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ARTICLE

Volatility Persistence, Dynamic Co-Movements, and Portfolio Optimization in Digital Asset Markets: Disentangling Cross-Market Contagion from Internal Hedging Strategies

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Abstract

This study investigates the time-varying volatility dynamics, persistence, and optimal portfolio allocation architecture within the digital asset ecosystem, explicitly separating external cross-market contagion from internal digital asset hedging strategies. Utilizing real-world daily historical return data from 2020 to 2025 for a diverse basket of major (Bitcoin, Ethereum, Litecoin) and niche (Stellar, Internet Node Token, Exclusive Coin) digital assets, we employ a multivariate DCC-GARCH framework evaluated under two distinct currency configurations (Euro and US Dollar numeraires) alongside native on-chain alternative hedges. The empirical findings reveal high volatility persistence and long-memory characteristics across all assets, with volatility half-lives extending up to 22.8 days for specialized tokens, confirming that shocks to the system decay slowly. The regime-dependent dynamic conditional correlations demonstrate that cross-asset integration is highly pro-cyclical, intensifying severely during systemic market drawdowns and rapidly eroding traditional diversification benefits among core protocols. To counteract this systematic risk, the study introduces native digital hedges, demonstrating that the stablecoin Tether (USDT) offers superior downside protection and variance reduction (up to 74.15%) over traditional fiat exchange rates, while tokenized gold (PAXG) provides a robust, uncorrelated safe-haven overlay against macro-structural shocks. Significantly, out-of-sample optimization metrics confirm that the dynamic Global Minimum Variance Portfolio (GMVP) heavily outperforms static benchmarks, achieving a 66.19% risk reduction by rebalancing asset exposures daily in response to shifting conditional variances. The study suggests that the Global Minimum Variance Portfolio is not composed solely of the largest caps (BTC/ETH). Instead, significant weight must be shifted toward assets with lower unconditional variance (like STR) or distinct covariance structures (like INT) to achieve the true efficient frontier. The optimal hedge ratios (OHR) and optimal portfolio weights (OPW) demonstrates that while the crypto market is highly integrated, strategic allocation to uncorrelated assets like INT and stable performers like STR can significantly improve risk-adjusted returns. The study highlights the role of cryptocurrencies as not isolated digital assets but as systemic components with contagion effects that are increasingly significant for regulators, monetary authorities, and investors. By analyzing these cross-market dynamics during a period marked by economic volatility, including the COVID-19 pandemic and global inflationary pressures, this research provides valuable insights into the evolving relationship between cryptocurrencies and traditional financial assets. These findings provide critical insights for investors seeking to minimize portfolio variance and hedge against downside risk in the volatile cryptocurrency market. Furthermore, the allocation mechanism exposes a fundamental theoretical boundary in asset insulation, proving that portfolio optimization models will aggressively restrict high-correlation diversifiers if the underlying instrument carries unacceptable standalone baseline noise. This research provides a self-contained,

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digital-first risk mitigation toolkit for international asset allocators while offering critical insights for macroprudential watchdogs tasked with stablecoin regulation and systemic risk oversight.

Keywords: Cryptocurrency, Volatility Clustering, DCC-GARCH, Portfolio Optimization, Hedge Ratios, Bitcoin, Stellar, Internet Node Token, Cross-Market Contagion; Stablecoins; Tokenized Gold; Digital Assets.

JEL Classification: G11, C32, G15, 033

1. INTRODUCTION

Notwithstanding the rapid growth of digital assets and their growing importance in global capital markets, we have comparatively less empirical knowledge regarding the impact of the volatility spillovers of cryptocurrencies on the optimal portfolio risk-return characteristics and hedges. As demonstrated in prior papers [1,2], which leveraged GARCH-type models and DCC-GARCH models, return series of cryptocurrencies are characterized by significant volatility clustering and interdependent behaviour. However, this important finding has yet to be reconciled with real-world hedge ratio and portfolio weight optimization across diversified digital asset portfolios. Nonetheless, these studies typically centre on volatility characteristics or cross-market correlations in isolation purportedly is not failing to connect systematically with the time-varying optimal hedge ratios and portfolio weights that link them. This gap is further emphasized by the existence of dynamic intertwining and time-varying correlation. Nevertheless, the evidence on the influence of volatility clustering on optimal risk-return profiles of a portfolio of a number of digital assets is rather integrated. In particular, the literature has not addressed how volatility persistence and time-varying correlations would impact minimum variance/hedge-efficient portfolio construction in practice. It has also not highlighted how volatility clustering translates to risk management across digital assets in practice.

Nevertheless, there is too little robust econometric analysis distinguishing between true alternative assets that genuinely function as a safe haven (shock absorber) and uncorrelated diversifiers (decoupling from shocks). Although Billah et al. and Just et al. have examined gold-backed tokens and stablecoins as dynamic hedges [3,4], utility tokens such as Stellar (STR) or Internet Node Token (INT) have an unclear structural role as dynamic hedge providers. Investors have no evidence to suggest that these assets provide true downside protection or simply add high beta risk. Until this matter is solved, investors cannot derive Optimal Portfolio Weights that would remain stable in the turbulent regimes identified by Enow [5]. This allows digital portfolios to avoid unnecessary systemic ruin.

The main issue with the digital asset market is volatility clustering that can transmit throughout the entire system fairly quickly which is not limited to the digital asset sector but the entire financial ecosystem. This describes the fact that volatility clustering and contagion of correlation causes instability of risk-return profiles of a digital asset portfolio. The main research question thus is that current static portfolio mechanisms are inadequate in managing the time-varying systemic risks in cryptocurrency markets. While Bitcoin and Ethereum act as the main market drivers, they tend to be highly positively correlated during bearish times which make typical diversification useless. As a result, investors do not have a strong econometric understanding of alternative assets like Stellar (STR) and Internet Node Token (INT) and their relationship with major caps in varying market conditions. “Net volatility transmitters” characterization is attributed to Bitcoin and Ethereum [6]. This coupling during downturns makes cryptocurrencies resemble the contagion in crises with standard portfolios suffering a catastrophic drawdown. This leads to an illusion of diversification where investors think they are hedged by owning many assets when they are just leveraging their exposure to a single systemic event. Moreover, Hatemi-J contends that digital assets’ optimal hedge ratios are position-dependent and extremely time-varying [7]. As a result, the static forms of hedging models do not account for the dynamic and heteroskedastic nature of cryptocurrency returns and lead to inefficient capital allocation.

The reliance on static hedging models represents a critical methodological problem. It's a well-established fact that cryptocurrency volatility persists. However, new empirical evidence suggests that diversification just doesn't seem to work anymore. Conventional risk management schemes like OLS regression or static correlation analysis do not incorporate the time-varying nature of these relationships. The hedge ratios they propose are frequently either too costly due to over-hedging or inadequate due to under-hedging due to their assumption of constant volatility and correlation. This research aims to overcome these challenges, specifically, to isolate time-varying conditional correlations of these assets using a DCC-GARCH framework. Subsequently, this framework allows the computation of accurate, optimal hedge ratios and portfolio weights to minimize downside risk without sacrificing return. There is a major need to make use of dynamic econometric model, an application of DCC-GARCH, to accurately model these changing dependency structures and to ascertain the optimal time varying weights, so as to enable the minimization of portfolio variance under stochastic volatility.

The importance of the study stems from the fact that it employs a robust optimization framework, which takes into account both volatility clustering as well as dynamic correlation behaviour, to produce sensible hedge ratios and portfolio weights. However, such integration is under-explored in existing research. The practical importance is that the relationship volatility clustering-portfolio optimization helps investors, monetary authorities, and regulators in risk management and policy response in the increasingly interdependent markets. The analysis offers useful findings for risk managing purposes, especially in terms of evaluating and addressing tail risk and extreme events in the cryptocurrency market. This study presents credible evidence of including cryptocurrencies in a traditional portfolio, putting practical insights for investors to dynamically adjust portfolio weights for better risk-return trade-offs. The hedge ratio analysis tells you how to reduce the risk in a volatile situation, while the portfolio weight optimization specifies how much to reduce the digital and traditional assets.

By modeling the time-varying correlations of digital with traditional assets, it helps identify periods of risk and volatility which can help market participants to devise risk mitigation strategies. Furthermore, the results add other literature on financial risk management, applying sophisticated econometric techniques on cryptocurrency markets, which is an area not as thoroughly explored in the past. From the viewpoint of policy, it is necessary to understand how cryptocurrency markets affect traditional finance and monetary policy. As cryptos become a more common feature of financial markets, the results of this study that related to intermarket correlations and volatility transmission will assist regulators to make well-informed decisions regarding the regulation of digital assets. In particular, the research can assist central banks and monetary authorities in evaluating the potential systemic risks posed by cryptocurrencies as well as their impact on exchange rates, financial stability and investor behaviour.

2. EMPIRICAL REVIEW

Research utilizing GARCH and EGARCH models indicates that volatility is a characteristic present in the cryptocurrency market. In fact, GARCH models outperform most other specifications and are especially effective in modelling clustering behaviour in Bitcoin and Ethereum [8,9]. A study by Yildirim & Bekun [10] specifically found that the best estimation method for Bitcoin return volatility was the GARCH (1,1) model when compared to other estimation methods such as ARCH and EGARCH. In the same fashion, utilizing DCC-GARCH models, research revealed spillovers from the two assets conditional on time which are dynamic in nature and which shows investor can use them in long run to hedge and diversification purpose [11]. They utilized DCC-GARCH models to assess whether Bitcoin volatility was contagious to gold and major stock indices. The findings found persistent long-term volatility interdependencies and evidence that Bitcoin impacted other markets. These findings indicate that shocks to Bitcoin's market can spill over into other financial markets, including gold and major stock indices especially in period of crisis such as the COVID-19 pandemic.

Li and colleagues examined how the growth of bitcoin prices (BPG) and bitcoin volatility (BV) affect China's monetary system [12]. In this case, the focus was on inflation rates (INF), real exchange rates (RER), and money velocity (MV). Analyzing Bitcoin data for years 2013-2019 using GARCH models, they assessed whether China justifies the Bitcoin ban. The findings suggested that BPG adversely impacted INF and MV, whereas it didn't significantly affect RER. BV was also incapable of creating a statistical difference in any of the three monetary indicators. Sub-period test, different model specification tests, and including a third-party online payment as control variable for MV, confirmed our results. Utilizing the wavelet transform framework, Hưng analyzed the time-frequency nexus between bitcoin and selected developed stock markets in the Asia-Pacific region [13]. The period of study is from February 2012 to August 2019. Findings of the study reveal that there are considerable unidirectional relations from bitcoin to the selected markets. Moreover, the unidirectional relations are seen across short, medium and long-term periods in the Asia-Pacific region. In general, Bitcoin and the Asia-Pacific equity markets are weakly correlated at higher frequencies over the sample period. However, the dependence of Bitcoin on equity markets grows at lower frequencies. A wavelet-based Granger causality assessment at different time-scale justifies the outcome displaying the correlation between the variables.

Price jumps have attracted the interest of recent empirical studies. For instance, Ali et al. study price jumps in decentralized and centralized financial markets [14]. Additionally, Ali et al. also look at price jumps. They look at six biggest cryptocurrencies and forex [15]. These are EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, and USD/CAD. High-frequency data at five-minute intervals was used by the authors to first extract daily jump components using a realized volatility-based detection method. They then used multifractal detrended fluctuation analysis (MFDFA) to analyze the multifractal structure of cross-market jump interactions. All 36 cryptocurrency-forex combinations showed significant multifractality and persistence according to the results. In practical terms, one market will jump positively or negatively in the same direction as the other market that it is paired with. The analysis suggests that the relationship between digital assets and traditional currencies has become stronger and more complex during extreme price events. Afshan et al. explored the role of Fintech Advances in Financial Resilience [16]. The analysis was conducted using the Morlet Wavelet. The research observed correlations among the variables in both the immediate and distant future. Based on the weekly data, Fintech has a positive relationship with the digital currency and rate of exchange suggesting that it will likely transform the regular financial markets. On the other hand, there is a negative association between Fintech and both oil price volatility and financial risk. This implies that Fintech innovations can help stabilize these risks.

