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Research Article

Analysis of the Dynamic Conditional Correlation among Financial Assets and the Value at Risk of the Portfolio, Featuring Gold USD and Cryptocurrency

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ARTICLE INFO	ABSTRACT
Received: 30 Oct 2024 Revised: 25 Dec 2024 Accepted: 01 Jan 2025	This paper examines the risk-return attributes, interrelations, and diversification capabilities of Gold and prominent cryptocurrencies—Bitcoin, Ethereum, and XRP—utilizing sophisticated econometric models, such as Dynamic Conditional Correlation (DCC-GARCH) and Value at Risk (VaR) techniques. The research indicates that gold demonstrates low volatility and functions as a reliable hedge against the high-risk, high-reward characteristics of cryptocurrencies, especially Ethereum. The weak correlations across cryptocurrencies indicate little co-movement, emphasizing their distinct risk profiles and diversification potential within the digital asset market. The results underscore the significance of adaptive risk management systems, since correlations and volatilities fluctuate under severe market situations. The findings provide essential insights for investors and regulators, providing direction for the creation of resilient portfolios that harmonize stability and growth across both conventional and digital assets. **Keywords:** Gold, Cryptocurrencies, Bitcoin, Ethereum, XRP, Dynamic Conditional Correlation (DCC-GARCH), Value at Risk (VaR), Diversification, Portfolio Management, Risk-Return Profile **JEL Classification:** C32, C58, G11, G15, G32

Introduction

In the current swiftly changing and linked financial systems, risk management has become more vital. Value at Risk (VaR) and Expected Shortfall (ES) are among the most often used instruments for evaluating risk, providing critical insights into possible portfolio losses. Value at Risk (VaR) quantifies the maximum anticipated loss over a designated time frame at a specified confidence level, serving as a standard for worst-case scenarios. In contrast, Expected Shortfall (ES) enhances this assessment by measuring the average loss in the tail beyond the VaR threshold, thereby presenting a more thorough perspective on extreme risks (Jorion, 2007). These indicators are widely acknowledged for their usefulness in risk assessment and their significance in regulatory frameworks like Basel III, highlighting their relevance for financial institutions (Bank for International Settlements, 2016). Dynamic Conditional Correlation (DCC) models provide a framework for comprehending the time-varying correlations among assets, therefore complementing static risk measurements. The DCC-GARCH model, proposed by Engle (2002), integrates univariate GARCH models with a dynamic correlation framework to elucidate the temporal evolution of correlations. This is especially significant in portfolios because asset interrelations are affected by market dynamics, economic occurrences, and investor conduct. DCC models provide a detailed comprehension of risk transmission and spillover effects in diversified portfolios by calculating conditional volatilities and correlations. This research analyzes a portfolio consisting of four unique financial assets: gold, Bitcoin, Ethereum, and XRP. Gold, a historically important safeguard against inflation and economic instability, is a crucial diversification instrument for conventional portfolios (Baur & Lucey, 2010). Bitcoin, sometimes referred to as "digital gold," has developed into a speculative asset marked by significant volatility and the possibility of substantial returns (Baur et al., 2018). Ethereum, the preeminent blockchain platform for decentralized apps and smart contracts, has a dual function as a cryptocurrency and a technical framework inside the decentralized finance (DeFi) ecosystem. XRP, engineered to enable rapid and economical cross-border transactions, provides a unique combination of liquidity and technical functionality. These assets include a combination of conventional and digital financial instruments, enabling the examination of their distinct risk profiles, interrelations, and diversification capabilities.

This article employs VaR, ES, and DCC-GARCH approaches to examine the risk-return dynamics of the portfolio. Value at Risk (VaR) and Expected Shortfall (ES) provide insights into prospective losses and severe risks. At the same time, the Dynamic Conditional Correlation (DCC) model elucidates the time-varying correlations across assets, emphasizing their interdependence. By amalgamating various methodologies, the study offers an extensive framework for comprehending portfolio risk attributes, including conventional and digital assets. The results are anticipated to enhance the existing literature on risk management within contemporary financial markets and provide pragmatic insights for investors and regulators seeking to maneuver through the intricacies of highly volatile and swiftly changing asset classes.

