CAN CRYPTOCURRENCY BE A HEDGE DURING CRISIS? A SYSTEMIC RISK POINT OF VIEW

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ABSTRACT

This study investigates the hedging possibilities of cryptocurrency assets using a systemic risk estimation approach during the COVID-19 crisis period. Using a quantitative research approach, the research uses S&P 500 index price data and cryptocurrency assets. The systemic risk is calculated by using the vine copula ΔCoVaR method and the APARCH-DCC approach on the portfolio of cryptocurrency assets calculated for both individual cryptocurrency assets and GMV portfolios to capture the non-linear and dynamic relationship between cryptocurrencies and other financial assets and to estimate the impact of risk induced by the asset portfolio on the index under extreme market conditions. As a result, in the short term, especially during the Covid-19 crisis, BTC is considered the first "safe haven," as it has minimal VaR, CoVaR, and ΔCoVaR both when estimated individually and in the form of a GMV portfolio. ETH and LTC take second and third place after BTC in terms of stability against global economic uncertainty.

Keywords: *Cryptocurrency; Systemic Risk; Vine copula ΔCoVaR*

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INTRODUCTION

Systemic risk can be contributed from the cryptocurrency market which has grown rapidly in the last decade, becoming one of the most significant innovations in the financial sector (Scaillet et al., 2018; Xu et al., 2019). Bitcoin, Ethereum, and various other cryptocurrencies have not only become attractive investment instruments but also show the potential to transform the global financial system (Duan et al., 2024). The cryptocurrency market is highly volatile and is affected by various external factors, such as regulation, technology adoption, and market speculation (Bouri et al., 2023). Cryptocurrencies have become an important asset class, and their speculative nature can result in large gains or losses (Mba, 2024).

Cryptocurrencies exhibit complex and dynamic behavior as there are network effects and investor sentiment that can lead to extreme price movements and spillover effects across cryptocurrencies and traditional assets (Fang et al., 2022). Therefore, investors and asset managers must understand and quantify the risks of cryptocurrencies and their interactions with other assets. Interactions between assets form a rapidly growing multivariate analysis including measures of systemic risk (Li & Tu, 2022; Duan et al., 2024; Stolbov et al., 2024; Stolbov & Shchepeleva, 2024). Research on systemic risk and spillovers has previously been conducted in the context of the banking industry (Betz et al., 2016; Li & Tu, 2022; Nan et al., 2023; Zhang et al., 2023), energy (Zhu et al., 2022; Deng et al., 2023; Zhao et al., 2024), stock markets (Feng et al., 2023), capital markets (Xie et al., 2023), commodity markets (Zhang et al., 2022), forex markets (Dai et al., 2020), as well as cryptocurrency markets (Fang et al., 2022; Bouri et al., 2023; Zhang et al., 2023; Mba, 2024; Duan et al., 2024). The operation and trading of cryptocurrencies have attracted a lot of attention from market participants and regulators given the huge profits derived from cryptocurrency trading which has been consistent and extensive (Li & Miu, 2023).

Based on a survey conducted by Fang et al. (2022) stated that research on the interrelationship of cryptocurrencies with financial markets still needs further research. Research on systemic risk spillover using cryptocurrency assets found that crypto investors can use Bitcoin to diversify risk when FTX trading collapses in November 2022 (Bouri et al., 2023). While many studies report weak and sometimes even negative correlations between stock market returns and cryptocurrencies (Dyhrberg, 2016; Bouri et al., 2017), some subsequent studies show strongly positive correlations, leading to the conclusion that cryptocurrencies are hedging assets against equity risk (Bouri et al., 2018; Conlon et al., 2020). Adding to these inconsistent findings, some studies measure the correlation of stock returns and cryptocurrencies during episodes of economic/financial distress to test whether cryptocurrencies can act as safe-haven assets for stock investors.

Modeling systemic risk using the vine copula delta Conditional Value at Risk (ΔCoVaR) because this model can help explain the systemic contribution of cryptocurrency assets to the financial system, during distress (Shahzad et al., 2018). This research utilizes the Asymmetric Power Autoregressive Conditional Heteroskedasticity (APARCH-DCC) approach as it considers the asymmetry in volatility, where volatility can react differently to price increases and decreases thus allowing for better handling of leverage effects or negative impacts that outweigh positive impacts (Mba, 2024). By utilizing portfolio weighting using Global Minimum Variance (GMV) for cryptocurrency assets during the Covid-19 crisis period, this study analyzes the risk of investment losses from diversification and individual assets.

