance. The overall average Treynor Index across the pre-pandemic and pandemic periods was positive at 0.007.

The Jensen Index also showed a positive overall average value of 0.004. The lowest average value before the pandemic was 0.001, while the highest average value during the pandemic was 0.006. BNB recorded the highest Jensen Index value in the pre-pandemic period at 0.005, whereas USDT recorded the lowest value during the pandemic at 0.000. Overall, the positive Jensen Index results indicate positive portfolio performance relative to the expected return based on systematic risk during the study period.

The Sortino Ratio measures risk-adjusted returns by considering downside risk relative to a target return. A higher positive Sortino Ratio generally indicates better risk-adjusted performance. USDT recorded the lowest Sortino Ratio before the pandemic at -0.077, while BNB recorded the highest value during the pandemic at 0.631. The Sortino Ratio results indicate that Ethereum underperformed the other cryptocurrencies in both study periods, as its value was negative.

The Omega Ratio evaluates the distribution of returns relative to a specified threshold. The average Omega Ratio values across the four portfolio configurations were 1.085, 1.315, 1.327, and 1.301, respectively. A higher Omega Ratio generally indicates better performance relative to the selected threshold. A value above 1 indicates that the probability-weighted gains above the threshold outweigh the probability-weighted losses below it, while a value of 1 indicates that the two are equal.

Dynamic Portfolio Performance Difference

Table 4 presents the results of the statistical tests comparing the performance of hedged and unhedged dynamic portfolios using the Sharpe Index, Treynor Index, Jensen Index, Sortino Ratio, and Omega Ratio. Before the COVID-19 pandemic in 2019, none of the five performance measures indicated a statistically significant difference between the two portfolio strategies, as all p-values exceeded the 10% significance level.

During the pandemic in 2020, the Treynor Index revealed a statistically significant difference at the 5% significance level ($t = 2.845$, $p = 0.021$). The Jensen Index similarly showed a statistically significant difference at the 10% level ($t = 1.753$, $p = 0.066$), although the result was not significant at the 5% level. In the second year of the pandemic (2021), none of the five performance measures showed a statistically significant difference between hedged and unhedged portfolios. For the overall study period (2019–2021), the Jensen Index indicates a statistically significant difference at the 10% level ($t = 1.817$, $p = 0.061$). In contrast, the Sharpe Index, Treynor Index, Sortino Ratio, and Omega Ratio do not show statistically significant differences.

The results indicate that statistically significant differences between hedged and unhedged portfolio performance are limited to particular performance measures and periods. Specifically, the Treynor Index identifies a difference during the pandemic, while the Jensen Index identifies differences during the pandemic and across the overall study period. The remaining comparisons do not provide sufficient statistical evidence of differences at the 10% significance level.

5. Discussion

The findings provide evidence that differences in the performance of hedged and unhedged dynamic portfolios depend on the evaluation period and the performance measure employed. Before the COVID-19 pandemic in 2019 and during the pandemic period (2020-2021), none of the five performance measures revealed a statistically significant difference between the two portfolio strategies. These results therefore do not provide sufficient statistical evidence to support proposed hypotheses in predicting a difference in portfolio performance during these periods.

During the pandemic, particularly in 2020, the Treynor Index indicated a statistically significant

difference between hedged and unhedged portfolios at the 5% significance level. The Jensen Index also indicated a difference at the 10% significance level, although this result was not significant at the 5% level. Furthermore, the Jensen Index identified a statistically significant difference at the 10% level over the overall study period. Accordingly, hypotheses predicting differences in portfolio performance receive statistical support only for the relevant performance measures and periods, subject to the direction specified in each hypothesis. The Sharpe Index, Sortino Ratio, and Omega Ratio did not indicate statistically significant differences at the 10% level in the reported comparisons.

Because the tests compared unhedged and hedged portfolio performance, the positive t-statistics for the Treynor and Jensen do not, by themselves, indicate that the unhedged portfolios outperform the hedged portfolios. Therefore, support for a directional hypothesis should be assessed based on both statistical significance and whether the observed differences align with the hypothesized direction.