Literature Review

The correlation between systemic risk and asset classes, particularly during market stress times like the COVID-19 epidemic, has increasingly garnered attention in financial research. Abuzayed et al. (2021) investigated the influence of COVID-19 on global and individual stock markets by the use of bivariate Dynamic Conditional Correlation (DCC) and GARCH models, emphasizing systemic tail dependence risk. The use of CoVaR and ΔCoVaR revealed heightened systemic risk contagion across global and individual stock markets as the epidemic escalated. Significantly, established markets in Europe and North America demonstrated more robust risk transmission with the global market than Asian ones. These results underscore the interconnectedness of global markets and the increased downside risk during crises, highlighting the need for comprehensive risk management systems. Jongadsayakul (2021) examined the Stock Exchange of Thailand (SET50) to assess Value at Risk (VaR) by non-parametric historical simulation, parametric GARCH models, and semi-parametric volatility-weighted historical simulation. The results indicated that asymmetric GARCH models, including TARCH and EGARCH, provide superior VaR forecasts at a 95% confidence level relative to other techniques. Moreover, it was noted that SET50 Index Futures investments had greater inherent risk compared to stock investments, attributable to their elevated volatility, highlighting the need for meticulous risk evaluation in futures trading. Akhtaruzzaman et al. (2022) used the CoVaR model to evaluate systemic risk contagion across cryptocurrencies throughout the COVID-19 pandemic. Their investigation presented the Systemic Contagion Index (SCI), which reached its zenith during the epidemic, indicating increased interconnection across cryptocurrencies, especially Bitcoin. The results indicate that while cryptocurrencies have systemic flaws, they provide essential insights for investors in mitigating portfolio risks during crises. Pajooyan et al. (2023) assessed systemic risk between cryptocurrencies and fiat currencies via CoVaR and Marginal Expected Shortfall (MES). Their findings indicated that cryptocurrencies, such as Bitcoin, Ethereum, and Ripple, demonstrated reduced systemic risk indices in comparison to fiat currencies, implying a relative robustness of virtual assets during systemic crises. The relationship between stock markets and commodities has been a notable focus of research. Liu et al. (2022) investigated the correlations and volatility spillovers between the S&P 500 Index and many commodities, including as gold, oil, and agricultural items, before to and during the COVID-19 pandemic. Their results indicated that gold became an essential asset for portfolio diversification, especially during the pandemic, because to its heightened association with the S&P 500. Furthermore, bidirectional return and volatility spillovers were detected between stock and commodity markets, highlighting the need of constantly modifying portfolio hedging ratios in response to fluctuating market circumstances.

A multitude of research has concentrated on methodological enhancements in the measurement of Value at Risk (VaR) and Expected Shortfall (ES). Addona and Khanom (2022) presented a semiparametric Value at Risk (VaR) and Expected Shortfall (ES) estimator that distinguishes variance estimates from distributional assumptions, therefore mitigating model misspecification bias. Their examination of meme stock returns with increased volatility revealed the enhanced efficacy of their suggested strategy, exhibiting fewer breaches of regulatory standards. Likitratcharoen et al. (2023) assessed Value at Risk (VaR) assessment methodologies for the Bitcoin market, namely Historical Simulation VaR, Delta Normal VaR, and Monte Carlo Simulation VaR. Their results demonstrated that Historical Simulation VaR was the most dependable technique under market stress, but Delta Normal and Monte Carlo VaR models sometimes exaggerated hazards at lower confidence levels. Finally, research examining the wider ramifications of systemic risks and asset interdependencies continues to provide significant insights. Systemic risk contagion routes have been shown to broaden considerably during crises such as the COVID-19 pandemic, especially inside cryptocurrency and global equities markets (Abuzayed et al., 2021; Akhtaruzzaman et al., 2022). The expanding literature highlights the function of gold and cryptocurrencies as hedging tools during financial instability, providing investors with avenues for diversification and risk reduction (Liu et al., 2022; Pajooyan et al., 2023).

Research Methodology

The daily pricing data for Bitcoin was collected from CoinMarketCap (www.coinmarketcap.com), while the Gold USD data was taken from the World Gold Council (www.gold.org). The information covers the period from January 1, 2020, to December 31, 2023, and includes a total of 1,043 trade days.

Daily **logarithmic returns** were calculated for both assets using the formula below:

$$r_t = In\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

r_t = Daily log return of Asset at day t

P_t = Closing price of Asset at day t

P_{t-1}= Closing price of Asset at day $t-1$

Unit Root Test

In order to avoid misleading regression results, stationary data must be available. Establishing a relationship or ma king a prediction becomes more difficult if the series is non-stationary and its distribution changes in each period. If the series maintains a constant mean, variance, and covariance throughout time, we say that the data structure is st able; this is known as stationarity.
The null hypothesis states that the data are non-stationary, and the augmented Dickey-Fuller (ADF) test was used to evaluate the unit root cause (Dickey and Fuller 1981).

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \quad (2)$$

In the mentioned above equation (2), 'y_t' represents the data at time t, 'n' is the optimal number of delays, '$\propto_0$ ' is th e constant, and 'e_t' is the error term.

Value at Risk

Value at Risk (VaR) is a prevalent risk management instrument that quantifies the probable maximum loss in the va lue of a portfolio or asset over a designated time frame at a certain confidence level.

The formula for parametric VaR is given by:

$$VaR_\alpha = Z_\alpha \times \sigma \times \sqrt{h} \quad (3)$$

In equation 3, Zα represents the Critical value from the standard normal distribution corresponding to the confidence level α, σ Standard deviation (volatility) of asset returns and h is the Time horizon (e.g., daily, weekly). This research calculates the Value at Risk (VaR) for individual assets (Gold, Bitcoin, Ethereum, and XRP) and the whole portfolio at a 95% confidence level, offering insights into possible losses under typical market circumstances.

Dynamic Conditional Correlation GARCH

The DCC-GARCH model, proposed by Engle (2002), extends the multivariate GARCH model by allowing the correlation matrix to fluctuate over time. It integrates distinct univariate GARCH processes for each asset with a dynamic framework for conditional correlations, making it appropriate for modeling volatility clustering and time-varying correlations.

The DCC-GARCH (1,1) model consists of two steps:

1. Univariate GARCH (1,1) for each asset:

$$h_{i,t} = \omega_i + \alpha_i(\epsilon_{i,t-1}^2) + \beta_i(h_{i,t-1}) \quad (4)$$

As per equation 4, $h_{i,t}$ is the Conditional variance of asset i at time t, ω_i Constant term, α_i Coefficient for past squared residuals $(\epsilon_{i,t-1}^2)$, and β_i Coefficient for past variances $(h_{i,t-1})$.