The selection of the COVID-19 crisis period considering the pandemic has created widespread bear market conditions for the first time since the emergence of cryptocurrencies (Conlon et al., 2020), also the systemic network of cryptocurrencies shows that the COVID-19 period encourages increased interconnection, highlighting a higher number of systemic contagion channels (Akhtaruzzaman et al., 2022). Cryptocurrency assets such as Ethereum (ETH), Bitcoin (BTC), and Litecoin (LTC) are used as the unit of analysis given their unique characteristics, including high volatility (Scaillet et al., 2018) and the complexity of their dependencies with traditional assets that can pose systemic risks that have not been widely explained in previous studies (Bouri et al., 2023).

LITERATURE REVIEW

The rapid growth and increasing popularity of cryptocurrencies have raised concerns about the potential systemic risks they pose to the broader financial system (Hedström et al., 2024; Ali et al., 2024). Cryptocurrencies, as a new and largely unregulated asset class, have been associated with issues such as volatility, speculative bubbles, and the potential for illicit activities, all of which can have far-reaching implications for financial stability (Arnell et al., 2023; Hoque et al., 2024; Kumar et al., 2024).

To understand the nature and importance of systemic risk in the cryptocurrency market, this literature review examines the current research on the topic (Elsayed et al., 2023; Woitschig et al., 2023; Hedström et al., 2024). The review will explore the key factors that contribute to systemic risk in the cryptocurrency market, the potential impact on the broader financial system, and the need for further research in this area (Arnell et al., 2023; Hoque et al., 2024; Kumar et al., 2024; Hedström et al., 2024). One of the primary concerns regarding the systemic risk of cryptocurrencies is their inherent volatility (Woitschig et al., 2023). Cryptocurrency prices have been known to experience significant fluctuations, with some studies finding that the volatility of cryptocurrency returns is much higher than that of traditional financial assets (Ali, Naveed, et al., 2024; Ali, Umar, et al., 2024; Yousaf, Youssef, et al., 2024). This volatility can be attributed to factors such as speculative trading, the lack of regulatory oversight, and the perceived risk associated with the new and untested technology behind cryptocurrencies (Kumar et al., 2024).

Another factor that contributes to the systemic risk of cryptocurrencies is the potential for the formation of price bubbles (Woitschig et al., 2023; Arnell et al., 2023). Concerns have been raised that the rapid growth of the cryptocurrency market may be driven by speculative behavior rather than fundamental factors, leading to the creation of asset price bubbles (Arnell et al., 2023). If these bubbles were to burst, it could have significant consequences for the broader financial system, as the interconnections between the cryptocurrency market and traditional financial institutions continue to grow (Chen et al., 2024).

Furthermore, the lack of regulatory oversight and the decentralized nature of cryptocurrencies have raised concerns about their potential for illicit activities, such as money laundering and terrorist financing (Akyildirim et al., 2023; Hoque et al., 2024; Kumar et al., 2024). These activities could have destabilizing effects on the financial system as a whole (Corbet et al., 2020). The importance of addressing systemic risk in the cryptocurrency market is underscored by the increasing integration of cryptocurrencies into the traditional financial system (Hedström et al., 2024; Woitschig et al., 2023; Yousaf, Arfaoui, et al., 2024). As more institutional investors and traditional financial institutions become involved in the cryptocurrency market, the potential for contagion and the transmission of shocks from the cryptocurrency market to the broader financial system increases (Corbet et al., 2020). Therefore, it is crucial to conduct further research on the nature and extent of systemic risk in the cryptocurrency market, as well as the potential policy and regulatory measures that can be implemented to mitigate these risks (Arnell et al., 2023; Hoque et al., 2024; Kumar et al., 2024).

RESEARCH METHOD

This study uses data on the S&P500 index and the daily price of cryptocurrency assets during the Covid-19 crisis period from January 02, 2020, to December 31, 2020, accessed from Thomson Reuters Datastream. Cryptocurrency assets used include BTC, ETH, and LTC. BTC is a cryptocurrency first created in 2009 with the largest market capitalization. ETH was created in 2015 and is the second-largest cryptocurrency by market capitalization. ETH differs from Bitcoin in that it allows the creation of decentralized applications (dApps) on its blockchain. LTC is a cryptocurrency created in 2011 that is similar to Bitcoin but has faster transactions and lower fees (Mba, 2024).

Table 1
Descriptive Statistics

	S&P500	ETH	BTC	LTC
Mean	0.001	0.007	0.006	0.004
Min	-0.128	-0.399	-0.322	-0.385
Max	0.089	0.165	0.159	0.244
SD	0.022	0.056	0.043	0.061
Kurtosis	8.468	10.47	14.16	7.518
Skewness	-0.856	-1.327	-1.541	-0.888
ADF Stat.	-5.206	-5.953	-6.414	-5.959
ADF P-Value	0.01	0.01	0.01	0.01