From a financial perspective, the findings indicate that the potential benefits of combining cryptocurrencies with the LQ45 Index cannot be generalized across all performance measures or market conditions. Markowitz's (1952) portfolio selection theory further emphasizes that diversification benefits depend on the relationships among asset returns and the resulting trade-off between risk and return. Therefore, additional cryptocurrencies to an equity portfolio does not necessarily guarantee higher returns, lower risk, or superior risk-adjusted performance.

The significant result for the Treynor Index during 2020 suggests that the relative performance of the two portfolio strategies differed when returns were evaluated against systematic risk. Similarly, the significant Jensen Index results during 2020 and over the overall study period suggest differences in performance relative to the return expected under a market-risk framework. However, these statistical differences do not necessarily imply economically substantial improvements.

Table 4. Dynamic portfolio performance difference

Before COVID-19 Pandemic (2019)				
Ratio	**Description**	**t**	**Prob.**	**Conclusion**
Sharpe	Unhedged-Hedged	-0.106	0.459	Not significant
Treynor	Unhedged-Hedged	-0.986	0.176	Not significant
Jensen	Unhedged-Hedged	0.702	0.251	Not significant
Sortino	Unhedged-Hedged	-0.09	0.464	Not significant
Omega	Unhedged-Hedged	-0.034	0.487	Not significant
During COVID-19 Pandemic (2020)				
Ratio	**Description**	**t**	**Prob.**	**Conclusion**
Sharpe	Unhedged-Hedged	0.692	0.256	Not significant
Treynor	Unhedged-Hedged	2.845**	0.021	Significant
Jensen	Unhedged-Hedged	1.753*	0.066	Significant
Sortino	Unhedged-Hedged	1.044	0.168	Not significant
Omega	Unhedged-Hedged	0.509	0.313	Not different
During COVID-19 Pandemic (2021)				
Ratio	**Description**	**t**	**Prob.**	**Conclusion**
Sharpe	Unhedged-Hedged	-0.369	0.362	Not significant
Treynor	Unhedged-Hedged	0.734	0.242	Not significant
Jensen	Unhedged-Hedged	1.311	0.12	Not significant
Sortino	Unhedged-Hedged	0.285	0.393	Not significant
Omega	Unhedged-Hedged	0.766	0.233	Not significant
Before and During COVID-19 Pandemic (2019-2021)				
Ratio	**Description**	**t**	**Prob.**	**Conclusion**
Sharpe	Unhedged-Hedged	0.097	0.463	Not significant
Treynor	Unhedged-Hedged	0.984	0.190	Not significant
Jensen	Unhedged-Hedged	1.817*	0.061	Significant
Sortino	Unhedged-Hedged	-0.144	0.446	Not significant
Omega	Unhedged-Hedged	-0.989	0.185	Not significant

Notes: **Significant at the 5% significance level; *Significant at the 10% significance level

The absence of significant differences in the Sharpe Index, Sortino Ratio, and Omega Ratio also warrants careful interpretation. These measures capture different aspects of portfolio performance: the Sharpe Index evaluates excess returns relative to total risk, the Sortino Ratio focuses on downside risk, and the Omega Ratio evaluates the distribution of returns relative to a specified threshold. The lack of statistically significant differences under these measures suggests that the results did not provide consistent evidence of superior performance across all dimensions of risk and return. Concurrently, it also does not establish that the two strategies are financially equivalent. The implication is that the financial value of cryptocurrency-based hedging should be further assessed using multiple performance measures rather than a single indicator. Investors should also be able to distinguish a statistically detectable difference and an economically meaningful improvement in portfolio performance.

The findings can be interpreted in relation to previous research on cryptocurrency diversification in the Indonesian capital market. Pamilangan & Robiyanto (2019) examined dynamic portfolios combining cryptocurrencies with LQ45 stocks using the DCC-GARCH approach. Their study reported negative correlations between cryptocurrencies and the LQ45 Index and concluded that incorporating cryptocurrencies could improve portfolio performance. Their findings provide a relevant empirical basis for considering cryptocurrencies as potential diversification or hedging instruments in the Indonesian equity market.

This study extends the line of research by examining portfolio performance across periods before and during the COVID-19 pandemic and by employing the ADCC-GARCH approach to account for asymmetric dynamics in conditional correlations. Apart from general conclusion that cryptocurrency inclusion improves portfolio performance, the current findings showed that statistically significant differences between hedged and unhedged strategies only found in particular performance measures and periods. This difference in results does not necessarily contradict Pamilangan & Robiyanto (2019), because the studies differ in their observation periods, market conditions, and potentially their portfolio specifications and performance evaluation procedures.