2. Dynamic Conditional Correlation: The correlation matrix $\boldsymbol{R_t}$ is decomposed as:

$$\boldsymbol{R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}} \quad (5)$$

In the above equation 5, $\boldsymbol{Q_t}$ Time-varying covariance matrix where $\boldsymbol{Q_t} = (1 - \alpha - \beta)\overline{\boldsymbol{Q_t}} + \alpha(\epsilon_{t-1}\epsilon_{t-1}') + \beta(Q_{t-1})$, $\overline{\boldsymbol{Q_t}}$ is the Unconditional covariance matrix of standardized residuals. α *and* β is the DCC parameters that control the influence of past shocks and past correlations, respectively.

The DCC-GARCH (1,1) model is used in this work to predict the ever-changing correlations among Gold, Bitcoin, Ethereum, and XRP. To better understand risk spillovers and diversification potential, the findings shed light on how correlations change over time, especially during times of market stress.

Data Analysis and Interpretation

The 2020–2024 time-series plots of Gold, Bitcoin, Ethereum, and XRP values in Figure 1 show how conventional and digital assets differ. Gold is a safe-haven asset amid economic instability, and its prices are stable and rising. Gold prices, especially in 2024, rise with macroeconomic threats such as inflation and geopolitical tensions, appealing to risk-averse investors (Bouri et al., 2021). Bitcoin, on the other hand, rose sharply during the 2020–2021 bull market, hitting around $60,000, then fell significantly in 2022.

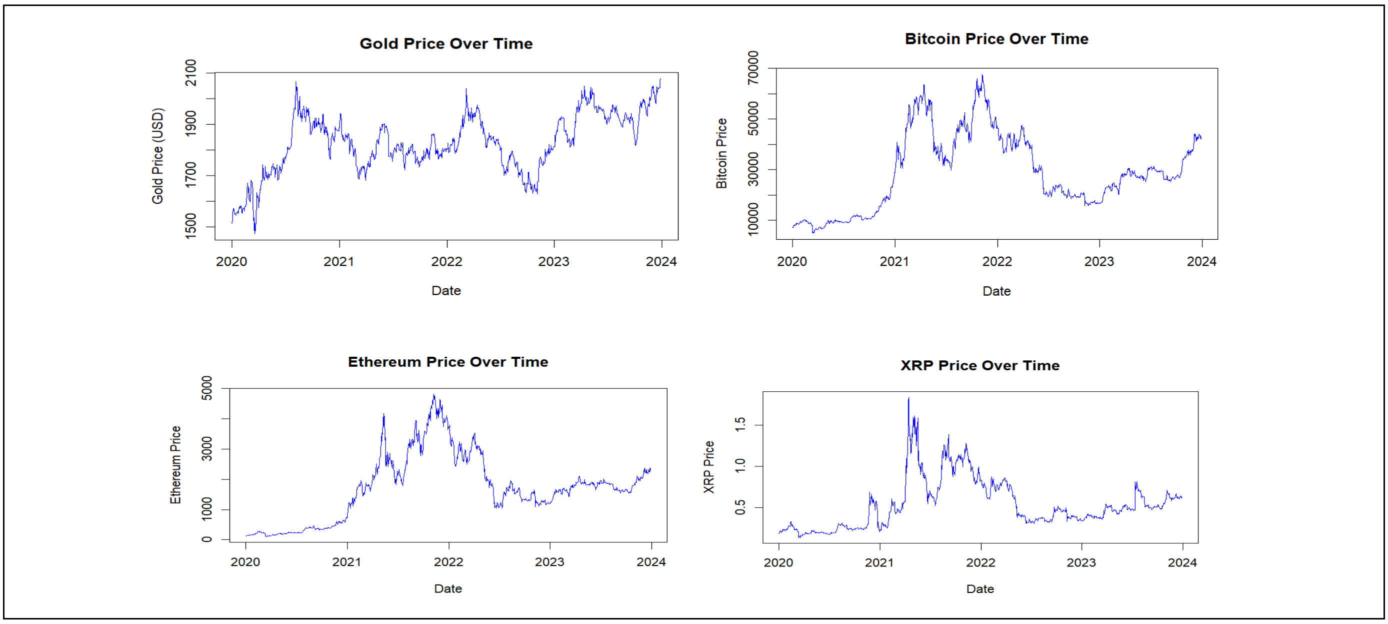

Figure 1: Assets Price Over Time

Bitcoin's price is affected by market sentiment, institutional acceptance, and legislative changes as a speculative asset and potential store of value. Its 2023 partial recovery shows durability and continued appeal as an alternative asset (Bouri et al., 2021). Ethereum, like Bitcoin, peaked at $5,000 during the 2021 boom because to its position in DeFi and NFT ecosystems. However, its 2022 rapid drop shows its fragility to speculative trading and market circumstances. Ethereum stabilizes by 2023, indicating growing trust in its blockchain technology (Ardia et al., 2019). Speculative trading and regulatory events like the SEC lawsuit cause XRP to soar even more in 2021. XRP fell sharply from $1.5 to $0.5, demonstrating its vulnerability to external causes and minimal usefulness relative to Bitcoin and Ethereum (Bouri et al., 2021). The comparison research shows that conservative investors seeking capital preservation prefer gold's low volatility and stability. Bitcoin and Ethereum have tremendous growth potential but are riskier owing to their speculative nature. XRP's wild price swings show how regulatory and market sentiment affect smaller-cap cryptocurrencies. These results emphasize the significance of portfolio diversification, where gold stabilizes and cryptocurrencies give better returns. To further understand these assets' behavior amid economic turmoil, future studies might use cointegration analysis and vector autoregression (VAR) (Jorion, 2007).