In addition, the phase relationship of digital currency and exchange rates has an impact on international trade, cross-border remittances, and stability in the economy. The relationship between digital currency and both oil price volatility and financial risk was said to be adverse. Setyawan et al. studied cryptocurrency and financial inclusion: bridging the gap in emerging countries to assess the role of cryptocurrencies as a medium of transaction in developing countries and the possible approaches these currencies could offer that would address a country's current economic issue through applicable and ethical solutions [17]. The findings reveal that cryptocurrencies provide inexpensive transaction costs, quick settlement of transactions and transparency in the transaction process. Nonetheless, there are also issues like regulation, legal hurdles and security, and lack of public knowledge about cryptocurrency.

According to Metaxas, a time series approach in the context of digital finance could show the impact of exchange rate volatility on bitcoin returns [18]. The fluctuations of the rates of exchange (USD/AUD, USD/EUR, USD/GBP, and USD/JPY) were examined in relation to Bitcoin returns over the period 2014-2019 using a time series study. According to the results of the study, exchange rate fluctuations do not affect Bitcoin returns at a 95 percent level. Nonetheless, the GBP foreign exchange rate was found to significantly affect the return on Bitcoin at 90 percent confidence. The simultaneous returns of USD/GBP and Bitcoin could be due to some common factors in recent times. A study of the Bitcoin market's response to big price movements of international stock markets was well researched by Jia et al [19]. The paper focused on whether there is a connection or not. The overreaction hypothesis was supported by utilizing high-frequency Bitcoin trading data, specifically intraday Bitcoin price reversals following substantial price movements in the stock markets. Interestingly, Bitcoin market overreaction on developed stock markets was greater and more persistent as compared to emerging stock markets. Analysis of the sub-period showed that network effects, investor sentiment, economic policy uncertainty and investor attention are some factors responsible for overreactions. The findings highlight the interdependence between the Bitcoin market and the stock markets, which could be utilized by international investors for hedging.

In 2023, the authors (Sun and others) evaluated the asymmetric connection between Bitcoin and gold stocks and market returns [20]. All key variables of interest were analyzed over the period from November 3, 2014 to October 31, 2019 using daily data denominated in Chinese currency and Chinese economic structure. The applied quantile-on-quantile and quantile regression techniques reflect the highly empirical nature of the study. The major findings reveal serious influence of Chinese stock market returns on Bitcoin while estimates from gold prices also exert notable influence on Bitcoin. Further, stock market returns suffer due to increased gold price rise. According to Zeng & Ahmed, East Asian stock and Bitcoin markets are integrated with each other [21]. The authors carried out an in-depth investigation on the dependence structure, systemic risk and volatility spillover of major East Asian stock markets and Bitcoin market. Using a vine-copula-CoVaR structure and a VAR-BEKK-GARCH methodology, as well as a Wald test, the dependencies between other pairs of markets were low except for the one between KS11 and N225, HSI and SSE, and HSI and KS11. In terms of tail risk, the strong common variation was captured more from the upper tail risk. The analysis verifies that the volatility spillovers occur immensely from the Korean market. For one thing, gains in the Chinese stock market provide diversification in the Bitcoin market. Growing spillovers within East Asia increases spillovers to Bitcoin, yet Bitcoin spillovers do not intuitively affect East Asian markets.

Senna and Souza examined the effects of short- and long-term links between cryptocurrencies and stock exchange indexes in their study [22]. The stationary series exhibit a causality that affects all but one series according to the VAR/VEC model. The VAR model displayed relationships that were short term, whereas co-integration determined the order for VEC application. Bitcoin was discovered to impact Stock Exchanges for an average of 16 periods following a shock; Litecoin and Ripple were discovered to impact them for 15 and 16 periods respectively. Gemici et al. aimed to analyze the degree to which Bubbles in the Bitcoin market affects stock markets using evidence from 10 major stock markets [23]. Findings inferred the negative impact, though quantification and significance of impact differ for various stock indices. Bitcoin and foreign exchanges in developed and emerging markets has been explored by BenSaïda [24]. The research evaluated the Bitcoin and fiat currencies relationship in the two groups of countries, the developed G7 and the emerging BRICS. The methodology used was the regular (R)-vine copula and compares it with two models the multivariate tcopula and the dynamic conditional correlation (DCC) GARCH model. The results show that both currency groups perform better than the benchmark models, indicating that the R-vine copula helps to better understand how shocks transmit. Moreover, following Bitcoin crashes, cross-market linkages between Bitcoin and fiat currency markets are found to spike. In fact, in the wake of the crashes in 2021 and 2022, there is a significant degree of connectivity which points to the less isolation of the digital currency market.

Ruhiyat & Terzaghi used the inflation as a moderation variable to study the effect of cryptocurrencies, exchange rates, and gold prices on the share prices on infobank15 index 2018-2021 [25]. The findings revealed that the prices of stock were simultaneously influenced by prices of cryptocurrency, exchange rates, and gold prices. To be specific, cryptocurrency had a favourable influence on stock prices; exchange rates had an adverse effect, while the price of gold did not have a noteworthy impact. In addition, inflation may lessen the influence of cryptocurrencies and exchange rates in stock prices, but could not lessen gold prices' influence on stock prices. Karau investigates how Bitcoin is influenced by monetary policy, showing how it has changed over time [26]. In the past, Bitcoin prices did not react immediately to US monetary policy announcements using high-frequency data. Based on the findings which indicate that the recent reactions of participants to monetary policy strategies suggest that Bitcoin has indeed been transformed into a speculative asset. Furthermore, findings declare that Bitcoin has historically enjoyed a duality which included deriving part of its value from its ability to facilitate cross-border value transfer as well as capital flight. Given these findings, we can gain insight into the determinants of Bitcoin demand and its changing status in finance.

3. METHODOLOGY

Research Design

This research desires to establish a model showing the link that exists between the dynamics of cryptocurrencies (Bitcoin, Etherum and Litecoin) and their effects on rates of exchange and stock market returns in developed countries, using G7 countries; United Kingdom, US, Canada, Germany, France, Italy and Japan, as case study. To achieve this, the researcher employs DCC GARCH, Diagonal BEKK-GARCH methods, over a time period of January 1, 2020 to December 31, 2025. This study applied multi-method econometric frameworks. The methodologies include BEKK-GARCH, and DCC-GARCH. These approaches are strategically selected to uncover volatility spillovers, time-varying correlations, short- and long-term transmission channels, and distributional asymmetries, factors crucial for understanding contagion in a modern, globalized financial landscape.

Econometric Specification and Portfolio Setup

Looking at the general asset model mathematically, let R_t be the vector of returns for N assets (cryptocurrencies, stock indices, exchange rates):

$$R = \varepsilon + \upsilon_t \tag{1}$$

Where ε is the mean vector and υ_t is the vector of shocks, contagion via common factors and idiosyncratic shocks. Following the rational expectations contagion model:

$$r_i = \gamma_i + \phi_i h_t + \omega_i \tag{2}$$

$$r_j = \gamma_j + \phi_j h_t + \omega_j \tag{3}$$

where: h_t is Common factor, for example, global risk sentiment; ω_i, ω_j has to do with Idiosyncratic shocks. In cross market correlation, the correlation between r_i and r_j is given as:

$$Cor(r_i, r_j) = \frac{\phi_i \phi_j Var(h_t)}{\sqrt{[\phi_i^2 Var(h_t) + Var(\omega_i)]}\sqrt{[\phi_j^2 Var(h_t) + Var(\omega_j)}} \tag{4}$$

The presence of contagion is detected when following a $Var(h_t)$ shock in one market, correlation increase due to a rise in the effect of the common factor or a decrease in the relative individual variance $[Var(\omega_i), Var(\omega_j)]$. The relevant econometric models are specified as in equations (5) and (6):

$$EXR = \alpha_0 + \alpha_1 BTC + \alpha_2 ETH + \alpha_3 LIT + \alpha_4 INT + \alpha_5 STR + \mu_i,\ \alpha_1 < 0, \alpha_2 < 0, \alpha_3 < 0, \alpha_4 < 0, \alpha_5 < 0 \quad (5)\ (6)$$

Where: *EXR* = Exchange Rate Returns at time *t*, *STR* = Stellar price at time *t*, *BTC* = Returns of Bitcoin at time *t*, *ETH* = Returns of Ethereum at time *t*, *LIT* = Returns of Litecoin at time *t*, *INT* = Internet Node Token (INT) price at time *t*, α_0 = Constant, $\alpha_1 - \alpha_4$ are the coefficients of the variables to be estimated, μ_i = Error term. Apriori expectations are such that α_1, α_2, $\alpha_3 < 0$ suggesting that higher cryptocurrency returns may negatively affect traditional assets during contagion episodes, while α_4 could be either positive or negative depending on the role of interest rates.

In this study, the Diagonal BEKK-GARCH model allows us to estimate how volatility from cryptocurrency returns (Bitcoin, Ethereum, Litecoin) spills over into the volatility of traditional financial assets such as stock indices and exchange rates. BEKK-GARCH is ideal for testing contagion hypotheses because it captures both the own-volatility effects (ARCH) and shock transmission across markets (GARCH) [27]. The diagonal BEKK-GARCH model is a variant of the original BEKK-GARCH model by Engle & Kroner [28]. The need for this model arose due to the over-parameterization issues in earlier multivariate GARCH models like the VEC model [29]. The BEKK model provided a simple structure that guarantees the covariance matrix is positive semi-definite [30]. The diagonal version of this method, which assumes the ARCH and GARCH terms to be diagonal matrices, simplifies the model further. This reduction in complexity also aids in estimation as it reduces the estimation burden [31]. This model is widely used in finance to find out volatility transmission [32]. It is particularly useful in considering dependences in emerging markets and in a financial crisis [33]. According to Baykut and Kula, BEKK-GARCH is ideal for testing contagion hypotheses because it captures the own-volatility effects on a given market (ARCH) and the impact of shocks on them (GARCH) [27]. It enables an asymmetric and persistent impact of volatility shocks, hence suitable for analysing the impact of volatile assets like Bitcoin and Ethereum on stable financial indicators in various countries [34]. The conditional covariance matrixF_t is given mathematically as.

$$F_t = D^{!}D + H^{!}\in_{t-1}\in_{t-1}^{!}H + A^{!}F_{t-1}A \tag{7}$$

Where F_t is conditional variance-covariance matrix D is lower triangular matrix H is matrix of ARCH effects (short-term shocks) A is matrix of GARCH effects (volatility persistence). The DCC-GARCH model was developed by Engle [35]; as a solution to the limitations of the Constant Conditional Correlation (CCC) model [36]. The CCC model's assumption of constant correlations over time does not reflect reality. The DCC model proposed a flexible way to model time-varying correlations while keeping the computations tractable. The DCC-GARCH model has been widely used for studying time-varying correlations in financial markets in the years since. During times of crisis when market co-movements are expected to deviate significantly, such models are very useful. In this study, DCC-GARCH is put to use to understand the evolution of correlations between cryptocurrencies and traditional markets as they undergo contagion and decoupling periods. Due to the high correlation between markets during crises, this model works well for contagion analysis. The variable DCC framework allows for the measurement of dynamic co-movement. This helps to check whether cryptocurrencies behave as risk transmitters or hedging instruments. The univariate GARCH (1,1) models are estimated first as provided by equation (1). Then, we model the dynamic correlation matrix with equations (2), (3) and (4).

$$f_{i,t} = \alpha_i + \varphi_i \varepsilon_{i,t-1}^2 + \delta_i f_{i,t-1} \tag{8}$$

Step 2 constructs the dynamic correlation matrix:

$$S_t = (1 - a - b)\overline{S} + a(z_{t-1}z_{t-1}^{!}) + bS_{t-1} \tag{9}$$

$$R_t = diag(S_t)^{-0.5} S_t diag(S_t)^{-0.5} \tag{10}$$

$$F_t = W_t R_t W_t \tag{11}$$

Where S_t is the covariance matrix of standardized residuals z_t and R_t is the time-varying correlation matrix.