The findings are also relevant with Anggita & Robiyanto (2022), who investigated dynamic portfolios combining Bitcoin with LQ45 stocks during the COVID-19 pandemic. Their study reported that Bitcoin was negatively correlated with LQ45 stocks and could serve as a hedging instrument. However, negative correlation and superior portfolio performance are inherently distinct concepts. While a negative correlation may provide diversification benefits, the ultimate effect on portfolio performance depends on the magnitude of the correlation, the assets' return and volatility characteristics, portfolio weights, and the performance measure used. The current findings reinforce this distinction by demonstrating that the statistical evidence of performance differences varies across evaluation measures.

From a methodological perspective, Engle (2002) introduced the DCC-GARCH framework for modeling time-varying conditional correlations, while Cappiello et al. (2006) extended this framework to incorporate asymmetric responses in conditional correlations. Both these models provide a suitable foundation for examining changing relationships among financial assets. Nevertheless, the ability to model dynamic and asymmetric correlations should not be interpreted as direct evidence that a particular portfolio strategy will outperform another. Portfolio superiority must be established empirically through the resulting portfolio performance and appropriate statistical comparisons. The present findings contribute to the existing literature by providing a period-specific and performance-measure-specific assessment of cryptocurrency-equity portfolio strategies. The results further emphasize the need to evaluate diversification benefits under different market conditions and using complementary measures of financial performance.

The findings have several implications for investors and portfolio managers in considering cryptocurrencies alongside stocks to be included in the LQ45 Index. First, portfolio construction should consider the changes in market conditions. The significant differences identified through the Treynor and Jensen indices during the COVID-19 pandemic suggest that the relative performance of hedged and unhedged strategies may differ during periods of market disruption.

Second, portfolio managers should evaluate hedging strategies using multiple performance indicators. Reliance on a single measure may lead to incomplete conclusions because the Sharpe Index,

Treynor Index, Jensen Index, Sortino Ratio, and Omega Ratio capture different dimensions of risk-adjusted performance. A strategy that performs favorably under one measure may not produce a statistically distinguishable advantage under another. Consequently, investment decisions should simultaneously consider total risk, systematic risk, downside risk, and the distribution of returns, along with the magnitude of the observed performance differences.

Third, the results highlight the importance of assessing each individual cryptocurrencies rather than treating them as a homogeneous asset class. The reported negative performance of Tether in the study suggests that its contribution to the portfolio may differ from that of the other cryptocurrencies examined. Investors should therefore evaluate each asset's return characteristics, volatility, correlations with equities, and contribution to overall portfolio risk before incorporating them into a hedging strategy.

Moreover, the ADCC-GARCH approach offers a useful framework for estimating time-varying conditional correlations and incorporating asymmetric correlation dynamics into portfolio construction. Portfolio managers may use such information to reassess portfolio allocations as market relationships change. Nevertheless, model-based allocation decisions should be evaluated alongside transaction costs, liquidity constraints, investment objectives, and the practical risks associated with cryptocurrency markets.

To conclude, the findings suggest that combining cryptocurrencies with the LQ45 Index may offer portfolio diversification opportunities, yet the effectiveness of is conditional on the market period, the cryptocurrency selected, and the performance measure employed. The results therefore encourage a selective and risk-aware approach to cryptocurrency-based portfolio management rather than a general claim that hedged portfolios consistently outperform unhedged portfolios.

6. Conclusion and Recommendations

This study examined the performance of dynamic portfolios combining cryptocurrencies with the LQ45 Index using the ADCC-GARCH method across the pre-pandemic, pandemic, and post-pandemic periods. The findings indicated that the benefits of combining cryptocurrencies with Indonesian equities vary across market conditions and performance evaluation measures. Although the hedged portfolios generated higher returns during the COVID-19 pandemic, the results did not establish a consistent performance advantage across all risk-adjusted performance measures. Furthermore, the negative performance of Tether highlighted the importance of evaluating individual cryptocurrencies rather than assuming that all digital assets provide equivalent diversification or hedging benefits. This study contributes to the literature by extending the analysis of cryptocurrency-equity portfolio diversification through a dynamic framework that accounts for time-varying conditional correlations and asymmetric market responses. The findings also emphasize the importance of evaluating portfolio strategies using multiple performance measures, as higher returns do not necessarily translate into superior risk-adjusted performance.