Descriptive Statistics

Gold, Bitcoin, Ethereum, and XRP descriptive statistics summarize their pricing features and fluctuation across time in Table 1. These measurements contrast gold's size, volatility, and distribution with cryptocurrencies.

Table 1 Descriptive Statistics of Assets

	Gold USD	**Bitcoin**	**Ethereum**	**XRP**
Nobs	1043.00	1043.00	1043.00	1043.00
NAs	0.000000	0.000000	0.000000	0.000000
Minimum	1474.250	4970.790	110.6100	0.139600
Maximum	2078.40	67566.830	4812.09	1.839200
1.Quartile	1756.80	17004.560	734.6600	0.321750
3.Quartile	1920.7250	40002.1650	2295.195	0.671750
Mean	1828.044008	28884.084190	1715.79043	0.537847
Median	1827.300000	27362.440000	1672.000000	0.471200
Sum	1906649.900000	30126099.810000	1789569.390000	560.974100
SE Mean	3.538171	467.839197	34.337895	0.009357
LCL Mean	1821.101256	27966.069888	1648.411100	0.519487
UCL Mean	1834.986759	29802.098492	1783.169706	0.556207
Variance	13056.953076	228285075.771612	1229791.977256	0.091311
Std.dev	114.267025	15109.105724	1108.959863	0.302178
Skewness	-0.384183	0.405109	0.477627	1.224229

Gold has a mean price of $1,828.04 and a standard deviation of $114.27, showing lower volatility than cryptocurrencies. Gold's restricted price range of $1,474.25 to $2,078.40 reinforces its stability as a store of wealth. Price clustering at higher values is shown by the slightly left-skewed distribution of -0.384. Gold's stability and safe-haven appeal are shown by its 95% confidence interval for the mean ($1,821.10 to $1,834.99$) (Bouri et al., 2021). Bitcoin has considerable price volatility, with a mean of $28,884.08 and a standard deviation of $15,109.11, suggesting severe changes. Bitcoin's dramatic price swings due to speculative trading and macroeconomic reasons are seen by its $4,970.79 low and $67,566.83 maximum. The minor right-skewness of 0.405 suggests occasional dramatic price increases. Bitcoin's huge variance (228,285,075.77) emphasizes its volatility. However, its median price of $27,362.44 indicates that its central tendency stays aligned with its mean, indicating its financial asset maturity (Ardia et al., 2019). Ethereum has comparable volatility as Bitcoin, with a mean price of $1,715.79 and a standard deviation of $1,108.96. Due to its use in decentralized finance (DeFi) and non-fungible token (NFT) applications, its price ranges from $110.61 to $4,812.09. Sharp rising price changes are indicated by the moderate right-skewness of 0.478. Ethereum is popular for speculative and utility investments because to its relative stability within its dynamic range ($1,648.41 to $1,783.17$). XRP has the lowest price scale among cryptocurrencies, with a mean of $0.54 and a standard deviation of $0.30, suggesting high volatility. Its $0.14 to $1.83 price range shows its vulnerability to regulatory measures. The strong positive skewness of 1.224 implies that severe price spikes occur more often than downward swings. This fits XRP's history of speculative trading and legal and regulatory sensitivity (Bouri et al., 2021).

Gold has the lowest variability and skewness, making it a safe asset for risk-averse investors. Bitcoin and Ethereum are ideal for high-risk, high-reward investing methods because to their volatility and broader price fluctuations. XRP is vulnerable to market sentiment and external shocks because to its significant positive skewness. Gold offers stability whereas cryptocurrencies provide speculative chances, as seen by their huge volatility and standard deviation variances.

Table 2: ADF Test of Assets Returns

	Gold USD	Bitcoin	Ethereum	XRP
T Statistics	-10.48	-9.412	-9.2182	-9.5034
P-Value	0.01	0.01	0.01	0.01

The Augmented Dickey-Fuller (ADF) Test as in Table 2 shows that Gold, Bitcoin, Ethereum, and XRP are stationary with 95% confidence. All assets reject the null hypothesis of a unit root (non-stationarity) due to significantly negative T-statistics (e.g., -10.48 for Gold and -9.5034 for XRP) and P-values of 0.01, which are below the significance level. Stationarity ensures that statistical features like mean and variance of return series stay constant across time, which is necessary for time-series models (Jorion, 2007). Gold returns have substantial stationarity (T-Statistic = -10.48), confirming its stability and mean-reverting nature. This supports gold's status as a safe-haven asset amid economic instability and its low long-term trend susceptibility. Despite its extreme price volatility, Bitcoin has stationary returns (T-Statistic = -9.412), indicating its financial maturity. Although market sentiment and macroeconomic variables affect Bitcoin's price, this shows that its returns follow consistent statistical features (Bouri et al., 2021). Ethereum returns are stagnant (T-Statistic = -9.2182), showing its rising use in DeFi and NFT ecosystems. Ethereum's stable behavior shows its statistical modeling potential despite its utility-driven price fluctuations (Ardia et al., 2019). Finally, XRP has stagnant returns (T-Statistic = -9.5034), notwithstanding its vulnerability to regulatory shocks and speculative trading.