Source: R Studio Output, 2024

In Table 1, it is known that although the average daily return of ETH is higher than the index when viewed from the minimum and maximum return values, all cryptocurrency assets show higher volatility than the index. This is also evidenced by the standard deviation values on all return values of cryptocurrency assets that are higher than the index. When viewed from a measure of asymmetry of the return distribution, the skewness of all cryptocurrency assets has a greater negativity compared to the index. This means that the data distribution tends to have a longer tail on the left side. When viewed from the tail risk measure, the kurtosis of ETH and BTC is greater than that of the index. This means that the interconnectedness of extreme values in the return distribution indicates a spike or there is a thicker tail indicating a higher potential for extreme events. Thus, cryptocurrencies assets offer higher average daily returns and greater risk as indicated by their volatility, kurtosis, and skewness. The ADF test results in Table 1, show the p-value for the three cryptocurrency assets is 0.01 < 0.05. This means that the null hypothesis stating that there is a unit root is rejected and the alternative hypothesis is accepted, there is no unit root in the data so the data can be used because it is stationary. Although there are fluctuations and volatility clusters in the short term, the basic properties of the data (such as mean and variance) remain consistent throughout the crisis period, which is indicated by the stationary ADF test results.

This study is quantitative research that uses S&P500 index price data and cryptocurrency assets which are then made into returns before being processed using APARCH-DCC in R Studio to generate the output of the ΔCoVaR copula for the portfolio based on GMV calculations compared to individual cryptocurrency assets. APARCH-DCC is a dynamic model used to model volatility heteroskedasticity and conditional correlation between two or more time series simultaneously (Curto & Serrasqueiro, 2022). This model is an extension of the ARCH/GARCH model that considers asymmetry and correlation between variables (Mba, 2024). DCC-APARCH is used to address the varying volatility in financial data and model the correlation between financial assets (Wei et al., 2023).

To address the complexity and volatility of the cryptocurrency market, an APARCH-DCC approach to the ΔCoVaR vine copula is used to better understand the dynamics of the cryptocurrency market in systemic risk and spillover analysis (Moutari et al., 2021). The use of the APARCH-DCC model is considered better than the DCC-GARCH given its ability to cope with unsymmetrical volatility and leverage effects (Chen & Yu, 2020) . This makes the APARCH-DCC model more suitable for analyzing systemic risk and spillovers in complex financial markets (Mba, 2024). Furthermore, the vine copula is a very flexible method in modeling complex and non-linear dependencies, it can also be used for multivariate analysis between variables and accommodates tail dependence, which is the dependence that occurs in the tail distribution for each variable used (Duan et al., 2024). The use of ΔCoVaR is to evaluate the contribution of an asset or institution to the systemic risk of the entire financial system (Pangestuti, 2019). In addition, ΔCoVaR measures the change in the Conditional Value at Risk (CoVaR) of the system when a particular institution is in distress compared to when the institution is in the median state (Zhang et al., 2023), ΔCoVaR also helps identify and measure risk spillovers on various time scales, providing details on contagion dynamics in commodity and currency markets (Dai et al., 2020).

Return

Following Girardi & Ergün (2013), bank i return distribution is written, R_t^i in this equation:

$$Pr\left(R_t^i \leq V_a R_q^i, t\right) = q \tag{1}$$

Diversivication Ratio (DR)

Choueifaty & Coignard (2008) and Choueifaty et al. (2012) discussed the theoretical and empirical properties of theoretical and empirical portfolios when diversification is used as a criterion with the DR equation as follows:

$$\boldsymbol{DR_{\omega\in\Omega} = \frac{1}{\sqrt{\rho + CR - \rho CR}}} \tag{2}$$

where ρ and CR denote the weighted average correlation and volatility concentration ratio, respectively. The diversification ratio measures the degree of diversification of a portfolio. The higher the DR, the more diversified the portfolio is. The Most Diversified Portfolio (MDP) is obtained by maximizing the DR.

$$\boldsymbol{P_{MDP} = argmaxDR_{\omega\in\Omega}} \tag{3}$$

the MDV ratio is obtained by minimizing $\omega^{T}C\omega$, C denotes the correlation matrix of the initial asset returns. Therefore, the objective function is the same as that of the GMV portfolio.

The return series is considered as rt = μt + αt where μt is the conditional expected return and αt = σzt is zero-mean white noise with zt ~ D(0,1) and D is the skewed Student's t distribution. Following Granger & Engle (1995) and Mba (2024) αt ~ APARCH (p,q) if:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \alpha_i (|a_t - i|: \gamma_i a_{t-i})^{\delta} + \Sigma_{j=1}^{q} \beta_j \sigma_{t-j}^{\delta} \quad (4)$$