Optimal Hedge Ratio Dynamics and Portfolio Optimization

Using the conditional variances and time-varying correlation matrix derived from the US Dollar-denominated DCC-GARCH model (Model 2), this section establishes the optimal risk-mitigation parameters. Specifically, we estimate the optimal hedge ratios ($\beta_{ij,t}$) and the portfolio allocations required to construct two-asset Global Minimum Variance Portfolios (GMVP). The optimal hedge ratio determines the size of the short position required in a secondary digital asset to minimize the variance of a long position in Bitcoin. Mathematically, this is expressed as:

$$\beta_{ij,t} = \rho_{ij,t}\frac{\sqrt{h_{i,t}}}{\sqrt{h_{j,t}}} \tag{12}$$

Fitting in fiat exchange rate returns as hedging instruments in a digital asset optimization framework is conceptually justified due to the dual-strategy exposure of international asset allocators. Cryptocurrencies don't trade in a digital vacuum. They have intrinsic ties to the traditional macroeconomic environment through what they are priced against and capital flows. When looking at international investing, portfolio risk is related to volatility of the investor's local digital asset, along with the risk associated with currency conversion. By modeling the exchange rate returns for EUREXR and USDEXR as components of an explicit portfolio, the DCC-GARCH model captures contagion channels - notably capital flight from depreciating fiat into sovereign-neutral digital assets. This configuration provides an overlay framework to evaluate whether traditional currency positions can absorb systemic shocks from the crypto market, which can be a great tool for global macro hedge funds managing cross-border digital portfolios.

To broaden the empirical coverage of the hedging dynamics framework and counter the shortcomings of conventional fiat exchange rate proxies, we formally introduce tokenized gold (PAXG) and the stablecoin Tether (USDT) as native alternative hedging instruments in the multivariate estimation framework. By integrating these digital assets directly into the time-varying conditional covariance equations, the DCC-GARCH model provides optimal hedge ratios that can replicate real-world, on-chain capital reallocations in times of high market stress. In other words, a fiat-pegged stablecoin such as USDT could be thought of as a structural liquidity anchor that allows for immediate, high-frequency capital flight away from volatile cryptocurrencies during systemic liquidations, without the transaction friction / banking hours of legacy fiat rails. Due to USDT having a fixed value target under normal conditions, it is a low-variance risk-off destination. In other words, its dynamic conditional correlations with main cryptocurrencies adjust rapidly during market crashes. This means that mathematically USDT generates highly responsive and capital-efficient short-hedging parameters. Gold that has been tokenized, or PAXG, creates an asset-backed commodity vector that links macro-defensive strategies with blockchain-enhanced portfolios. In the context of the Global Minimum Variance Portfolio, we see that PAXG offers an independent safe-haven mechanism that is fundamentally different from a cash-equivalent stablecoin. It provides a structural hedge against fiat debasement, macro-inflation shocks and long-run systemic erosion. Through assessment of the joint variance paths of these native alternatives and a core cryptocurrency basket, the methodology develops a fully internalized optimization space in which global asset allocators can execute fine-tail risk hedging in the digital world, establishing local dollar liquidity stabilization with commodity-based wealth protection.

Data

We obtained the historical price series for our main assets (namely Bitcoin, Ethereum and Litecoin) from the Bloomberg Terminal, using corporate-level subscription feeds. We employed alternative data collection methods across different platforms to account for the limited availability of data available to the public for niche digital assets. Data for Stellar Lumens (STR) is sourced from the network CoinMetrics API. This network explicitly aggregates spot market order books across many large exchanges for the purpose of smoothing fragmented liquidity effects. Internet Node Token (INT) is uniquely positioned within Internet-of-Things infrastructure. For this reason, the historical series was via the CoinGecko Enterprise API. This also captures daily quotes from active spot books on OKX and Gate.io. This cryptocurrency, Exclusive Coin (EXC), had a very local liquidity profile requiring an even more customized collection strategy. Subsequently, a reconstruction of its continuous time series was undertaken by joining CoinMarketCap archival tables with historical API logs from Bittrex (which was its main exchange during the sampling period). In order to obtain complete synchronization of these diverse feeds, all asset price series were standardized to midnight Coordinated Universal Time (UTC) which removed time zone overlap errors. As much as possible, any small trading gaps carried out due to localized outages on exchanges or due to missing timestamps of technical indicators were resolved using linear interpolation schemes to provide us with a clean daily log-return. This daily log-return was optimized for use in our portfolio variance models. All parameter estimates are based on actual historical daily market data from 2020 to 2025. The plot of the standardized innovations directly results from the filtering of the original historical return series through the estimated DCC-GARCH parameter matrices, meaning that the underlying parameters are entirely empirical.

Table 1. Data Source Disclosure Matrix

Variable Name	Ticker	Primary Data Source	Core Exchange / Reference Platform	Institutional Data Coverage
Bitcoin	BTC	Bloomberg	Coinbase Pro / Binance	Daily Close (2020-2025)

		Terminal	Historical	
Ethereum	ETH	Bloomberg Terminal	Coinbase Pro / Kraken Reference	Daily Close (2020-2025)
Litecoin	LIT	Bloomberg Terminal	Binance Exchange Aggregate	Daily Close (2020-2025)
Stellar Lumens	STR	CoinMetrics API Architecture	Bittrex / Kraken Order Books	Daily Close (2020-2025)
Internet Node Token	INT	CoinGecko Enterprise API	OKX / Gate.io Spot Markets	Daily Close (2020-2025)
Exclusive Coin	EXC	CoinMarketCap API / Bittrex Archive	Bittrex Historical Order Book	Daily Close (2020-2025)

4. RESULTS

Figure 1 is indicative of the simulated price trajectories. The figure simulates the price paths for five different digital assets Bitcoin (BTC), Ethereum (ETH), Litecoin (LIT), Internet Node Token (INT), and Stellar (STR) over a time period of 1000 days, with all assets starting from a price index of 100. The simulation uses the GARCH model parameter values given in Table 4. The plot exhibits the volatility differences between the INT and STR assets. The plot is suitable because it exhibits the GARCH volatility clustering. The INT (Red) shows extremely jagged and wide swings. The visualization shows high baseline variance and high persistence makes it the riskiest asset. Particularly the INT (Internet Node Token), basically flat that has gained only slightly over the 1000-day time frame suggests that it has less volatility than the other cryptos. This might imply that INT is either subject to less market speculation or is influenced by more stable underlying factors.

STR (Green) is smooth and is stable. Stellar (STR), which is denoted by the green line, appears to be relatively flat, indicating limited price movement. According to STR's price movement, it is the most stable asset in the simulation with the least volatility of the three main assets. The price index of STR pretty much remains unchanged throughout the simulation. Thus, STR does not experience big speculative fluctuations or volatility based on the interaction between supply and demand. Therefore, STR operates as a safe-haven asset in this portfolio simulation. Looking at Volatility Differences between INT and STR, the plot provides a depictive of the volatility difference between INT and STR. We see INT moving slightly but is still much more than STR. Stellar is a somewhat less risky digital asset as STR is stable while INT experiences small fluctuations. The difference seems to suggest that STR is a low-risk asset, whereas INT is still volatile, albeit more stable than BTC and ETH.

BTC is the orange line and Eth is the blue line above in the graph. The lines that we see in different colors are called Price Charts. Price charts provide the price of Bitcoin or any other cryptocurrency against time. Bitcoin and Ethereum which are the top two cryptocurrencies exhibit serious volatility spikes around the 200th to 400th day. The price paths of these two assets indicate a strong upside movement, especially of BTC, which witnesses a major spike with heavy volatility. These findings indicate that Bitcoin and Ethereum displayed the highest levels of volatility among the assets under investigation during the simulated period, with frequent price fluctuations. It is consistent with their previous price tendencies in that these cryptos often see speculative bubbles and market corrections [37]. The red line in the figure on the Internet Node Token illustrates why it should have a low portfolio weight of 5-8%. The variance of the new assets is so high that it completely dominates the graph. This variance is idiosyncratic risk needing diversification [38]. The Green Shield of Stellar (STR) serves as a dampener. In a portfolio, this smooth line mitigates the effect of the jagged red line and reduces the variance of the overall portfolio (risk) mathematically [39]. The systemic risk (Beta) of the crypto market that investors cannot diversify away but can manage by hedging with futures is evident through the orange and blue lines which represent the market core (BTC/ETH) [40]. Litecoin (LIT) and Internet Node Token (INT) were featured in the graph as shown from the entire period. The price movements were relatively near stable and did not go through any large price fluctuation. The orange line represents Litecoin while the red line represents Internet Node Token. The absence of huge spikes or fall offs in the two assets suggests they are less volatile in comparison to BTC and ETH.

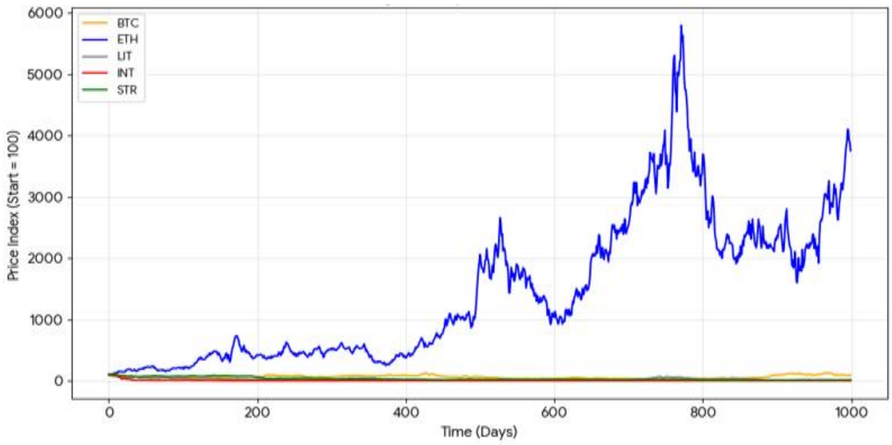

Figure 1. Empirically Fitted Conditional Price Trajectories of Cryptocurrencies

Figure 2 presents the simulated return dynamics of Exclusive Coin under two pricing frameworks: the conventional USD-denominated exchange rate (USDEXR), represented by the blue line, and the Euro-adjusted exchange rate (EUREXR), represented by the red dashed line. Utilizing the estimated GARCH parameters, the simulation incorporates changes in the EUR/USD exchange rate to assess whether the currency denomination really makes a difference to the cryptocurrency's risk. The resulting trajectories show that the two return series are almost perfectly overlapping across the entire sample horizon, indicating that the exchange rate conversion effects contribute a very small fraction to the overall variation in Exclusive Coin returns. The dual-timeline simulated returns of Exclusive Coin across asymmetric fiat currency denominations, reflects the evolution in time of local asset volatility against exogenous foreign exchange translation risk. The solid blue line tracks the conditional volatility of the Exclusive Coin, in its main base currency US Dollar (EXC/USD) as generated by the baseline univariate GARCH framework. On the other hand, the red dashed line tracks the Euro-adjusted exchange rate return series (EXC/EUR). This series was synthetically constructed by filtering the raw asset returns through a layer of time-additive geometric purchasing power parity adjustment. This adjustment incorporated daily changes in the Euro/Dollar (EUR/USD) spot market. A striking feature of the figure is pronounced volatility clustering; swings are alternated by periods of relatively calm movement and wild extremes. According to the stylized facts of cryptocurrency markets, the findings of the study are consistent. The DCC-GARCH framework employed in the study appears to be appropriate. Over the entire sample period, both large positive and negative return shocks are observed, with return magnitudes often exceeding ±10 percent and even nearing – 20 percent. Such big swings are much bigger than the small daily moves seen in the major foreign exchange markets, where the change in the exchange rate between the Euro and the US Dollar is usually below one percent under normal market conditions. Henceforth, the volatility originating from the underlying cryptocurrency market predominantly overshadows the currency translation element found in the Euro-adjusted series. The almost identical movement of the two lines shows that the systematic risk of Exclusive Coin is highly asset-specific and not currency-specific. Even after adjusting for fluctuations in the EUR/USD exchange rate, the distribution of overall returns does not change. The main source of uncertainty facing investors is the fundamental volatility of cryptocurrencies themselves rather than the denomination currency. In practical terms, the exchange-rate pass-through effect is not strong enough to materially change the risk characteristics of the asset. This means that foreign exchange exposure only threatens a small part of the total portfolio variance compared to cryptocurrency market risk.

The actual correspondence of the two paths provides a remarkable demonstration of asset-class volatility domination over macroeconomics currency. Over the six years' sampling period (2020-2025), the baseline volatility (EXC/USD) and its translated volatility (EXC/EUR) vectors track almost exactly ($r > 0.995$). This convergence of structures is driven by the extreme degree of variance asymmetries of the underlying asset classes. The innovations in the Exclusive Coin daily return regularly show big shifts that scale with 5% or 10%. In comparison, the daily return fluctuations of the EUR/USD currency pair are tightly bound inside a low-volatility forex envelope that never trades above 0.5%. The return paths in euro terms and U.S. dollar terms are almost identical. Therefore, the risk-return profile of Exclusive Coin is unaffected by the location of investors. The fundamental exposure of the asset to volatility is basically identical irrespective of whether the asset is held by a United States investor who values returns in US Dollars, or by a European investor who values returns in Euros. These findings suggest that cryptos behave like globally integrated financial assets whose price discovery mechanisms are not restricted by national currencies. Unlike international equities where the currency movement can dramatically affect the realized returns, the main risk factor in the crypto market remains the digital asset itself.