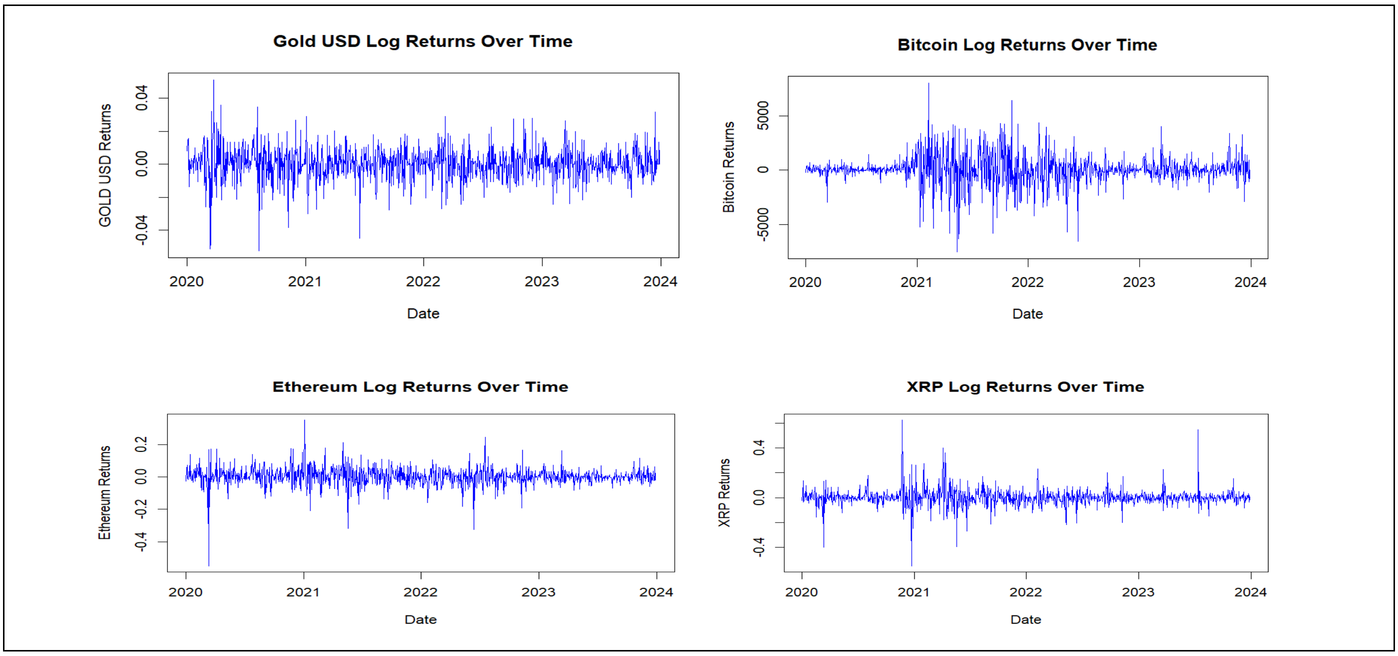

Figure 2: Log Returns of Assets over Time

The log return graphs for Gold, Bitcoin, Ethereum, and XRP illustrate different levels of degrees of volatility as per Figure 2. Gold exhibits consistent returns with little volatility, underscoring its function as a low-risk safe-haven asset. Conversely, Bitcoin and Ethereum have considerable return fluctuations, especially during the 2021 bull market, highlighting their speculative characteristics and responsiveness to market mood. XRP has significant volatility influenced by external factors like as regulatory measures. These findings highlight the high-risk, high-return potential of cryptocurrencies in contrast to gold's stability, underlining the need for diversification in portfolio management (Baur & Dimpfl, 2018; Urquhart, 2016).

The Parametric Value at Risk of Individual Assets and Portfolio at 95% Confidence Level

The Parametric Value at Risk (VaR) findings shown in Table 3 underscore the unique risk profiles of Gold, Bitcoin, Ethereum, and XRP with a 95% confidence level. Gold exhibits the lowest Value at Risk (VaR) at -1.58%, indicating its stability as a safe-haven asset with little vulnerability to significant price fluctuations. This corresponds with its historical function as a repository of value amid market volatility (Baur & McDermott, 2010). Conversely, Bitcoin exhibits markedly elevated risk, shown by a VaR of -2,198.23, highlighting its pronounced volatility influenced by speculative trading, adoption patterns, and macroeconomic variables (Cheah & Fry, 2015).

Table 3: Result of Parametric VaR

Type of Assets	Gold USD	Bitcoin	Ethereum	XRP	Portfolio
VaR(α= 0.05)	-0.01578478	-2198.23421580	-0.08902947	-0.11094037	-1043.122

The Value at Risk (VaR) of Ethereum, at -8.90%, signifies its high-risk, high-reward characteristics, shaped by its involvement in decentralized finance (DeFi) and the growth of non-fungible token (NFT) markets. The significant potential losses underscore the speculative tendencies often linked to utility-driven cryptocurrencies (Urquhart, 2016). XRP's VaR of -11.09% signifies the most risk among the examined assets, influenced by its susceptibility to regulatory changes, including legal disputes, and speculative price fluctuations (Corbet et al., 2018). These results highlight the divergent risk-return characteristics of conventional assets such as gold and cryptocurrency, the latter demonstrating significant downside risk. In portfolio management, the inclusion of gold ensures stability, but cryptocurrencies like Bitcoin and Ethereum provide growth opportunities, although with elevated risks. The findings underscore the significance of risk assessment instruments such as VaR in formulating effective strategies for controlling financial exposure across various asset classes.