ω > 0, $\alpha_i \geq 0$, $\beta_j \geq 0$, δ > 0, dan -1 < γ_i < 1. γ_i to capture the leverage effect which allows the model to account for asymmetries in the volatility response to positive and negative shocks. δ can capture a wide range of volatility dynamics observed in financial markets. Persistence in the autocorrelation |αt||αt-1| can be modeled more effectively with an APARCH specification, capturing the long memory property (Engle & Sheppard, 2001). The use of (*p*,*q*) = (1,1) because it is considered a good fit for financial time series data. Following Brooks (2002) that GARCH with first order lags is sufficient to describe volatility clustering of asset returns. The innovation in this model is in the skewed Student's t distribution with density function:

$$\boldsymbol{d(x;\eta,\lambda)} = \begin{cases} \boldsymbol{bc}\left(\boldsymbol{1} + \frac{1}{\eta-2}\left(\frac{bx+a}{1-\lambda}\right)^2\right)^{\frac{-\eta+1}{2}}, \boldsymbol{if x > -\frac{a}{b}} \\ \boldsymbol{bc}\left(\boldsymbol{1} + \frac{1}{\eta-2}\left(\frac{bx+a}{1+\lambda}\right)^2\right)^{\frac{-\eta+1}{2}}, \boldsymbol{if x \leq -\frac{a}{b}} \end{cases} \quad (5)$$

which, $\boldsymbol{a = 4\lambda c \frac{\eta-2}{\eta+1}}$; $\boldsymbol{b = 1 + 3\lambda^2 - a^2 c}$; $\boldsymbol{c = \frac{\Gamma\left(\frac{\eta+1}{2}\right)}{\sqrt{\Pi(\eta-2)\Gamma\left(\frac{\eta}{2}\right)}}}$

ᴦ is gamma function.

Although the DCC-GARCH model allows for time-varying conditional correlation, it fails to reproduce the non-linear dependence that may exist between variables and does not provide information about tail dependence, so a vine copula approach is used (Mba, 2024). The following vine copula equation is used following Sklar (2023). Assume $F = (F_1, \ldots, F_n)$ is an n-dimensional joint distribution function with marginal distribution function Fi(i = *1*, . . . , *n*). Then there exists a copula C such that for all x = ($x_1, \ldots, x_n$) ϵI^n,

$$\boldsymbol{F_{(x)} = ((F_1(x_1), \ldots) Fn(x_n))} \quad (6)$$

$$\boldsymbol{C(u_1, \ldots, u_n) = \frac{\partial^n C(U_1,\ldots,Un)}{\partial u_1 \ldots \partial u_n}} \quad (7)$$

the following relationship is used to obtain the density of the *n*-dimensional distribution *f*:

$$f(x_{1,\ldots,}x_h) = C(F_1(x_1), \ldots, Fn(x_n)) \Pi_{i=1}^{n} f i(x_i) \quad (8)$$

the paired upper and lower tail coefficients, denoted by λ_U and λ_L respectively, are given by the following equations:

$$\lambda_u = \lim_{u \to 1} \frac{1-2u+C(u,u)}{1-u} \quad (9)$$

$$\lambda_L = \lim_{u \to 1} \frac{C(n,u)}{n}$$
(10)

Vine copula addresses the problem of high-dimensional probabilistic modeling by decomposing the probability density into conditional probabilities and then decomposing the conditional probabilities into bivariate copulas (Bedford & Cooke, 2001; Bedford & Cooke, 2002).

ΔCoVaR

CoVaR is calculated as a quantile-based measure of systemic risk (Adrian & Brunnermeier, 2016) . CoVaR estimates the potential loss of a portfolio, given a severe loss experienced by asset *i* that pushes asset *i* to a lower quantile of its distribution.