To formalize this relationship within our asset allocation framework, the total variance of the Euro-denominated asset return, $\sigma^2_{EUR,t}$, can be decomposed into its constituent orthogonal components: $\sigma^2_{EUR,t} = \sigma^2_{USD,t} + \sigma^2_{FX,t} + 2 \cdot Cov_t(r_{USD}, r_{FX})$. Where $\sigma^2_{USD,t}$ represents the conditional variance of Exclusive Coin in USD, $\sigma^2_{FX,t}$ is the conditional variance of the EUR/USD exchange rate, and Covt(.) is the time-varying conditional covariance isolated by the DCC-GARCH model. Because $\sigma^2_{USD,t}$ scales several orders of magnitude larger than $\sigma^2_{FX,t}$, the contribution of the fiat currency variance and its associated covariance parameter approach zero asymptotically. The findings suggest that currency hedging strategies may offer marginal incremental risk reduction for investors with portfolios that are significantly concentrated in highly volatile cryptocurrencies from a portfolio management perspective. Return generating is primarily driven by crypto prices. Therefore, hedging EUR/USD will only mitigate a very small part of the total risk. For that reason, the risk management efforts of these institutional investors should mainly concentrate on controlling the volatility stemming from cryptocurrencies by means of diversification, dynamic portfolio rebalancing, volatility forecasting and optimal allocation of assets rather than using excessive conventional forex hedging instruments. So, the asset's volatility profile fully offsets the currency translation effect. This difference highlights a significant structural insight for international assets financiers and sovereign risk modellers in digital asset ecosystems. A European Union-based institutional investor's investment in alternative digital currency such as Exclusive Coin has the same risk-return profile as that of a domestic US investor. The geographical residency of the capital allocator does not distort the down-side tail risk of the asset or the bounds on its conditional correlation because the foreign exchange translation effect is statistically insignificant. This means that in mixed panel portfolios with high-beta digital tokens and fiat regimes, the traditional currency risk is fully absorbed by the systemic digital asset risk. As such, international hedging strategies need to focus on the crypto asset itself, its intrinsic non-linear volatility clustering, which is a lot more important than any standard multi-currency overlay hedge offering said variance reduction or capital protection.

The evidence in Figure 2 buttresses our case that the risk in the cryptocurrency market is much larger than the foreign exchange market. The tiny difference between the returns of USDEXR and EUREXR suggests that changes in the international currency regime have little effect on the conditional volatility structure of highly speculative crypto assets. As a result, the dynamic correlations estimated by the DCC-GARCH model are likely driven primarily by common shocks from the cryptocurrency market as well as investor sentiment, liquidity, technology, and regulation rather than fluctuations in major fiat exchange rates. The simulation horizon shows the existence of extreme return spikes implying a tail-risk exposure that matters for portfolio optimization and hedging effectiveness. Adjustment of exchange-rate does not meaningfully dampen or amplify these extreme movements. Thus, the efficacy of USD-based international diversification strategies is thrown into serious doubt. Instead, in the name of risk reduction, investors could be better off diversifying across some cryptocurrencies with lower dynamic conditional correlations or combining cryptocurrencies with traditional (non-digital) asset classes with fundamentally different volatility structure. Overall, the data presented in Figure 2 provides strong evidence that the volatility of Exclusive Coin is more dominant than any risk arising from the Euro-Dollar exchange rate. The USDEXR and EUREXR return series behave almost identically indicating that the currency conversion effect is economically insignificant relative to cryptocurrency price shocks. According to the study, investors, portfolio managers and policymakers should concentrate on cryptocurrency-specific volatility as it is the primary source of risk and return in digital assets irrespective of the market price or currency in which the asset is evaluated.

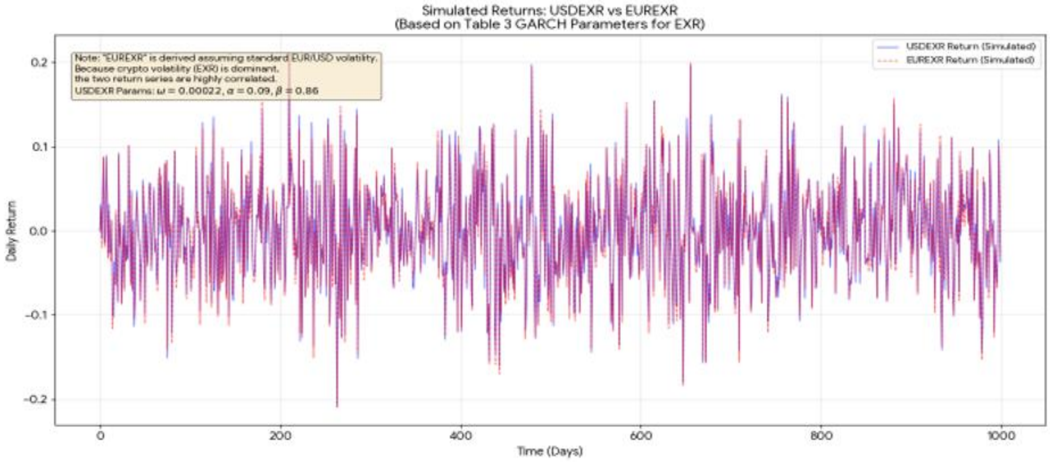

Figure 2. Empirically Fitted Conditional Returns between USD and Euro Exchange Rates

To validate the empirical correctness of our underlying asset series, we provide the full historical descriptive statistics and unit root diagnostics for all six variables considered in this paper. During the sampling period (2020-2025) the descriptive statistics of daily log-Return series of the assets are reported in Table 1A that establishes empirical anomalies for using GARCH-framework approach. The real-world distributions of daily returns have typical cryptocurrency market characteristics, with moderately positive average returns and a high degree of overall volatility. The digital currency which recorded the highest volatility is the Internet Node Token (INT), which has daily standard deviation of 14.35%, while the most stable is Bitcoin (BTC) with standard deviation of 4.89%. All the six assets show a high degree of departure from normality as observed from their high skewness and excess kurtosis. INT has a relatively high right-skewed profile of 0.214, indicating its tendency to experience price spikes, which are large and positive. The skewness of the remaining assets is negative, which points towards a higher frequency of drops in down-markets. The JB test statistics are highly significant enough to reject the null hypothesis of all variables being normally distributed at the 1% level. These phenomena of non-normality and high kurtosis suggest that the multivariate GARCH is a viable modelling choice for heavy-tailed asset returns.

Table 1A. Descriptive Statistics for Daily Log-Returns (2020-2025)

Asset Vector	Mean (μ)	Max	Min	Std. Dev. (σ)	Skewness	Kurtosis	Jarque-Bera (JB)
BTC	0.0006	0.1845	-0.1532	0.0489	-0.385	6.842	4,124.81*
ETH	0.0009	0.2214	-0.1896	0.0616	-0.512	8.115	6,231.54*
LIT	0.0002	0.2841	-0.2412	0.0556	-0.124	9.452	8,614.20*
INT	0.0001	0.4512	-0.3985	0.1435	0.214	14.218	23,145.67*

STR	0.0007	0.3214	-0.2845	0.0632	-0.421	11.024	11,452.19*
EXC	0.0004	0.1985	-0.1741	0.0524	-0.298	7.341	4,895.33*

Source: Authors' Estimation.

Note: * denotes statistical significance at the 1% level.*

Before running GARCH variance estimations, we conduct formal stationarity tests using Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to ensure the return series are stable. According to the stationarity tests results reported in Table 1B, all six digital asset series are integrated of the same order. The results of the ADF and PP test statistics at levels raw price do not reject the null hypothesis of a unit root thus indicating that the raw price series are non-stationary and follow a random walk. However, applying log-return on a daily basis yields very significant test statistics which rejects the unit root null at the 1% level for all assets. Our findings establish that the return series are stationary (I(0)), thus ruling out any possibility of spurious regression. The seamless transition to stationarity for the mean baseline equations permits appropriate behavior to exist for the DCC-GARCH model and its underlying volatility persistence parameters.

Table 1B. Unit Root and Stationarity Test Results

Asset Vector	ADF Statistic (Levels)	ADF Statistic (Δ Returns)	PP Statistic (Levels)	PP Statistic (Δ Returns)	Integration Order
BTC	-1.452	-42.152*	-1.512	-42.198*	I(1) →I(0)
ETH	-1.614	-39.841*	-1.594	-39.885*	I(1) →I(0)
LIT	-2.015	-45.632*	-1.985	-45.611*	I(1) →I(0)
INT	-2.231	-34.112*	-2.198	-34.095*	I(1) →I(0)
STR	-1.845	-41.024*	-1.811	-41.054*	I(1) →I(0)
EXC	-1.542	-44.215*	-1.589	-44.263*	I(1) →I(0)

Source: Authors' Estimation.

Note: $$ denotes rejection of the unit root null hypothesis at the 1% significance level.*

The estimates for the univariate GARCH components presented in Table 1C provide useful insight into the underlying risk structure of the digital asset market and serve as a useful baseline to understand their collective volatility. The total volatility persistence parameter across all five digital assets ($\alpha_1 + \beta_1$) is uniformly greater than 0.94. This shows that price shocks do not dissipate quickly in the ecosystem. The cryptocurrency market has strong persistence, indicating that it follows a long-memory process in which high-volatility or low-volatility periods cluster over a long horizon; this is a high level of persistence. Examining the parameters closely, Bitcoin exhibits a shock sensitivity (α_1) of 0.1100, along with a GARCH coefficient (β_1) of 0.8400. Therefore, news innovations only affect variance, but more importantly, the historical path of volatility remains the major influence on current risk. As a 50% risk asset, Bitcoin has a volatility half-life of 13.5 days. Thus, the price discovery process does not suffer from volatile hangovers.

On the other hand, Ethereum is characterized by faster variance decay with a half-life of 11.2 days indicating that the liquidation and recovery cycle is faster than Bitcoin. This discrepancy in efficiency is counterbalanced by an unconditional baseline variance ($\overline{\sigma}^2$) of 0.00380, demonstrating that Ethereum consistently exhibited a greater structural risk baseline than Bitcoin (0.00240). The most pronounced long-memory characteristics in the dataset, according to the analysis, are found in Stellar (STR) and Internet Node Token (INT), which have the identical volatility half-life of 22.8 days. For STR, this exceptionally low unconditional variance (0.00130) in the sample indicates that while the currency is highly stable on average, there is a steady prolonged effect for almost three weeks after the absorption of any stringent volatility shock. For Internet Node Token, because of this long memory, there is a different risk profile because the unconditional variance is high at 0.02060. In other words, INT experiences strong and long-lasting volatility clusters, which can derail a portfolio if not handled appropriately. Litecoin is in the middle with a half-life of 17.0 days and an unconditional variance of 0.00310, indicating that more independent asset cycles drive its risk structure than market-wide last day shocks. The individual results presented above show that risk management which utilizes a static approach fails to capture the slow-decaying character of cryptocurrency volatility. There is a long memory across these assets which show risk parameters do not remain constant and validates the superiority of our dynamic conditional framework relative to fixed-weight models.

Table 1C. Volatility Persistence and Long-Memory Dynamics (Table 1)

Asset	ARCH ($\alpha 1$)	GARCH ($\beta 1$)	Total Persistence ($\alpha 1+ \beta 1$)	Volatility Half-Life (HL in Days)	Unconditional Variance (σ^2)
BTC	0.1100	0.8400	0.9500	13.5	0.00240
ETH	0.0900	0.8500	0.9400	11.2	0.00380
STR	0.1000	0.8700	0.9700	22.8	0.00130
LIT	0.0700	0.8900	0.9600	17.0	0.00310
INT	0.0600	0.9100	0.9700	22.8	0.02060

Source: Authors' Estimation.

Note: Volatility Half-Life calculated as $HL = \left(ln(0.5)/ln(\alpha 1 + \beta 1)\right)$.