The Portfolio Value at Risk (VaR) value, computed at the 95% confidence level, signifies a possible maximum loss of -1,043.12 units (e.g., dollars, euros) for the portfolio within a single day. This composite risk metric considers the collective variability and interrelations among the assets within the portfolio. The portfolio VaR being less than the aggregate of individual asset VaRs illustrates the diversification effect, whereby risk diminishes by maintaining a combination of assets with differing volatility and return characteristics (Markowitz, 1952).

The incorporation of gold in the portfolio likely mitigates risk due to its low individual Value at Risk (VaR) and consistent return attributes, serving as a buffer against the heightened volatility of cryptocurrencies such as Bitcoin and Ethereum. The substantial risk posed by volatile assets like Bitcoin and XRP underscores the need for meticulous allocation to optimize the portfolio's risk-return equilibrium. These results emphasize the importance of risk management methodologies, such as Value at Risk (VaR), in developing robust portfolios capable of enduring unfavorable market fluctuations (Jorion, 2007; Alexander, 2008).

Expected Shortfall, both parametric for individual assets and historical for the portfolio

Essential insights into the tail risk associated with catastrophic market situations are provided in Table 4 by the Expected Shortfall (ES) outcomes, which are parametric for individual assets and historical for the portfolio. Gold has the lowest parametric ES (0.0205), underscoring its stability and durability during financial crises, in alignment with its function as a safe-haven asset (Ciner et al., 2013). Conversely, Bitcoin has the biggest expected shortfall (2832.17), indicating its vulnerability to significant losses due to speculative trading, elevated volatility, and macroeconomic influences.

Table 4: Result of Expected Shortfall

Type of Assets	Gold USD	Bitcoin	Ethereum	XRP	Portfolio
VaR (α= 0.05)	0.02047906	2832.16793484	0.11784904	0.14166340	-1744.889

Ethereum's ES (0.1178) signifies considerable tail risk, highlighting its susceptibility to market volatility, especially due to its dependence on utility-driven factors like decentralized finance (DeFi) and non-fungible tokens (NFTs) (Liu & Tsyvinski, 2021). XRP has the greatest ES among cryptocurrencies (0.1417), demonstrating its susceptibility to regulatory difficulties and speculative market fluctuations (Dyhrberg, 2016).

The portfolio's historical expected shortfall (ES) of -1744.89 demonstrates the average loss in extreme circumstances when all assets are aggregated. The reduced ES value relative to the aggregate of each asset ES underscores the diversification effect, whereby gold's stability mitigates some extreme risks associated with cryptocurrencies. Nonetheless, cryptocurrencies, especially Bitcoin and XRP, continue to be substantial contributors to the portfolio's tail risk. These results highlight the need for effective portfolio management methods, whereby assets with divergent risk-return profiles are judiciously integrated to optimize returns and minimize extreme risks.

DCC GARCH

Table 5: LOG Return Matrix

Gold USD Returns	Bitcoin Returns	Ethereum Returns	XRP Returns
0.008120103	-214.70	-0.026259206	-0.02469261
0.014077642	359.41	0.051697420	0.02883555
0.015600041	424.34	0.072786813	0.13514508
-0.003342941	394.47	-0.005280724	-0.03491397
0.002611633	-83.83	-0.016011578	-0.02317436
-0.013578202	-200.79	-0.016272126	-0.01981220

The daily return data for Gold, Bitcoin, Ethereum, and XRP in Table 5 shows their different volatility and return dynamics. Gold, a safe-haven asset amid market instability, has stable returns of -1.36% to 1.56%. Gold attracts risk-averse investors seeking stability due to its low volatility. Bitcoin, on the other hand, fluctuates between -214.70% and 424.34%, making it vulnerable to speculative trading, macroeconomic variables, and investor emotion. Bitcoin's large fluctuations demonstrate its high-risk, high-reward characteristics. Ethereum is less volatile than Bitcoin, returning -2.63% to 7.28%. Ethereum's utility-driven pricing behavior, especially in DeFi and NFT markets, is reflected in these returns. High positive returns like 7.28% indicate speculative interest or technical improvements. XRP's volatility is caused by external shocks, including regulatory changes, with returns ranging from -3.49% to 13.51%. XRP's greatest return (13.51%) suggests quick price increases due to speculation. This shows how conventional and digital assets have different risk-return characteristics. Gold is stable, unlike Bitcoin and XRP, which are volatile. Diversification in portfolio management is crucial, with gold stabilizing and cryptocurrencies offering better returns. Diversification may balance risk and reward for different investor risk tolerances.

The DCC-GARCH (1,1) model findings in Table 6 provide significant insights into the dynamic conditional correlations and volatility dynamics among the four examined assets: Gold, Bitcoin, Ethereum, and XRP. The model presumes a multivariate normal distribution (mvnorm) and estimates 24 parameters from 1,042 data, resulting in a log-likelihood of -4874.287 and an average log-likelihood of -4.68.