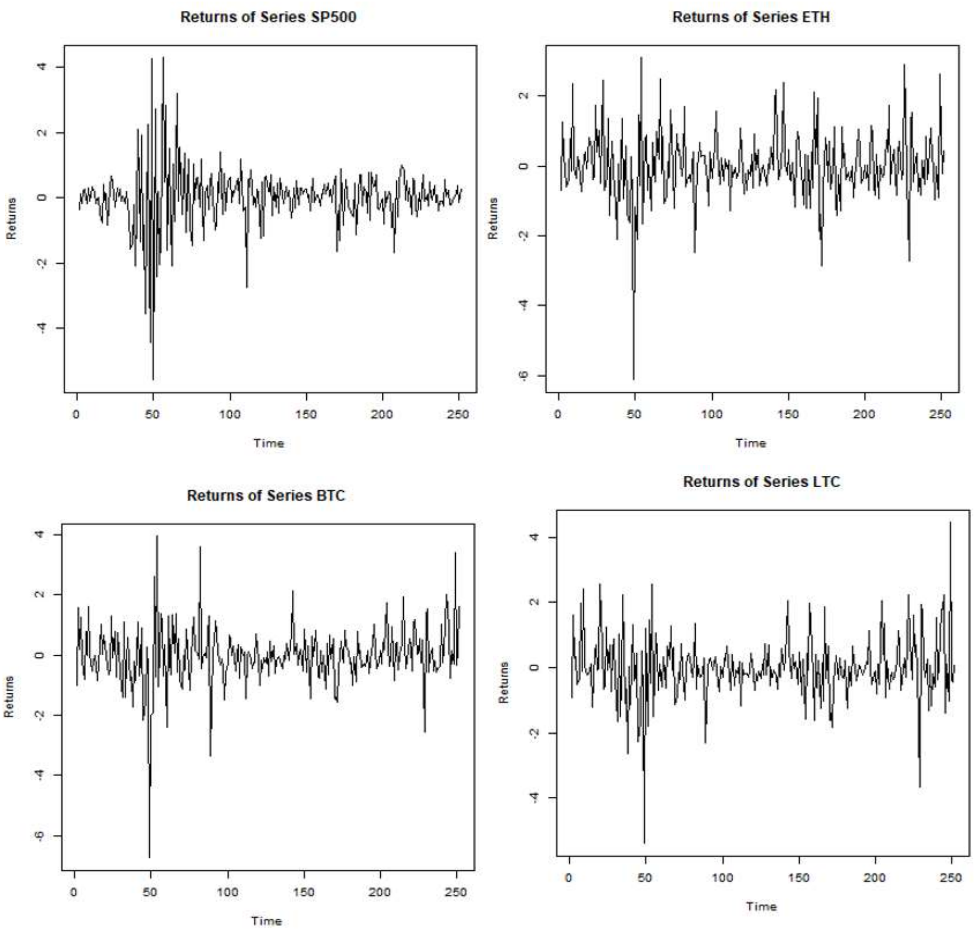
$$\Delta\, CoV\, aR_q^{p|i} = \left(CoVa\,R_q^{p|i} \middle| r_i = V_aR_q^i\right) - \left(CoVa\,R_q^{p|i} \middle| r_i = V_aR_{0.5}^i\right) \tag{10}$$

The difference between the portfolio's CoVaR conditional on the distress of a particular asset i and the median condition (i.e., q = 0.5), i.e. during normal market conditions. Hence, the larger (in absolute value) ΔCoVaR is, the higher the portfolio's vulnerability to contagion from the tail risk event of asset *i*. in this study, the systemic risk of each crypto asset and GMV portfolio is calculated separately to see the difference in the contribution of each asset to the system both individually and when a portfolio is formed.

RESULTS AND DISCUSSIONS

Return

Return is the profit or loss of an investment which in this systemic risk calculation is calculated by today's return deducted by the previous return divided by the previous day's return which is then defined as the quantile of the asset conditional to the system (Pangestuti, 2019).