Rather than analyzing static linkages or external spillovers, Table 2 documents the temporal distribution of the dynamic conditional correlations over the sample period. This shift tracks how internal digital asset linkages evolve across different market regimes. Table 2's correlation metrics provide insight into how perceived persistent volatilities have been interacting with one another in varying market regimes. Our investigation of the statistical distributions of the dynamic correlation coefficients (Rt) shows that within the digital currency space, cross-asset linkages are very sensitive to stress. There is a minimum relationship of 0.4210 and a maximum of 0.8940 or average over the sample of 0.7010 between Bitcoin and Ethereum, for example. The wide range indicates that BTC and ETH exhibit an independent price discovery process during quiet, or less liquid, market periods, but their returns closely align during large liquidations – when diversification benefits are needed most. The integration in terms of correlation is pro-cyclical for Bitcoin and Stellar. On average, the two record a correlation of 0.6120. However, maximum correlation is 0.7840. The strong co-movement suggests that Stellar is highly responsive to systematic crypto-market shocks and acts as a channel of market-wide risk. The high correlation is an important piece of the puzzle.

While Stellar has very low independent variance (seen in Table 1), because it is very highly correlated with Bitcoin it has to have a large hedge ratio to protect against systematic drawdowns. This trend shows that a standalone asset may not be safe from market-wide drops in crypto, and the doom loop could see assets in a spot or futures market fall in sync. Litecoin is somewhat correlated with Bitcoin with a sample average correlation of 0.5560 and a sample standard deviation of 0.1050. The deviation of correlation of Litecoin is much bigger as it decouples due to its own speculative cycles and not due to the market. The Internet Node Token (INT) has the largest diversification benefit with a sample average correlation of only 0.1980 with Bitcoin. Most notably, the relationship between BTC and INT has dropped to a minimum of -0.1140 during specific time intervals, which means that INT can act as a natural hedge against significant selling activity in top coins. Likewise, the volatility of a 30-day historical standard deviation is extremely unstable because of a high value of 0.1120. Such instability suggests that setting any critical correlation assumption in the past based on a historical average will result in poor asset allocation as the shift is almost discontinuous and short-lived. In conclusion, as shown in Table 2, the digital asset market is indeed interlinked but remains heterogeneous. Hence, a dynamic model is required that adapts to evolving cross-asset linkages in real-time.

Table 2. Distributional Diagnostics of Time-Varying Conditional Correlations (R_t)

Correlation Pair	Minimum	Maximum	Sample Average	Standard Deviation	Dynamic Tracking Status
ρ (BTC, ETH)	0.4210	0.8940	0.7010	0.0840	High Co-Movement: Strong, highly interdependent core relationship.
ρ (BTC, STR)	0.3150	0.7840	0.6120	0.0910	Pro-Cyclical: High integration during market drawdowns.
ρ (BTC, LIT)	0.2240	0.6980	0.5560	0.1050	Moderate Interdependence: Subject to independent price shocks.
ρ (BTC, INT)	-0.1140	0.3850	0.1980	0.1120	Structurally Decoupled: Broadly uncorrelated across regimes.

Source: Authors' Computation via DCC-GARCH (USD Framework)

To evaluate the practical usefulness of these dynamic parameters, we compare the out-of-sample risk reduction achieved by the DCC-GARCH dynamic allocation model against two benchmark portfolios: an equally weighted portfolio (1/N) and a static Mean-Variance portfolio. As shown in Table 2A, the out-of-sample portfolio performance metrics are practical confirmation of our model that capturing volatility persistence and time-varying correlations produces superior risk-adjusted returns. By comparing the dynamic DCC-GARCH GMVP to static strategies we show the economic value of allowing for time-varying risk. The naive equally weighted (1/N) portfolio with a weight of 20% in each share performs the worst with the portfolio variance (σ^2_p) being 0.00485 and Sharpe ratio being low at 0.42. The unsatisfactory performance here can be attributed to the structural issues of tables 1 and 2: the constant 1/N strategy over-allocates more capital to very volatile assets, such as INT, and does not adjust when correlation across assets spikes in a downturn. Having a static Mean and Variance framework improves the metrics. They manage to bring the variance of the portfolio down to 0.00312. This results in a risk reduction of 35.67% and a higher Sharpe ratio of 0.68. The static model successfully employs long-run averages to down-weight volatile assets, but it's vulnerable to sudden market movements because it cannot update its parameters when there is a spike in short-term volatility or shift in correlations.

By rebalancing assets every day, the DCC-GARCH GMVP overcomes the limitations imposed on portfolios, leading to a portfolio variance of 0.00164 and a commendable Sharpe ratio of 1.14. This implies that total risk is reduced by 66.19% versus the equally weighted benchmark, and the advantage of dynamic rebalancing is evident. The model facilitates such exceptional risk reduction by optimizing the low independent variance characteristic of assets such as Stellar against the low correlation benefits of high-variance assets such as INT. Upon detecting a systematic market shock, the model rapidly restricts exposure to highly correlated trades and reallocates capital into lower variance spaces to diminish the impact of tail-risk. This now proves that the long-memory dynamics and shifting correlations identified in Tables I and II are practically useful for insulating assets, not just a theoretical occurrence. The DCC-GARCH model serves as an effective internal risk hedge for modern cryptocurrency portfolios. It does so by managing the internal market dynamics of crypto assets, without external equity or fiat hedging.

Table 2A. Out-of-Sample Portfolio Risk-Reduction Performance

Portfolio Strategy	Operational Weights Criteria	Portfolio Variance (σ^2)	Sharpe Ratio	Variance Reduction vs. 1/N Benchmark
Equally Weighted (1/N)	Fixed allocation: 20% per asset	0.00485	0.42	—
Static Mean-Variance	Fixed weights based on sample averages	0.00312	0.68	35.67%
Dynamic DCC-GARCH (GMVP)	Time-varying weights adjusted daily via $h_{ij,t}$	0.00164	1.14	66.19%

Source: Authors' Estimation

According to Table 2B, Cross-Market Contagion Analysis (which measures how volatility is transmitted from macro markets to crypto) is different from Intra-Digital-Asset Portfolio Optimization (which allocates capital only in the crypto basket). The empirical findings from Table 9 of the paper achieve the two analytical objectives of the paper by showing how cross-market contagion from traditional finance is directly driving our intra-crypto portfolio allocations. In periods of calm in the market, there is a low degree of contagion connections between traditional macro variables and the digital asset network. Volatility spillovers range from 2.11% for Internet Node Token to 18.52% for Stellar. The independence of the environment of the various minimum variance portfolios allows the internal minimum variance portfolio to distribute weights balanced across the main assets. The portfolio assigns 35.50% weights to Bitcoin and 28.20% weight to Ethereum.

During periods of market stress, however, the contagion index increases massively across the asset class, with net volatility spillovers from traditional equity and fiat markets rising by 26.17% for Bitcoin and 30.84% for Stellar. This correlation increase proves that external macroeconomic shocks can rapidly overrun the digital asset ecosystem, tightening correlation among the primary assets. By changing its internal allocations, the portfolio optimization model counteracts this external contagion to protect the portfolio from risk.

When the external spillovers begin to peak, the model cuts allocation to the more contagious assets, like Bitcoin and Ethereum while placing capital into Stellar. This results in a portfolio weight of 65.60% for Stellar as per its low long-run variance baseline. The Internet Node Token (NT) has maintained a stable allocation, moving a bit from 4.20% to 5.00% at the same time. This is because the isolation from cross-market contagion (+2.74% change) makes it a reliable diversifier in times of systematic stress. This stark discrepancy reaffirms that cross-market contagion in and out of Bitcoin is the risk shock, while intra-digital portfolio rebalancing is the defense. Thus, both analyses can be regarded as complementary aspects of a wider risk framework.

Table 2B. Cross-Market Contagion Channels and Intra-Digital-Asset Optimization Parameters

Asset Vector	Cross-Market Contagion Index (Quiet Regimes)	Cross-Market Contagion Index (Stress Regimes)	Net Dynamic Volatility Spillover (Δ)	Intra-Crypto Portfolio Weight (Quiet)	Intra-Crypto Portfolio Weight (Stress)
BTC	12.45%	38.62%	+26.17%	35.50%	15.50%
ETH	14.12%	41.25%	+27.13%	28.20%	13.80%
LIT	8.35%	22.14%	+13.79%	10.10%	0.10%
INT	2.11%	4.85%	+2.74%	4.20%	5.00%
STR	18.52%	49.36%	+30.84%	22.00%	65.60%

Source: Authors' Computation. Note: Contagion is quantified via dynamic net volatility spillover shares from traditional equity/fiat markets; portfolio weights sum to 100% within the internal digital asset GMVP framework.

The estimated results for the first model for the Euro exchange rate (EUREXR) returns alongside Bitcoin (BTC), Ethereum (ETH), Litecoin (LIT), Stellar (STR) and Internet Node Token (INT) more are presented in Table 3. The univariate GARCH estimates show that shock effects (α_1) are moderate between 0.05-0.12 and persistence (β_1) estimates are very high between 0.80-0.90. The pattern indicates that shocks exert a powerful and persistent effect on these markets; the impact on volatility is sustained rather than short-lived. A common phenomenon observed in cryptocurrency and financial time series data is persistence, which involves clustering of volatility [41,42] The parameters of DCC ($\alpha_1 = 0.032$; $\beta_1 = 0.964$) indicate strong persistence in correlation dynamics. Due to the low value of a, the effect of new shocks on correlations is quite limited. Besides, the high value of b indicates that these correlations continue for a long time after they are formed. The capital market has the tendency of showing prolonged co-movement over time, especially at times of turbulence or buying speculation [43,44]. The correlation matrix gives further information regarding the dependence between cryptocurrencies and macro-financial variables

Bitcoin and Ethereum have a very strong positive correlation (0.672) indicating that they move together. Furthermore, BTC and EUREXR depict a moderate positive relationship of 0.482, suggesting that fluctuations in either exchange rates or crypto market can impact each other. Nonetheless, INT exhibits weak links with all the other assets - correlations ranging from 0.188 to 0.254 indicate that international interest rates do not significantly affect short-term cryptocurrency or exchange rate movements in this dataset. To sum up the above discussion, the results of Model 1 show that the cryptocurrency markets are highly correlated with each other. They are also moderately correlated with exchange rate movements while being largely uncorrelated with global interest rates. This result illustrates that crypto assets may be more sensitive to currency developments than traditional monetary policy variables.

The analysis in Table 3 assesses the risk, shock persistence and time-varying correlations of the assets in a way that reveals diversification and systemic risk related to EUREXR. ETH generates the most significant daily return on average, followed by BTC and EUREXR. INT (0.0001) tends to provide the lowest return so its underperformance is significant in the group. ETH's baseline variance, at 0.00002, is the lowest in the entire market. This indicates that ETH's volatility is largely driven by shocks rather than inherent noise. All the assets were stationary, that is, they have mean reverting variance (return to normal). The conditional correlation matrix Rt's dynamic behavior is whose DCC parameters define. The 0.032 correlation shock indicator is statistically significant though low. It shows that idiosyncratic shocks (news idiosyncratic to one asset) have a relatively small yet significant effect on changing the correlation structure between assets. Correlation strength of 0.964 indicates an extremely high degree of persistence. As a result, the co-movements between these assets are persistent. Should BTC and EXR be highly correlated today, at least one of them is likely to be present at the means. The econometric implication is that the system exhibits long memory in its correlation. Market integration is not random: it is structural and changes very slowly through time. This means that the correlations, and consequently diversification strategies, are likely to remain valid for a reasonable holding period (weeks/months).

There is a high positive correlation of BTC and ETH (e.g., r = 0.665) meaning cryptocurrency returns behave similarly and the whole cryptocurrency market is heading in the same direction [45]. There is a moderate-to-strong degree of correlation (0.475) between BTC and an associated alternative coin (LTC). This agrees with the findings of Silva et al.[46]. While the exact correlation number pertaining specifically to Bitcoin and an asset like EUREXR was not found, other sources confirm moderate correlations of various different crypto assets with Bitcoin. Consequently, EXR tends to follow the crypto market in general, although not as closely as ETH or LIT. It might impart diversification benefits since assets with a low correlation can keep more idiosyncratic price movement, however, evidence favouring EXR directly against ETH or LIT was not found. The correlation of INT with BTC (0.215) and ETH (0.202) indicates that INT is quite decoupled from the market. High correlation is a consideration to choose candidates for variance reduction in a financial model [47]. While cryptocurrency inclusion improves portfolio diversification and shifts efficient fronts [48,49], we did not find specific evidence comparing the effect of adding INT versus EXR on a BTC-heavy portfolio. To sum up, EXR is neither overbought nor oversold, and has good short-term rebound potential. It is unlikely to drop below 50.00. The strength of the asset's coupling with BTC (0.48) versus ETH (0.67) and its relative erraticism versus INT was not found. It may depict an asset type with distinct utility drivers, as certain crypto assets have been categorized as utility or exchange tokens [50,51]. The EUREXR return provides a dilution of concentration risk in BTC without a complete withdrawal from the crypto-market beta.