Table 6: DCC GARCH Fit Model

Parameter	Value
Distribution	Multivariate Normal (mvnorm)
Model	DCC (1,1)
No. Parameters	24
No. Series	4
No. Observations	1042
Log-Likelihood	- 4874.287
Avg. Log-Likelihood	-4.68
Akaike IC	9.4017
Bayesian IC	9.5157
Shibata IC	9.4007
Hannan-Quinn IC	9.4449

The Akaike Information Criterion (AIC = 9.40) and Bayesian Information Criterion (BIC = 9.51) indicate a satisfactory model fit. The comparatively low Shibata (9.40) and Hannan-Quinn (9.44) criteria substantiate the model's effectiveness in encapsulating the combined volatility dynamics of the assets.

Table 7: DCC Optimal Parameters

	Estimate	Std. Error	t value	P value
Gold USD mu	0.000000	0.038665	0.00000	1.000000
Gold USD omega	0.061551	0.036786	1.67322	0.094284
Gold USD alpha1	0.104310	0.073390	1.42130	0.155229
Gold USD beta1	0.881136	0.059831	14.72708	0.000000
Bitcoin mu	0.000000	0.037050	0.00000	1.000000
Bitcoin omega	0.001569	0.003507	0.44742	0.654571
Bitcoin alpha1	0.040577	0.013134	3.08955	0.002005
Bitcoin beta1	0.956050	0.013747	69.54396	0.000000
Ethereum mu	0.000000	0.218843	0.00000	1.000000
Ethereum omega	0.000900	0.004847	0.18575	0.852640
Ethereum alpha1	0.062011	0.145812	0.42528	0.670632
Ethereum beta1	0.935789	0.213124	4.39082	0.000011
XRP mu	0.000000	0.015032	0.00000	1.000000
XRP omega	0.001659	0.001186	1.39911	0.161781
XRP alpha1	0.074349	0.031242	2.37980	0.017322
XRP beta1	0.922387	0.024669	37.39053	0.000000
DCC alpha1	0.041651	0.006756	6.16493	0.000000
DCC beta1	0.950222	0.012226	77.72272	0.000000

As observed in Table 7, the beta coefficients for all four assets are extremely significant and range from 0.881 to 0.956, demonstrating robust volatility persistence. This indicates that historical volatility significantly affects future volatility, a prevalent trait in financial markets (Engle, 2002). The alpha coefficients, indicative of the influence of historical shocks on present volatility, are statistically significant for Bitcoin (0.0406, $p = 0.002$) and XRP (0.0743, $p = 0.017$), suggesting that these assets exhibit volatility clustering, characterized by high volatility periods being succeeded by additional high volatility. The computed DCC parameters (dcca1 = 0.0417, dccb1 = 0.9502) are statistically significant ($p < 0.0001$), indicating that asset correlations change dynamically over time. The elevated dccb1 value (~0.95) indicates that conditional correlations are enduring, implying that once asset correlations rise (or fall), they often sustain those values for prolonged durations. This has substantial consequences for portfolio diversification, since asset correlations may vary markedly during periods of financial crisis (Cappiello et al., 2006).

The data indicate that volatility clustering and persistence are prevalent across all assets, underscoring the need of risk management in the construction of cryptocurrency-dominant portfolios. The robust conditional connections suggest that in market downturns, assets may co-move, diminishing diversification advantages. The fluctuating nature of correlations emphasizes the need for proactive portfolio modifications instead of fixed allocation techniques. Subsequent studies may enhance this analysis by integrating asymmetric DCC models (ADCC-GARCH) to investigate if correlations escalate more during downturns than in phases of market expansion (Cappiello et al., 2006).

Table 8: DCC Matrix

	Gold USD	**Bitcoin**	**Ethereum**	**XRP**
Gold USD	1.0000000000	0.0001969314	-0.36236088	0.20361830
Bitcoin	0.0001969314	1.0000000000	0.06091857	0.04411235
Ethereum	-0.3623608846	0.0609185703	1.00000000	-0.07147596
XRP	0.2036183043	0.0441123484	-0.07147596	1.00000000

The correlation matrix for Gold, Bitcoin, Ethereum, and XRP in Table 8 elucidates significant insights into the interrelationships between conventional and digital assets. The slight negative correlation of gold with Ethereum (-0.3624) implies that both assets often fluctuate in opposing directions, suggesting that gold may act as a hedge against Ethereum's volatility. In contrast, gold's negligible correlation with Bitcoin (0.0002) indicates that Bitcoin functions independently of conventional safe-haven assets, consistent with studies demonstrating that Bitcoin's risk-return characteristics markedly vary from those of gold (Shahzad et al., 2020). The poor positive correlation between gold and XRP (0.2036) indicates a minimal link, showing that XRP has unique price behavior in comparison to gold.

Bitcoin and Ethereum have a modest positive correlation (0.0609), indicating that their price fluctuations are mostly independent, despite both being prominent digital assets. This discovery corresponds with evidence that Bitcoin operates primarily as a speculative asset, but Ethereum's value is propelled by its use in decentralized finance (DeFi) and smart contracts (Bouri et al., 2021). Likewise, the modest correlation between Bitcoin and XRP (0.0441) suggests that both cryptocurrencies do not exhibit significant co-movement, highlighting XRP's distinct market influences, such as regulatory changes and payment network integration (Charfeddine & Mauck, 2019). Moreover, Ethereum and XRP have a slight negative connection (-0.0715), indicating sporadic inverse price fluctuations, but not considerably.