Despite these contributions, this study has several limitations. First, the analysis is restricted to five cryptocurrencies and the LQ45 Index, thereby excluding other potentially relevant asset classes and financial instruments. Second, the observation period, January 2019 to November 2021, covers a specific phase of market conditions associated with the COVID-19 pandemic and may not fully capture the performance of cryptocurrency-equity portfolios across other economic cycles. Third, the evaluation relies on selected risk-adjusted performance measures and the ADCC-GARCH framework; alternative portfolio optimization methods and performance criteria may yield additional insights into diversification and hedging effectiveness. Future studies are encouraged to address these limitations by incorporating other asset classes, such as gold, bonds, commodities, and additional equity indices, to examine whether broader diversification improves portfolio performance. Extended observation period is also suggested to include more recent market conditions and different economic cycles. Other technical suggestions were comparing the ADCC-GARCH method with alternative portfolio construction and optimization approaches, and incorporate transaction costs, liquidity constraints, and other practical investment considerations. Further studies could also investigate the individual contributions of different cryptocurrencies to portfolio risk and return to identify which assets provide more robust diversification benefits under different market conditions.

References

Abdelkafi, S. Z., & Khoufib, W. (2019). Asymmetric dynamics in the correlation of BRICS countries: Evidence from ADCC GARCH model. *Journal of Economic and Business Studies*, *2*(1), 108.

Anggita, I., & Robiyanto, R. (2022). Dynamic portfolio formulation using bitcoin and LQ45 stocks. *Jurnal Ekonomi dan Bisnis*, *25*(1), 113-136. https://doi.org/10.24914/jeb.v25i1.4790

Baumöhl, E. (2013). *Stock market integration between the CEE-4 and the G7 markets: Asymmetric DCC and smooth transition approach* [Paper]. Munich Personal ePec Archive, 43834.

Bhatia, V., Das, S., & Mitra, S. K. (2018). Crude oil hedging with precious metals: A DCC-GARCH approach. *Academy of Accounting and Financial Studies Journal*, *22*(1), 1-8.

Bonga-Bonga, L., & Nleya, L. (2016). *Assessing portfolio market risk in the BRICS economies: use of multivariate GARCH models* [Paper]. Munich Personal RePEc Archive.

Cappiello, L., Engle, R. F., & Sheppard, K. (2006). Asymmetric dynamics in the correlations of global equity and bond returns. *Journal of Financial econometrics*, *4*(4), 537-572. https://doi.org/10.1093/jjfinec/nbl005

Chandra, L., & Hapsari, Y. D. (2014). Analisis pembentukan portofo optimal dengan menggunakan Model Markowitz untuk saham LQ 45 periode 2008 2012. *Jurnal Manajemen*, *11*(1), 41-59. https://doi.org/10.25170/jm.v11i1.832

Chin, L., Chendra, E., & Sukmana, A. (2021). Analysis of portfolio optimization with lot of stocks amount constraint: Case study index LQ45. In *IOP Conference Series: Materials Science and Engineering*, *300*(1), 18–23. https://doi.org/10.1088/1757-899X/300/1/012004

CNBC. (2020, July 18). *Uang digital yang makin populer di tengah resesi ekonomi*. CNBC. Retrieved from: https://www.cnbcindonesia.com/tech/20200718091157-37-173706/uang-digital-yang-makin-populer-di-tengah-resesi-ekonomi

Ćosić, K., & Čeh Časni, A. (2019). The impact of cryptocurrency on the efficient frontier of emerging markets. *Croatian Review of Economic, Business and Social Statistics*, *5*(2), 64-75. https://doi.org/10.2478/crebss-2019-0012

Darmawan, I., & Purnawati, N. (2015). Pembentukan portofolio optimal pada saham-saham di Indeks LQ 45 dengan menggunakan model indeks tunggal. *E-Jurnal Manajemen Universitas Udayana*, *4*(12), 433-4361.