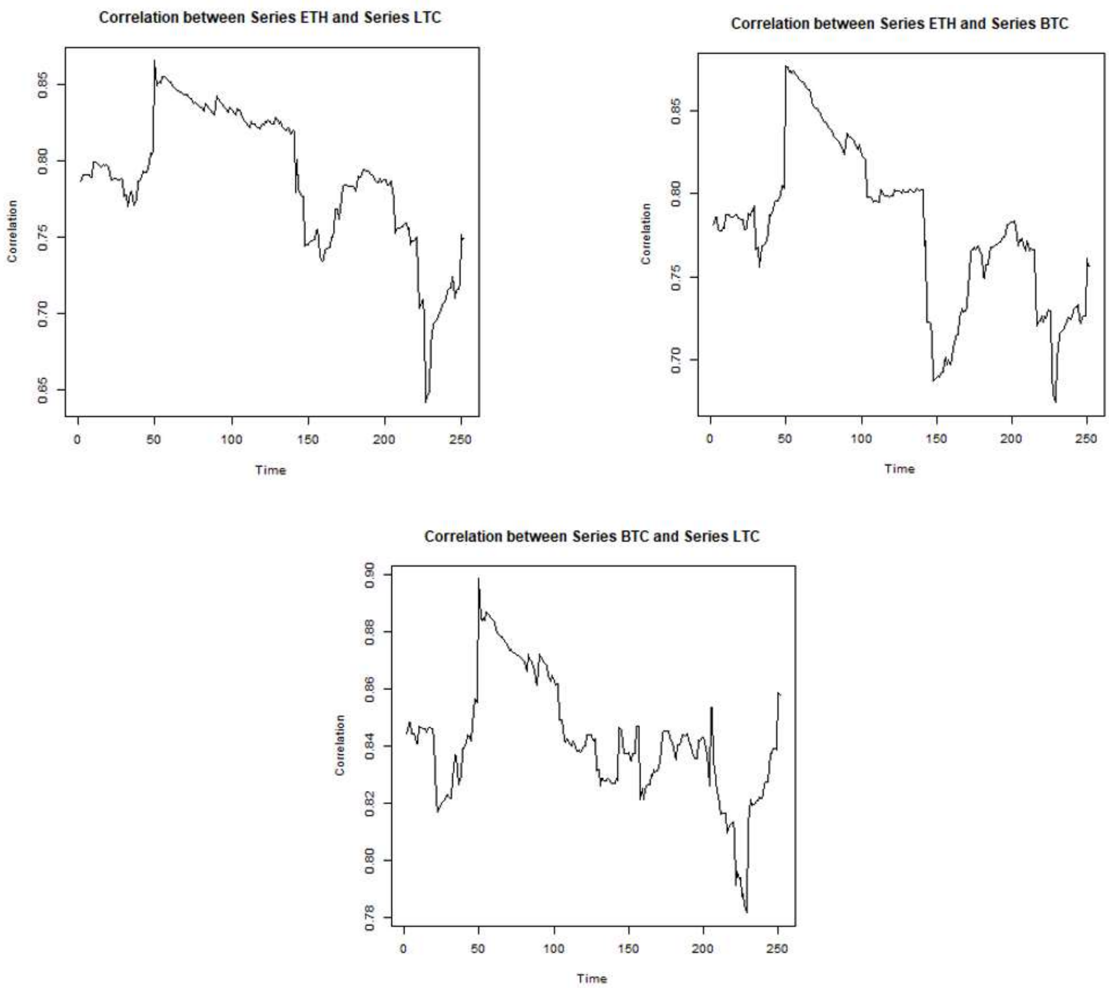
Source: R Studio Output, 2024

Figure 1
Returns Index and Cryptocurrency Assets

Figure 1 shows that in the early period of 2020, stock return fluctuations experienced tremendous volatility in both the S&P500 index and cryptocurrency assets with a sharp decline in BTC and ETH to more than -6%. However, the S&P index shows a longer pattern of instability at the beginning of the period and tends to stabilize after the 100th day. This contrasts with BTC returns, which tend to still show sharp fluctuations until the end of the year although not as sharp as the movement of ETH let alone LTC especially after the 200th day which still shows prominent return instability.

Conditional Correlations

Conditional correlation is used to measure the relationship between two series, which in this case uses assets taken from the crypto market (Mba, 2024; Pangestuti, 2019).



Source: R Studio Output, 2024

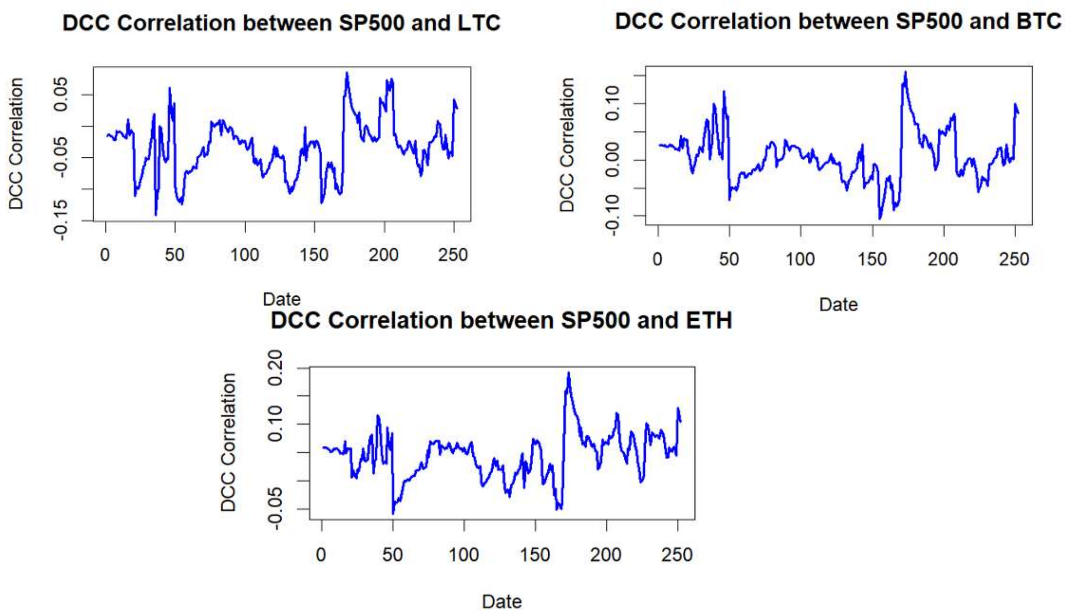
Figure 2
Conditional Correlations Cryptocurrency Assets

Figure 2 shows that during the COVID-19 crisis period in early 2020, all cryptocurrency assets (BTC, ETH, and LTC) and indexes (S&P500) experienced high volatility with significant price fluctuations. BTC, ETH, LTC, as well as the S&P500

experienced extremely high volatility at the beginning of the period, demonstrating the stock market's strong reaction to COVID-19-related news and uncertainty. The COVID-19 crisis had a significant impact on all markets. The difference in correlation between BTC, ETH, and LTC with the S&P 500 suggests that each crypto asset responded to market conditions in different ways , which the results of conditional correlation at the asset level are in line with research conducted by (Chen & Yu, 2020) those who examine at the same level but with different financial assets. Positive correlations indicate that there are periods where cryptocurrencies and the S&P 500 move in the same direction, possibly due to investor reaction to economic stimulus or monetary policy (Mba, 2024). Negative correlations indicate periods where cryptocurrencies serve as diversification, moving in the opposite direction to the stock market and providing protection against stock market declines (Hsu et al., 2024).