From a portfolio management standpoint, our data indicate that cryptocurrencies provide no diversification advantages when aggregated, owing to their poor intercorrelation. The negative correlation between gold and Ethereum (-0.3624) underscores gold's potential function as a stabilizing asset in cryptocurrency-dominant portfolios, aiding in the reduction of total risk. The poor correlations across digital assets underscore the need for proactive risk management measures, since significant volatility in one cryptocurrency may not always result in analogous fluctuations in others (Conlon et al., 2021).

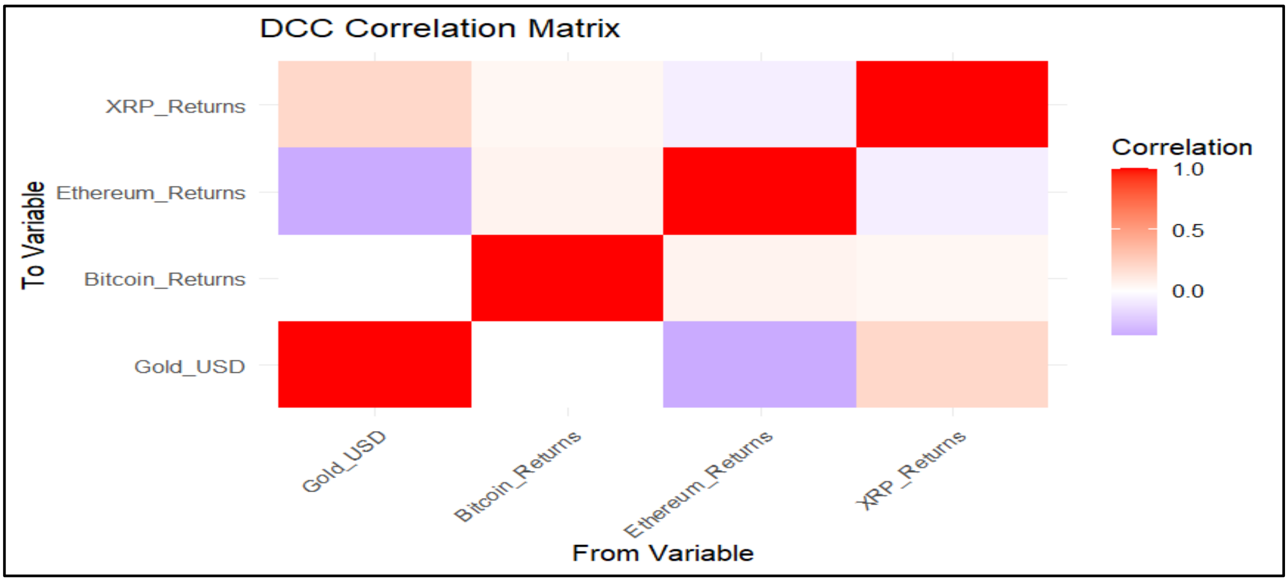

Figure 3. DCC Correlation Matrix

The DCC Correlation Matrix in Figure 3 illustrates the fluctuating relationships of Gold, Bitcoin, Ethereum, and XRP. The relationship between Gold and Ethereum is weakly negative, indicating that gold may serve as a hedge against Ethereum's volatility. The correlations between gold and Bitcoin/XRP are around zero to weakly positive, suggesting that both assets function mostly independently. Bitcoin and Ethereum have a modest positive connection, indicative of their unique market influences, but XRP has poor correlations with both Bitcoin and Ethereum, suggesting little co-movement. The results indicate that gold improves diversification in cryptocurrency-dominant portfolios, but the limited dependency across cryptocurrencies highlights their distinct risk profiles.

Conclusion

This research uses complex econometric models like DCC-GARCH and Value at Risk (VaR) to thoroughly examine t he risk-return characteristics and interdependencies of digital assets (such as Bitcoin, Ethereum, and XRP) and con ventional assets (gold) in terms of these assets. Based on the results, gold is a good hedge against the high-risk natu re of cryptocurrencies like Ethereum because of its low volatility. The fact that cryptocurrencies have low correlatio ns with each other and with gold highlights their diversification potential in diversified portfolios. Nevertheless, cry ptocurrency prices are unpredictable and subject to ever-changing correlations, especially when the market is unsta ble. The significance of effective risk management and dynamic allocation techniques for optimizing a portfolio is u nderscored by these qualities. Portfolios that include both conventional and digital assets allow investors to better weather market fluctuations by striking a

balance between stability and growth potential.

Future Research

This study may be expanded upon in several ways by future investigations. An asymmetric DCC-GARCH model (AD CC-GARCH) may provide light on the question of whether correlations rise excessively in down markets. The secon d point is that these assets' tail risks and systemic risk contributions may be better evaluated with the use of models like CoVaR or Extreme Value Theory (EVT). Third, time-varying interactions may be better captured by comparing t he interdependencies under various market regimes using wavelet coherence analysis or Markov-switching models. The risk-return dynamics of cryptocurrencies and their linkages with conventional assets should be further investig ated in future studies by looking at how macroeconomic factors like inflation and monetary policy affect them. In co nclusion, expanding the dataset to include more digital currencies or more conventional safe-haven assets like gover nment bonds might provide more comprehensive understanding of diversification methods for portfolios and ways t o reduce risk.

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