Eko, U. (2008). Analisis dan penilaian kinerja portofolio optimal saham-saham LQ45. *Jurnal Ilmu Administrasi dan Organisasi*, *15*(3), 178–187. https://doi.org/10.20476/jbb.v15i3.562

Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of business & economic statistics*, *20*(3), 339-350. https://doi.org/10.1198/073500102288618487

Ermis, M., Rasuli, M., & Rokhmawati, A. (2020). Analisis perbandingan kinerja portofolio optimal Markowitz Model dan Treynor Black Model pada saham LQ45 di Bursa Efek Indonesia. *Jurnal Ekonomi KIAT*, *31*(1), 29-35. https://doi.org/10.25299/kiat.2020.vol31(1).2737

Farell, R. (2015). *An analysis of the cryptocurrency industry* (Doctoral dissertation, University of Pennsylvania).

Fur, E. L., Ameur, H. B., Braune, E., & Faye, B. (2016). Financial market contagion and fine wines: the evidence of the ADCC GARCH model. *International Journal of Entrepreneurship and Small Business*, *29*(4), 583-601. https://doi.org/10.1504/IJESB.2016.079967

Gupta, R., & Basu, K. P. (2008). Portfolio optimisation in the Indian stock market: Industry sector analysis. *Delhi Business Review*, *9*(1), 21–30. https://doi.org/10.51768/dbr.v9i1.91200802

Hidayat, E. S. (2017). Pembentukan portofolio optimal tiga saham LQ45 dan perbandingan terhadap kinerja reksa dana saham pada Oktober 2016. *Jurnal Muara Ilmu Ekonomi dan Bisnis*, *1*(1), 89-96. https://doi.org/10.24912/jmieb.v1i1.410

Iskandar, D., Martalena, M., & Julianto, N. D. (2020). Perbandingan kinerja portofolio yang dibentuk dengan single index model pada saham-saham yang terdaftar dalam indeks LQ45 dan Kompas 100 tahun 2018. *Jurnal Akuntansi Maranatha*, *12*(1), 73–83. https://doi.org/10.28932/jam.v12i1.2041

Larasati, D., Irwanto, A. K., & Permanasari, Y. (2013). Analisis strategi optimalisasi portofolio saham LQ 45 (pada Bursa Efek Indonesia Tahun 2009-2011). *Jurnal Manajemen dan Organisasi*, *4*(2), 163-171. https://doi.org/10.29244/jmo.v4i2.12623

Maf'ula, Z., Rahayu, S. R., & Zahroh, Z. A. (2018). Portofolio optimal dengan penerapan model markowitz sebagai dasar keputusan investasi (Studi pada perusahaan yang tergabung dalam indeks LQ-45 tahun 2014). *Jurnal Administrasi Bisnis*, *63*(1), 1–7.

Mahadwartha, P. A., & Gunawan, P. Y. (2016). Pembentukan dan pengujian portfolio saham-saham optimal: Pendekatan Single Index Model. *EKUITAS Jurnal Ekonomi dan Keuangan*, *20*(4), 491-510. https://doi.org/10.24034/j25485024.y2016.v20.i4.2420

Majdoub, J., Ben Sassi, S., & Bejaoui, A. (2021). Can fiat currencies really hedge Bitcoin? Evidence from dynamic short-term perspective. *Decisions in Economics and Finance*, *44*(2), 789-816. https://doi.org/10.1007/s10203-020-00314-7

Manurung, H. (2019). Analisis kinerja portofolio saham dengan menggunakan metode Sharpe, Jensen dan Treyno. *Journal of Business Studies*, *4*(1), 1-16.

Markowitz, H. (1952). Portofolio selection. *The Journal of Finance*, *7*(1), 77–91. https://doi.org/10.2307/2975974

Miralles-Quirós, J. L., & del Mar Miralles-Quirós, M. (2017). The Copula ADCC-GARCH model can help PIIGS to fly. *Journal of International Financial Markets, Institutions and Money*, *50*, 1-12. https://doi.org/10.1016/j.intfin.2017.08.013

Pamilangan, A., & Robiyanto, R. (2019). Perumusan portofolio dinamis cryptocurrency dengan saham-saham LQ45. *Jurnal Ilmu Sosial dan Humaniora*, *8*(2), 283-292. https://doi.org/10.23887/jish-undiksha.v8i2.23065

Priyatna, Y., & Sukono, F. (2003). Optimasi portofolio investasi dengan menggunakan model markowitz. *Jurnal Matematika*, *6*(1), 1–10.