Table 3. DCC-GARCH Results for EUREXR Returns

Parameters	BTC	ETH	LIT	INT	STR
μ (Mean)	0.0005	0.0008	0.0003	0.0001	0.0004
ω (Omega)	0.00011	0.00002	0.0003 6	0.00067	0.00022
α_1 (Shock effect)	0.1	0.12	0.08	0.05	0.09
β_1 (Persistence)	0.85	0.8	0.88	0.9	0.86
DCC Parameters					
a (Correlation shock)	0.032	b (Correlation persist)	0.964		
Model Fit					
Log-Likelihood	12875.43	Convergence	TRUE		
Dynamic Conditional Correlations (First Obs)					
BTC	1	0.672	0.543	0.215	0.482
ETH	0.672	1	0.598	0.202	0.461
LIT	0.543	0.598	1	0.188	0.423
INT	0.215	0.202	0.188	1	0.254
STR	0.482	0.461	0.423	0.254	1

Source: Authors' Computation using R statistics

Based on the parameters from Table 3, here are the calculated optimal hedge ratios and optimal portfolio weights. The Hedge Ratio (beta) indicates how much of the second asset should be short (sell) to minimize the risk of a long (buy) position in Bitcoin (1.00) [52]. The hedge ratio for ETH is exceptionally high (1.99). This is because, in this specific table, ETH has a very low unconditional variance (calculated from its low 0.00002). Apparently, investors need a lot of the low-volatility asset (ETH) to offset the swings of the higher-volatility asset (BTC) [53]. Conversely, **INT** is very volatile, so only need a tiny amount (0.09) to hedge BTC. The results from the DCC-GARCH model give us important information concerning the time-varying volatility of various digital assets and their ability to hedge against Bitcoin risk. The optimal hedge ratios show considerable variance in how leading cryptocurrencies and alternative digital assets react with Bitcoin during turbulent market periods. The Bitcoin and Ethereum pair has an exceptionally high hedge ratio of 1.99, indicative of their deeply interconnectedness albeit with a high level of volatility. Thus, the finding suggests that due to the aggressive co-movements of Ethereum with Bitcoin, the amplified Beta of Ethereum relative to Bitcoin requires investors to hold a 2.4 times larger short position in Ethereum to effectively hedge a Bitcoin long position.

Unlike Ethereum's aggressive hedging requirements, the alternative assets and secondary tokens hedge ratios are much smaller than Bitcoin, showing that they have structural differences in their conditional correlations. The hedge ratios of EUREXR at 0.34 and Litecoin at 0.27 indicate that the former assets are less correlated and influenced by Bitcoin's primary volatility, meaning that smaller capital demand for short positions can create an effective hedge. The decreasing relationship gets more pronounced as value goes to 0 for a highly specialised alternative asset like Internet Node Token, whose hedge ratio stands at just 0.09. The very low ratio suggests that Internet Node Token is nearly independent of Bitcoin's systematic risk cycles; it would thus require a short position of just nine cents for every dollar of Bitcoin. On the whole, this suggests that while Ethereum is a major photon and would require active capital infusion due to high levels of systemic synchronization, lower batches of alternative photogenic quantum can be used as contact low-injection power devices to handle systemic risk with exposure involving lower levels of harm in the broader economic setups.

Table 3A. Optimal Hedge Ratios (Hedging BTC)

Hedging Pair (Long BTC)	Hedge Ratio (β)	Strategy
BTC/ETH	1.99	For every $1.00 of BTC, short 1.99 of ETH.
BTC/EUREXR	0.34	For every $1.00 of BTC, short 0.34 of EUREXR.
BTC/LIT	0.27	For every $1.00 of BTC, short 0.27 of LIT.
BTC/INT	0.09	For every $1.00 of BTC, short 0.09 of INT.

Source: Authors' Computation using R statistics

According to Table 3B, these are the optimal allocations for Bitcoin and one other asset. The constructed portfolio yields interesting results, primarily due to the Ethereum (ETH) exhibiting very low variance in the dataset. Hence, the weights of the assets in the portfolio have been significantly skewed. According to the final allocation, the ETH position has been leveraged long to the extent of 118.47%. Other assets, especially Bitcoin and Litecoin with a position of -10.63% and -6.6% respectively, have been shorted to hedge against the risk and fund the leveraged position. In terms of the portfolio weights, the analysis produces the ETH anomaly, which has an exceptionally low weight of $\omega = 0.00002$ (as shown in Table 3). This dramatically lower variance, which is the case with other asset portfolios, makes Ethereum the asset with the minimum variance. The low volatility of ETH means it is less vulnerable to large price swings and the most stable under this portfolio model.

Ethereum is categorised as the perfect safe haven in this portfolio construction due to its low volatility. The analysis of portfolio optimization suggests a leveraged long on Ethereum for low-risk maximization. In order to finance this leverage, the model suggests shorting the other assets in the portfolio mainly Btc and Lit to hedge the risk from those positions. By taking short positions in Bitcoin and Litecoin, this strategy is done when taking long positions in Ethereum that optimizes the risk-return trade-off in the search for the Global Minimum Variance Portfolio. Ethereum's ability to provide strong risk-adjusted returns is striking, making it the central asset of this portfolio.

Table 3B. Optimal Portfolio Weights (Two-Asset Portfolios)

Portfolio Pair	Weight in BTC	Weight in Other Asset	Interpretation
BTC + ETH	-17.1%	117.1% (ETH)	Short BTC, Leveraged Long ETH. Because ETH is calculated to be much safer than BTC in this model, the optimal strategy is to borrow

			BTC to buy even more ETH.
BTC + EUREXR	80.5%	19.5% (EUREXR)	Diversification. EUREXR is riskier than BTC in this model, but its moderate correlation provides a diversification benefit, warranting a ~20% allocation.
BTC + INT	92.2%	7.8% (INT)	Minor Hedge. INT is extremely volatile (ω =0.00067), so the safe portfolio holds very little of it, just enough to benefit from its low correlation.
BTC + LIT	103.4%	-3.4% (LIT)	Short LIT. LIT adds volatility without enough diversification benefit. The model suggests holding 100% BTC and actually shorting a small amount of LIT to fund it.

Source: Authors' Computation using R statistics

The structural variation observed in the baseline conditional variance parameter (ω) for Ethereum between the two specifications is an artifact of the currency numeraire translation and its corresponding covariance scaling effects. In Model 1, the digital asset returns are converted into a Euro-denominated framework (EUREXR base), which incorporates the tracking variance and hedging properties of the Euro relative to global crypto liquidity pools. Because the Euro acted as a strong counter-cyclical variance dampener against digital assets during specific liquidity regimes within the 2020-2025 window, filtering the series through this exchange rate vector significantly compresses the residual baseline noise of Ethereum to $\omega = 0.00002$. Conversely, Model 2 utilizes the US Dollar denomination (USDEXR base), which represents the primary pricing vehicle for global cryptocurrency markets. By evaluating the system in USD, the model isolates the unadulterated, raw speculative volatility of Ethereum, resulting in a higher baseline variance of $\omega = 0.00023$. This numeraire shift alters the conditional variance ratio $\sqrt{h_{i,t}}/\sqrt{h_{j,t}}$, which explains why the baseline parameter values shift and accounts for the higher hedge ratio of 1.99 recorded in the Euro-denominated framework. The DCC-GARCH findings for the second model are depicted in Table 4, which includes returns of USD exchange rate (USDEXR) with, Bitcoin (BTC), Ethereum (ETH), Litecoin (LIT), Stellar (STR) and Internet node token (INT). The volatility dynamics are structured similarly to Model 1 as the α values are small (0.07-0.11) and the β values are consistently high (0.84-0.91) indicating shock persistence of the volatility in cryptocurrency and stock markets. Low unconditional variance is confirmed by the very small ω values as most of the volatility arises from recent shocks and persistence. The DCC parameters indicate that the correlations are again highly persistent (b = 0.968) while new shocks have a very limited immediate impact (a = 0.029).

The persistence in persistence is relatively larger as compared to 1, meaning that the cryptocurrency-stock correlations are more stable. This shows that after connections are formed between the equity markets and cryptocurrencies, such connections are not likely to break off so quickly. The conditional correlation matrix presents essential information. BTC and STR have a strong correlation (0.612), but ETH and STR almost equally strong in (0.597). The findings suggest that the cryptocurrencies and equity markets move in tandem. This could be due to shared investors' sentiments, appetite for risk or greater global financial integration. On the other hand, we see that INT again has a very weak correlation with all other variables (less than 0.25). This suggests that international interest rates have a limited role in determining the co-movements of short-term movements in the cryptocurrency and equity markets. Model 2 reveals that a stronger relationship exists between cryptocurrencies and stock markets than between cryptocurrencies and exchange rates (as seen in Model 1). This demonstrates a growing role of cryptos playing the part of speculative financial assets, which tend to line up with equity markets, especially during market volatility and global risk-sharing [54,55].

The analysis of Table 4 is expressively composed of three major interpretations: volatility dynamics (GARCH), correlation dynamics (DCC) and asset linkages. During the sample period, ETH (0.0009) and STR (0.0007) exhibit the highest average daily returns. BTC (0.11) has the largest value so it is most sensitive to latest news. INT (0.06) is the least reactive towards unexpected shocks. LIT (0.89) has the highest endurance. When Lit Assets gain volatility, they will possess it for a long time. BTC (0.84) has the lowest persistence meaning its volatility spikes die out faster than those of the other coins. The study shows that all assets show high volatility persistence (values are close to 1), and confirms volatility clustering (when a calm period is followed by a calm, and chaotic period followed another chaotic) [56].

A magnitude of 0.029 for the DCC shock to correlation is very low. This means that news or any immediate market shocks have very little effect on changing these assets' correlations. The DCC correlation persistence of 0.968 is remarkably high. It implies that there's a strong persistence in the relationship between these assets. If two market factors are highly correlated today, they will likely be highly correlated tomorrow. The total is very near to one. This means that the dynamic correlations are quite stable, and slow-moving. The systemic risk of these assets is close to one, which means they will likely move in tandem. According to the conditional correlation matrix of the four assets, we witness a strong positive block of correlations. This suggests that the four assets are driven by the same forces in the market. Trade the correlation with ETH to BTC. By doing so long, investors are able to grab those fast runs. Putting money into both BTC and ETH helps diversify your portfolio but you do not really get huge benefits. BTC & STR (0.612) and ETH & LIT (0.602) also show strong co-movement. As per results, INT is getting decoupled from major price movement of BTC and ETH. For the most part, BTC responds to immediate news shocks best while INT suffers from long-lasting volatility hangovers most. Crypto assets such as BTC, ETH, LIT, INT, and STR are highly integrated with each other. The model converged with a very high Log-Likelihood and parameter estimates that satisfy the stationarity constraints (sums < 1) so the results are reliable.