DCC Correlation Index with Cryptocurrency Assets

DCC digunakan untuk menganalisis hubungan dinamis antara mata uang kripto dengan index selama periode sampel model yang mencakup perubahan struktural yang menggambarkan kemampuan mata uang kripto dalam kaitannya dengan index (Hsu et al., 2024).



Source: R Studio Output, 2024

Figure 3
DCC Index and Cryptocurrency Assets

Figure 3 shows a graph of the dynamic correlation between S&P and each cryptocurrency asset during the crisis period. A positive correlation means that both assets move in the same direction, while a negative correlation means that both assets move in the opposite direction. A correlation close to zero indicates a weak relationship or no correlation (Hsu et al., 2024). The correlation goes from mildly positive, down to near zero or negative, and backs up slightly. These changes indicate the uncertainty faced by global financial markets due to the initial news about the COVID-19 pandemic, which affected the way investors treated traditional and crypto assets.

VaR, CoVaR, ΔCoVaR Vine Copula using APARCH-DCC Approach

VaR is used to measure the risk of possible losses, CoVaR (which is calculated based on the result of VaR) is used in the measurement of systemic risk because this model can describe the contagion effect of assets into the system, dCoVaR is the VaR of crypto assets conditional on market distress (Pangestuti, 2019; Mba, 2024).

Table 2
Output: VaR, CoVaR, ΔCoVaR vine copula using APARCH-DCC Approach

	VaR	CoVaR	ΔCoVaR
Portfolio A: GMV per Weight of Cryptocurrency Assets Determined			
ETH(0.5)			
LTC(0.5)			
	0.9474	0.9443	-0.00309
	0.9357	0.9414	-0.00573
Portfolio B: GMV per Weight of Cryptocurrency Assets Determined			
BTC(0.4)			
ETH(0.3)			
LTC(0.3)	0.9145	0.8722	-0.04229
	0.9130	0.8931	-0.01989
	0.9620	0.9614	-0.00059
Non-GMV (Individual Cryptocurrency Assets)			
BTC	0.9471	0.9322	-
ETH	0.9514	0.9462	0.01489
LTC	0.9641	0.9582	-
			0.00522
			0.00594

Source: R Studio Output, 2024.

VaR at the 95% level is the maximum value expected to be lost under normal conditions such that there is a 5% chance that losses will exceed that value in a given period. CoVaR measures the risk of loss on a particular asset (e.g. BTC) under the assumption that other assets or the financial system are also under stress (loss). CoVaR considers the risk of extreme conditions that could occur at the same time. ΔCoVaR is the difference between CoVaR and VaR. It measures the additional risk an asset faces when the market is already in bad shape.

Discussions

Based on Figure 3, The correlations of S&P500 and LTC tend to be negative despite some spikes in the early period and around days 150 to 200. Slightly different from BTC and ETH, which tend to have a similar pattern of zero and positive correlations in the early period and positive in the days 150-200. Thus, the early period of COVID-19 was characterized by high volatility in the financial markets, which was reflected in the fluctuations in the DCC correlation between the S&P 500 and all cryptocurrency assets. Further, these volatile correlations reflect market uncertainty during times of crisis, where investors may respond differently to new information about the pandemic. There is a significant peak in correlation around days 150 to 200 which suggests there was a specific event or change in market sentiment that caused the two assets to move more in sync at that time. Investors react to crisis situations in different ways, and the relationship between traditional assets and crypto assets can change significantly in a short period of time. Some of the main factors affecting the correlation between the two assets could be the increase in widespread information of the Covid-19 case and the potential for the pandemic to cause panic in the financial markets. This is reflected in the synchronization of the dynamic correlation movements of both BTC, ETH, and LTC against the S&P500 during the first 50 days of 2020. The combination of information on the increase in COVID-19 cases, actions and statements from health and government authorities, and panicked and volatile market reactions created conditions where the correlation between the S&P 500 and Bitcoin became more synchronized at some point during January 2020.