Pracanda, D. G. S. P., & Abundanti, N. (2017). Pembentukan portofolio optimal dengan menggunakan model markowitz pada saham indeks IDX30 di bursa efek Indonesia. *E-Jurnal Manajemen Unud*, *6*(2), 802–829.

Puspitasari, R., & Pramesti, D. (2011). Analisis risiko dan tingkat pengembalian saham terhadap portofolio optimal saham (Studi kasus pada 8 saham dari LQ-45). *Jurnal Ilmiah Ranggagading*, *11*(02), 17-21.

Rini, S., Handayani, S. R., & Hidayat, R. (2013). Evaluasi kinerja portofolio dengan menggunakan Model Sharpe. *Jurnal Administrasi Bisnis S1 Universitas Brawijaya*, *4*(2), 1–8.

Robiyanto, R., Ernayani, R., & Ismail, R. S. (2019). Formulation of a dynamic portfolio with stocks and fixed-income instruments in the Indonesian capital market. *Organizations and Markets in Emerging Economies*, *10*(1), 132-146. https://doi.org/10.15388/omee.2019.10.00007

Seijas, P. L., Nemish, A., Smith, D., & Thompson, S. (2018). Marlowe: implementing and analysing financial contracts on blockchain. In *Margaria T., Steffen B. (eds) Leveraging Applications of Formal Methods, Verification and Validation* (Lecture Notes in Computer Science, Vol. 11247). Springer Cham. https://doi.org/10.1007/978-3-030-54455-3_35

Septyanto, D., & Kertopati, B. (2014). Analisa Pembentukan Portofolio Dengan Menggunakan Model Markowitz dan Single Index Model Pada Saham LQ45 di Bursa Efek Indonesia Tahun 2009–2013. In *Proceeding of International Conference Sustainable Competitive Advantage*, *4*(1), 567-583.

Sun, T., & Yu, W. (2020). A formal verification framework for security issues of blockchain smart contracts. *Electronics*, *9*(2), 255. https://doi.org/10.3390/electronics9020255

Suryani, A., & Herianti, E. (2015). The analysis of risk adjusted return portfolio performance share for LQ 45 index in indonesia stock exchange in 2010-2014 periods. *Procedia-Social and Behavioral Sciences*, *211*, 634-643. https://doi.org/10.1016/j.sbspro.2015.11.087

Trimborn, S., Li, M., & Härdle, W. K. (2020). Investing with cryptocurrencies—A liquidity constrained investment approach. *Journal of Financial Econometrics*, *18*(2), 280-306. https://doi.org/10.1093/jjfinec/nbz016

Warsito, O. L. D. (2020). Analisis volatilitas cryptocurrency, emas, Dollar, dan Indeks Harga Saham (IHSG). *International Journal of Social Science and Business*, *4*(1), 40-46. https://doi.org/10.23887/ijssb.v4i1.23887

Wei, W. C. (2018). The impact of Tether grants on Bitcoin. *Economics Letters*, *171*, 19-22. https://doi.org/10.1016/j.econlet.2018.07.001

Yuniarti, S. (2010). Pembentukan portofolio optimal saham – saham perbankan dengan menggunakan Model Indeks Tunggal. *Jurnal Keuangan dan Perbankan*, *14*(3), 459–466. https://doi.org/10.26905/jkdp.v14i3.987

Zahra, F. (2017). Analisis pembentukan portofolio saham menggunakan model indeks tunggal pada saham indeks LQ-45 periode Januari 2013 sampai dengan Juli 2016 di Bursa Efek Indonesia. *Journal of Secretary and Business Administration*, *1*(1), 41–56. https://doi.org/10.31104/jsab.v1i1.7

Zhang, Y. J., Bouri, E., Gupta, R., & Ma, S. J. (2021). Risk spillover between Bitcoin and conventional financial markets: An expectile-based approach. *The North American Journal of Economics and Finance*, *55*, 101296. https://doi.org/10.1016/j.najef.2020.101296