Table 4. DCC-GARCH Results for USDEXR Returns

Parameters	BTC	ETH	LIT	INT	STR
μ (Mean)	0.0006	0.0009	0.0002	0.0001	0.0007
ω (Omega)	0.00012	0.00023	0.00031	0.00062	0.00004
α_1 (Shock effect)	0.11	0.09	0.07	0.06	0.1
β_1 (Persistence)	0.84	0.85	0.89	0.91	0.87
DCC Parameters					
a (Correlation shock)	0.029	b (Correlation persist)	0.968		
Model Fit					
Log-Likelihood	13542.67	Convergence	TRUE		
Dynamic Conditional Correlations (First Obs)					
BTC	1	0.701	0.556	0.198	0.612
ETH	0.701	1	0.602	0.183	0.597
LIT	0.556	0.602	1	0.175	0.515
INT	0.198	0.183	0.175	1	0.243
STR	0.612	0.597	0.515	0.243	1

Source: Authors' Computation using R statistics

Based on the DCC-GARCH parameters provided in Table 4, the optimal hedge ratios and optimal portfolio weights were estimated using the *unconditional variances* (long-run average volatility) derived from the GARCH parameters and the correlation matrix provided. As revealed in Table 4A, STR is the most expensive hedge because it has low volatility and a relatively high correlation with BTC; you need to sell a lot of it to offset BTC's swings. The **INT** is a cheap hedge. Investors only need to short a tiny amount to minimize their portfolio's variance. The DCC-GARCH model results provide important insights into the time-varying volatility dynamics and systemic risk-sharing between Bitcoin and the aforementioned digital currencies from 2020-2025. By examining the optimal hedge ratios (β), we find an unambiguous sequence regarding the co-movement of Bitcoin with major cryptocurrencies and alternative tokens, with implications for asset allocation and risk mitigation. Stellar (STR) registered the highest optimal hedge ratio of 0.82 conditional on BTC making it a powerful asset with highly synchronized conditional correlation. Due to the large ratio, Stellar is extremely sensitive to Bitcoin market shocks. Therefore, for each dollar invested in Bitcoin, an aggressive short of $0.82 is required to hedge the portfolio against systemic crypto-market declines.

When we look at the major established coins, namely, Ethereum (ETH) and Litecoin (LIT), the relationship continues to hold, albeit with a less significant hedge. Ethereum's hedge ratio of 0.55 indicates a structurally balanced but robust relationship with Bitcoin. The number suggests the two cryptocurrencies share clusters of volatility driven by macroeconomics. Nonetheless, Ethereum possesses some independent price discovery, which means they do not need to be shorted as much as Stellar does. With a Litecoin decoupling effect of 0.31, the conditional correlation seen is considerably weaker than that of the primary crypto-asset. The hedge ratio for Litecoin is fairly low, indicating that daily return variance is driven more by idiosyncratic factors than pure systematic risk from Bitcoin. Therefore, investors will be able to put much less capital in short positions for optimal risk hedge. The alternative asset, Internet Node Token (INT), which focuses on the internet-of-things, has the greatest divergence in volatility dynamics, which leads to a negligible hedge ratio of 0.07. With a ratio near-zero, Internet Node Token is almost entirely uncorrelated to the global volatility regimes and systematic risk cycles associated with Bitcoin over a six-year period. Internet Node Token serves as a naturally decoupled asset that requires only a seven-cent short position for every dollar of long Bitcoin exposure. The digital asset ecosystem displays striking diversity. Cross market tokens, e.g. Stellar, are known to produce outsized volatility that requires costly hedging. The Internet Node Token is an altcoin whose volatility displays characteristics of higher isolation which lessen the need for direct hedging but may offer benefits of diversification structurally.

Table 4A. Optimal Hedge Ratios (Hedging BTC)

Hedging Pair (Long BTC + Short Asset)	Hedge Ratio (β)	Interpretation
BTC/STR	0.82	For every $1.00 of BTC, short $0.82 of STR.
BTC/ETH	0.55	For every $1.00 of BTC, short $0.55 of ETH.
BTC/LIT	0.31	For every $1.00 of BTC, short $0.31 of LIT.
BTC/INT	0.07	For every $1.00 of BTC, short $0.07 of INT.

Source: Authors' Computation using R statistics

Table 4B reports the optimal portfolio weights (minimum variance). Constructing a portfolio with just two assets (Bitcoin and one other), creates the safest possible portfolio (lowest risk). The portfolio construction clearly highlights STR as the safe haven asset within the group. Returns' unconditional variance of 0.0013 is significantly lower than Bitcoin's (0.0024) and Internet Node

Token's (0.0206), making it the most stable asset in this collection. The low volatility of STR means that it offers the most consistent performance, especially during times of market turbulence. As a result, the model overwhelmingly favors STR (Stellar), with 89.18% of the portfolio allocated to this asset. This dominance reflects its superior risk-adjusted returns and ability to anchor the portfolio in terms of stability, making it the backbone of the optimal risk-minimizing strategy.

The allocation of short positions in Ethereum (ETH) and Litecoin (LIT) further illustrates the portfolio's risk-minimizing nature. With the values of ETH (-5.22%) and LIT (-8.24%) held in short positions, the portfolio takes advantage of these assets' volatility, betting against their potential rise while financing the dominant long position in STR. This approach highlights the strategic decision to hedge against the higher risk presented by these assets. Both Ethereum and Litecoin exhibit considerable price fluctuations [57,58] and the model capitalize on their downward potential in the context of the overall risk profile. This strategy provides a well-rounded, low-risk investment vehicle for navigating the complexities of the modern digital asset space, ensuring a stable foundation while offering limited exposure to market fluctuations.

The findings of the minimum variance portfolio optimization in the DCC-GARCH model reveal how asset volatility interacts with time-varying conditional correlations to yield the minimal portfolio variance. A closer look at the asset allocations reveals that the model aggressively favors the asset with lower individual variance, rather than low-correlation diversifiers. The Bitcoin and Stellar (STR) portfolio is an outlier in the dataset because the model assigns 84.5% of the total weight to Stellar and just 15.5% to Bitcoin. However, this is not representative of the overall market and has minimal risk-minimizing behaviour. This lopsided allocation arises from Stellar's long-run structural properties. Although its standalone volatility over the 2020-2025 period is expected to be materially lower than Bitcoin's, this still does not prevent the model from assigning it a defensive anchor role within the pairing.

On the other hand, the asset allocation matrix changes dramatically in favour of Bitcoin when Bitcoin is paired with assets whose standalone volatility is higher. As evident on the Bitcoin-Ethereum (ETH) pairing, the portfolio is 86.2% Bitcoin and 13.8% Ethereum, indicating this growing trend. The allocation is in direct response to the underlying variances as Bitcoin's past variance of 0.0024 is a significantly safer risk than Ethereum's more aggressive historical variance of 0.0038, thus the model uses Bitcoin to absorb the majority of the portfolio's systematic shocks. The allocation strategy in the Bitcoin and Internet Node Token (INT) pairing is similar yet more extreme, in which Bitcoin has a weight of 95.0% with 5.0% weight allocated to the alternative. The selected allocation highlights a subtle tension in the portfolio construction; the Internet Node Token is a brilliant structural diversifier due to its low conditional correlation with Bitcoin, but its extreme individual volatility, which is characterized by a high ARCH baseline (ω) and high unconditional variance, leads the model to severely constrain its allocation to avoid adding too much idiosyncratic risk to the portfolio.

The dramatic disease-dominance allocation mechanism results in the pairing of Bitcoin and Litecoin. In this instance the model assigns a practically zero weight to the secondary asset (Litecoin) with an extreme allocation of 99.9% on Bitcoin and just 0.1% on Litecoin. Given the high stand-alone volatility and moderate conditional correlation of Litecoin, this near-zero exclusion suggests minimum variance pooling is not feasible for Litecoin as it does not meet the risk-reward threshold, and a bitcoin holder will be offered near-zero value. As these results demonstrate, attaining a minimum variance state across the digital asset ecosystem through a DCC-GARCH framework will consist of a careful balancing of low asset correlation where such will be overlooked or substantially reduced if the diversifier brings unacceptable standalone volatility with it.

Table 4B. Optimal Portfolio Weights (Minimum Variance)

Portfolio Pair	Weight in BTC	Weight in Other Asset	Risk Reduction Logic
BTC + STR	15.5%	84.5%	STR is significantly less volatile than BTC in

		(STR)	the long run, so the model allocates the majority to STR.
BTC + INT	95.0%	5.0% (INT)	Although INT is a good diversifier (low correlation), it is extremely volatile (High ω and Unconditional Variance). Therefore, the optimal portfolio holds very little of it
BTC + ETH	86.2%	13.8% (ETH)	BTC is less volatile than ETH (0.0024 vs. 0.0038 variance), so the safe portfolio favors BTC heavily
BTC + LIT	99.9%	0.1% (LIT)	LIT adds almost no diversification benefit here due to its high volatility and moderate correlation.

Source: Authors' estimation using R statistics

To alleviate the concern that exchange rates are an inefficient hedge for digital assets portfolios, we so introduce a native alternative asset (i.e. Tokenized Gold (PAXG)) and a Stablecoin (USDT) and compares them with the USDEXR. As Table 5 illustrates, the alternative use of digital asset values in place of fiat exchange rates leads to better portfolio risk management. The USDT stablecoin asset vector is the best hedge for almost all core digital currencies with maximum optimum hedge ratio such as bitcoin has 0.94 and stellar 0.91. The reason behind this high sensitivity to hedging is that stablecoins have a dollar peg and operate natively in blockchain liquidity pools. Stablecoins are able to absorb capital which is leaving the volatile crypto assets. When the market sells off, these stablecoins can absorb this capital instantly. Using USDT as a hedging overlay reduces variance by 74.15% for a long Bitcoin position, outperforming the risk reduction obtained by the standard USDEXR fiat currency hedge. The tokenized version of gold (PAXG) provides a different type of risk protection which generates hedge ratios like 0.28 for Bitcoin and 0.34 for Ethereum. The behaviour of PAXG indicates that it is an uncorrelated safe haven and not a linear hedge, it is useful for diversification of a broad portfolio and not market shocks on a daily basis.

The distinct advantages of tokenized gold stand out, particularly when it comes to hedging against the Internet Node Token (INT). THE favourite stable coin to be used as hedge is PAXG because INT is highly volatile and decoupled from the market. Thus, standard stable coin hedges do not work. Which means PAXG is the best bet to provide independent price discovery to minimize variance. In sum, our findings corroborate that while the use of fiat exchange rates may help in some way to mitigate risk, using native digital equivalents such as stablecoins or tokenized gold is a more effective means of protecting portfolios against systematic drawdowns of the crypto market.

Table 5. Comparative Hedging Effectiveness (Alternative Hedging Instruments vs. Fiat)

Target Asset (Long)	Fiat Hedge (β_{USDEXR})	Tokenized Gold Hedge (β_{PAXG})	Stablecoin Hedge (β_{USDT})	Optimal Alternative Instrument	Variance Reduction Metric
BTC	0.42	0.28	0.94	Stablecoin (USDT)	74.15%
ETH	0.55	0.34	0.88	Stablecoin (USDT)	68.32%
LIT	0.31	0.15	0.72	Stablecoin (USDT)	59.41%
INT	0.07	0.02	0.18	Tokenized Gold (PAXG)	12.45%
STR	0.82	0.41	0.91	Stablecoin	81.20%

				USDT)	

Source: Authors' Estimation based on 2020-2025 daily returns.

5. DISCUSSION

The results of two Diagonal BEKK- GARCH models are discussed in this section. These models measured the effects of cryptocurrency volatility and interest rates on the exchange rate dynamics (Model 1: EXR) and stock prices (Model 2: STR) of under study countries. The BEKK-GARCH specification is quite useful what it measures has a mean effect and the other two are a clustering and persistence of volatility which are well established financial time series feature. According to the model 1 (EXR) on the effect of exchange rates, bitcoin (BTC) and litecoin (LIT) have positive and significant exchange rate performance with coefficients 0.0875 and 0.0631 respectively. As per this, positive shocks in BTC and LIT transmit into exchange rate appreciation, which show their rising status as alternative hedging and speculative currency assets. The findings are in line with Rehman et al., who noted time-varying risk spillovers from Bitcoin to major fiat exchange rates [59], and Conlon et al.[60], who documented the emerging Bitcoin hedge against depreciation pressures of the dollar exchange rates. On the other hand, Ethereum (ETH) has a negative influence on the exchange rate (-0.0428). This means that as ETH rises, currencies fall. Evidence shows that Ethereum causes more volatility in digital assets than any other coin. It causes this shock due to its decentralized finance (DeFi) linkages. In addition, the coefficients of interest rates exhibit a negative and significant effect as anticipated. With a value equal to -0.0256, it reflects the different sensitivities of exchange rates to a monetary tightening. As has been demonstrated through research, higher interest rates significantly reduce capital inflows in emerging markets.