Investors tended to seek safer or more liquid assets, which led to high volatility in both assets. Global stock markets, including the S&P 500, experienced high volatility and significant declines due to concerns about the economic impact of the pandemic. This created an environment where correlations between different assets became more dynamic and volatile. During the early period of the COVID-19 crisis, investors showed an inconsistent pattern of treating Bitcoin, sometimes as a high-risk asset and sometimes as a store of value. The synchronized price movements of Bitcoin and the S&P 500 during certain periods may reflect similar reactions from investors to the dominant market news and sentiment at the time, including policy actions and pandemic-related news.

Based on Table 2, Looking at the estimation results on the individual non-diversified cryptocurrency assets analysis, it is found that LTC shows the highest VaR, CoVaR, and ΔCoVaR values compared to BTC and ETH. This means that at the same confidence level, LTC has a greater potential risk in the event of extreme market conditions. Furthermore, if ΔCoVaR is positive, it means that the risk of loss of the asset under adverse market conditions is greater than the risk of loss under normal market conditions. Conversely, the more negative ΔCoVaR is, the greater the negative difference between CoVaR and VaR. This means that under adverse market conditions, the additional expected loss of the asset is very little different from normal conditions. BTC has the largest negative ΔCoVaR, indicating a good degree of relative stability under adverse market conditions. This indicates that BTC has protective mechanisms or characteristics that make it more resilient or can be considered a "safe haven" against declines in value under extreme market conditions, in the short term. This finding is in line with Barbu et al. (2022) who stated that BTC and ETH exhibited short-term "safe haven" properties in the stock and bond markets during the COVID-19 pandemic. Also, Thi et al. (2024) found that BTC was a strong safe-haven asset for the stock markets of several European countries.

The findings in this study can also be approached with the explanation that BTC and ETH are cryptocurrency assets that have the first and second largest capitalization, so it is natural to have high liquidity which makes these two crypto assets more stable. High daily trading volumes make BTC and ETH more resilient to extreme price fluctuations compared to crypto assets with small market capitalizations. Crypto assets that are widely used in various applications and by various parties tend to be more stable. ETH is used for various decentralized finance (DeFi) applications and non-fungible tokens (NFTs), providing a strong fundamental basis and consistent demand. ETH is not only used as a currency but also as a platform for smart contracts, providing diversification in functionality and value.

Crypto assets with strong technology and high security tend to be more trusted and stable. The Bitcoin blockchain has historically demonstrated security and reliability and is supported by a community of developers who are active in maintaining and improving the network. In Portfolio A, Table 2, it is known that in general the VaR, CoVaR, ΔCoVaR values of ETH and LTC formed into a portfolio with a weight of 0.5 each, have decreased risk both in normal conditions and market distress compared to before diversification. This condition becomes better when diversified using all three cryptocurrency assets in Portfolio B. In Portfolio B, it is known that the lowest VaR, CoVaR, ΔCoVaR is BTC. This supports the results of the previous estimation of VaR, CoVaR, ΔCoVaR of individual crypto assets that BTC tends to be stable both in normal conditions and in response to market distress. In fact, when diversified into Portfolio B, the lower the VaR, CoVaR, ΔCoVaR value of BTC, which indicates that investors should diversify by creating a portfolio of cryptocurrency assets in order to reduce risk. Not only BTC, but also ETH and LTC, if included in the portfolio, show increased stability against vulnerability to losses during market distress and under normal conditions. This result supports Feng et al. (2018) and Bhuiyan et al. (2023) who found that cryptocurrency assets can be a good diversification tool especially in the short term in times of crisis, especially BTC which can be used as an effective diversification tool during the pandemic and the Russia-Ukraine war Kayral et al. (2023).

CONCUSIONS AND SUGGESTIONS

Based on the VaR estimation results, it is known that investing in cryptocurrency assets is indeed high risk considering that under normal conditions the potential loss can exceed 90% both on individual assets and portfolios. However, this also supports the concept of high-risk high return considering that when diversification is carried out, the potential loss becomes relatively lower, especially in cryptocurrency assets with large market capitalization. Conversely, cryptocurrency assets with small capitalization tend to have a high potential risk of loss even after diversification, the tendency to decrease the estimated loss is not too large. So, if you want to invest in crypto assets, you can choose in the order of the strongest market capitalization, the most liquid and high daily trading volume, the strongest technology, and security so that in the short term it will tend to be more stable, especially in conditions of global economic uncertainty. Also, it is more advisable to diversify the risk for investments with a very high risk of loss especially in cryptocurrency assets.

The limitation of the research is in the period used considering that the research focuses more on the COVID-19 crisis period which has different characteristics from the previous financial crisis. In the future, research can be carried out by dividing a longer period or using other economic uncertainty issues, such as the Covid-19 pandemic which has become a global pandemic, uncertain economic conditions due to Russian-Ukrainian war sanctions or geopolitical issues, technological uncertainty, and innovation in terms of crypto cyber security, and so on.

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