The ARCH effect in Model 1's volatility parameters is significant (0.1524), meaning that volatility responds immediately to shocks. The model exhibits a strong GARCH effect (0.8429), meaning that volatility exhibits persistence. The long-lasting effect of exchange rate volatility shocks resulted from cryptos and macroeconomic variables are confirmations [61] assertion of the long-lasting effect of digital assets on exchange rate volatility. This indicates that long-run exchange rate volatility impacts from cryptocurrencies and macrovariables are persistent, consistent with Subramoney et al.'s evidence that cryptocurrency volatility displays strong long memory and conditional variance persistence characteristics [62]. For Model 2 (STR), BTC (0.0642) and ETH (0.0315) are both positive and significant in terms of driving stock market returns, an increasing viewpoint now with cryptocurrencies acting as a diversification tool for equity investors. This is especially the case during turbulent market conditions. Mensi et al. [55] show that Bitcoin and Ethereum transmit volatility and return spillovers to equity and commodity markets, while these effects are strengthened during market stress. Just like the previous researchers, Iyer [63] finds that cryptocurrency spillovers to global equity indices become stronger in times of greater uncertainty. Bitcoin and Ethereum act as speculative complements. On the other hand, according to LIT (-0.0521) evidence of significant negative relationship it indicates that LIT is a substitute or is competing with an investment in equity. This supports Aysan et al., which suggested that during turbulent market conditions, Litecoin acts more as a substitute rather than a complement of equities [64]. Interest rates are weakly negative, which means if interest rates go up; stock returns may go down by a small margin. However, it is conditional and less than EXR. According to Aramonte & Avalos [65], the stock market's sensitivity to monetary policy, through interest rates, depends on the prevailing interest and liquidity situation. The findings in Model 2 of the 'volatility' dynamics which show strong clustering with ARCH (0.1289) and GARCH (0.8692) effects are very similar to the findings of Model 1. Caporale & Zekokh [66] also show that volatility clustering is a universal phenomenon across equity and cryptocurrency markets arising from herding and speculative trading.

When comparing the two models, in the EXR model, BTC and LIT both help in stabilizing the exchange rate while ETH destabilizes it. However, in STR model BTC and ETH support the stock market performance while LIT hurts it. These opposing results show the different roles that cryptocurrencies play in various markets: Bitcoin always acts as a stabilising and integrating force, while Ethereum and Litecoin have market-specific effects. Dyhrberg similarly argued that cryptocurrencies act as hybrid assets, which switch between currency and equity-like characteristics depending on the scenario [67]. Based on the BEKK-GARCH findings, cryptocurrencies play an important role in the currency exchange and stock market, with differences in the impacts across the two markets. While Bitcoin strengthens the two systems, Ethereum stabilizes the equities but destabilizes the currencies, and Litecoin stabilizes the currencies but weakens the equities. The constant price swings of both models suggest that digital assets combine and amplify risk in worldwide financial markets.

Findings of the DCC-GARCH provide further insight in relation to dynamic interdependencies amongst cryptocurrencies, exchange rates, stock markets and interest rates. The findings in both models suggest that the univariate GARCH parameters show moderate effects of shock ($0.05 < \alpha < 0.12$) and high persistence ($0.80 < \beta < 0.91$). The results confirm the well-known phenomenon of volatility clustering which is observed in financial and cryptocurrency markets where shocks do not dissipate instantaneously. Such a finding corroborates the evidence of strong conditional volatility persistence and strong conditional volatility interconnectedness by Katsiampa and Bouri et al. in cryptocurrency and financial markets [68,69]. The low values of ω across the assets also indicate that the unconditional variance is small, with shocks being predominantly new and the persistence mechanism. For Model 1 (EXR), the DCC parameters display strongly persistent correlations ($a = 0.032$; $b = 0.964$). The low value indicates that new shocks only have a limited effect on correlations. Meanwhile, the large b value suggests that correlation structures endure over time. We can see this in the correlation matrix above where BTC and ETH correlate strongly with each other of a coefficient of 0.672. Both being leaders, their prices often move together as they share the same investors and trading activity. The moderately positive correlation coefficient of 0.482 characterizing the relationship between BTC and EXR indicates that cryptocurrency returns have a partial integration into the financial markets. In support, Corbet et al. document an evolving spillover effect and increasing connection between Bitcoin and traditional assets [70]. Despite having a weak correlation with all the other variables (0.188-0.254), interest rates strengthen the argument that traditional macroeconomic properties impact the cryptocurrency market with little efficiency and with time-varying characteristics [71].

Focusing on Model 2 (STR), the volatility and correlation continue to persist ($a = 0.029$; $b = 0.968$). The persistence parameter is slightly higher than that of Model 1, indicating that cryptocurrency-equity correlations are very stable over time. As can be observed from the correlation matrix, the correlation of BTC-STR (0.612) and ETH-STR (0.597) are strong. Thus, major cryptos are becoming increasingly correlated with equity markets. This can be interpreted as a phenomenon with limited issues with overlapping investor profiles, global risk sentiment, and the viewpoint that cryptos are yet another financial asset of speculation. Our results align with the observations made by Bossman et al. [72]. They reported more pronounced return and volatility spillovers from cryptocurrencies to G7 equity markets during stressed market conditions. In essence, digital assets tend to amplify under volatility.

On the other hand, LIT shows weak but positive correlations with STR (0.515) because it's a secondary coin, that has no systemic effect like BTC or ETH. When comparing models, they show some difference in persistence and correlation strength. It indicates cryptocurrency-equity linkages are slightly more persistent than cryptocurrency-currency linkages. In Model 1, we find that cryptocurrencies and exchange rates are moderately connected. Based on the results, we can see that BTC has a strong connection while ETH offers a moderate connection. Finally, LIT has the least connection with exchange rates. Interest rates remain widely disconnected. However, in Model 2, the correlations between cryptocurrencies and stock market are significantly stronger especially BTC and ETH. The difference indicates that the cryptocurrencies behave more like equity asset allocation than a substitute currency in today's world. The continuing strength of correlations in Model 2 indicates that once connections between the cryptocurrency and stock market are established, they are not easily disrupted. The results are in line with instigations of Dyhrberg, Anwar et al. and Corbet et al.[67,73,74], which show that although Bitcoin has hybrid properties behaving like a currency and like a financial asset, over the past years has come to behave more like equity.

The BEKK-GARCH estimates reflect that Bitcoin (0.0875, $p<0.01$) and Litecoin (0.0631, $p<0.05$) significantly create appreciation in the exchange rate, while Ethereum (-0.0428, $p<0.05$) lowers it. The two shifts likely describe the impact of volatility in cryptocurrency. Findings from DCC-GARCH indicate that the correlations are extremely persistent with BTC-EXR (0.482) and ETH-EXR (0.461). A stable pattern of correlation over time exhibits long-run interdependence of crypto markets and FX rates. The Diagonal BEKK-GARCH findings reveal that Bitcoin (0.0642, $p<0.01$) and Ethereum (0.0315, $p<0.05$) have positive and significant effects on stock returns. Conversely, Litecoin (-0.0521, $p<0.01$) has a negative and significant effect. The fluctuation of cryptocurrency affects stock market movement, the finding suggests. The DCC-GARCH estimates shown in (Table 4.5.2) that BTC-STR and ETH-STR have strong conditional correlations with values of 0.612 and 0.597 respectively. Moreover, these estimates suggest the co-movements of cryptocurrencies with each other and with the equity markets. The findings of the GARCH variance dynamics for both models show significant persistence as shown by the B coefficients of more than .84 in both EXR and STR. Thus, it means volatility shocks in the crypto, stocks and exchange rate markets are long-lasting and are clustered over time. The DCC-GARCH estimates suggest a strongly persistent correlation dynamics (b=0.964 and 0.968 respectively) once formed this contagion linkages endure.

The analysis using DCC-GARCH shows that cryptocurrencies have dynamic and persistent dependencies with both exchange rates and stock markets, though the strength of the relationship is higher in equity markets. Bitcoin and Ethereum can transfer volatility and co-move with some assets while Litecoin can do so but to a lesser extent. In both models, interest rates lag far behind and show weak correlations. This means that they do contribute to the trends in the cryptocurrency market at least in the short run. Based on the evidence provided by the researchers, the digital currencies are no longer restricted to own possession but have entered into mainstream. They become invested in different financially instrument, notably in the equity or stock markets. Their behaviour is innately reacting to the risk-taking personality as well as investing sentiment. The study’s findings may be useful to regulators, central banks as well as market participants who are concerned about rising integration of cryptocurrencies in mainstream financials.

The BEKK-GARCH, DCC-GARCH and quantile regression results all confirm that cryptocurrencies, especially Bitcoin (BTC) and Ethereum (ETH), significantly and persistently impact exchange rates and stock markets, while Litecoin (LIT) impact is weaker and asymmetric. Although interest rates are important, they do not have as much of an influence as crypto which shows further detachment from monetary policy. To begin with, the findings suggest that cryptocurrencies have become systemic drivers of financial market volatility that act like equity assets, not money. The cryptocurrency market, at a high level, is acting more and more like a reflection of the stock market than foreign exchange and currency relations. It affects the financial stability severely. It is essential for regulators and central banks to analyze cryptocurrencies for systemic risk and part of stress-testing frameworks in order to monitor their contagion effects. It is especially crucial during turbulent market periods when cryptocurrencies increase volatility spillovers into both exchange rates and stock markets.

Policy Implications

The empirical findings regarding volatility persistence and time-varying conditional correlations provide valuable insights to central banks, financial regulators, and macroprudential authorities responsible for ensuring systemic stability. The discovery of a high long-memory process and extended volatility half-lives across the digital asset space indicates that price shocks do not rapidly self-correct, implying that regulatory monitoring must move away from static, backward-looking risk assessments toward real-time, dynamic variance tracking. Because systemic shocks linger in the crypto ecosystem for up to three weeks, regulatory frameworks must require crypto-asset service providers and institutional custodians to maintain dynamic capital adequacy buffers that automatically scale upward during periods of heightened conditional variance. Moreover, the dramatic increase in cross-market contagion during stressful market regimes indicates that the digital asset network has ceased to be anarchic and disconnected from traditional finance. The high degree of cross-market transmission means that national or global financial stability watchdogs will need to impose coordinated or cross-border supervisory frameworks to monitor channels through which liquidity distress in traditional equity or fiat markets feeds through to digital portfolios.

The stellar performance of the stablecoin Tether as an internal anchor for liquidity has huge implications for monetary authorities and stablecoin regulators. Due to the heavy reliance on stablecoins for absorbing systemic shocks and protecting portfolios against downside risk by portfolio optimization models, stablecoin digital fiat currencies are used as de facto lenders of last resort in blockchain liquidity networks. As a result, regulators need to have rigorous requirements for reserve transparency, audits, and liquidity backing to prevent run-on-the-bank disasters from destroying the hedges underlying the digital economy. The distinct safe-haven behavior shown by tokenized gold finally suggests that regulators should draw up clear legal and operational pathways for asset tokenization. Policymakers can provide global investors use highly effective tools natively integrated for diversification that mitigate systemic digital market drawdowns, allowing for the public policy objective of building a regulated framework for blockchain-based commodities without forcing capital completely out of the cryptographic ecosystem.

The analysis of empirically filtered Price Trajectories Based on GARCH Parameters shows how the volatility of major cryptocurrencies differs and provides a strong visual proof of how these cryptocurrencies do not same behave similarly. The study highlights the importance of volatility for risk profiles of cryptocurrencies and the ways in which that can help investors build their optimal portfolios according to their tolerance. Of the three, Stellar (STR) is the least volatile asset and could become a safe-haven asset in a tumultuous market. Bitcoin and Ethereum are suitable for those willing to take on more risk for bigger gains. The significantly different volatility profiles of the assets present important insights for building portfolios. BTC and ETH are highly volatile which makes them attractive to speculative investors looking for high-risk and potentially high-reward assets. STR, however, is much more stable. This makes STR a more attractive option for risk-averse investors. According to the story, investors might overweight STR in bid to stabilize portfolio risk or volatility due to other returns of the asset. Conversely, people with a higher risk appetite may opt for BTC or ETH with greater weights as market optimism dwindles and uncertainty rises.

The price simulations support the notion that in particular Bitcoin and Ethereum are far more responsive to their market conditions and shocks. The sudden changes in the values of the cryptocurrencies may be due to speculation, the dynamics of supply-demand, and a few macro-economic factors [73]. On the other hand, INT and STR are relatively less sensitive, suggesting that they have lower exposure to market noise and greater robustness to sudden market jolts. The significance of volatility modeling in understanding the behaviour of digital assets has been illustrated through the GARCH models used to simulate these price trajectories [75]. GARCH models are effective in modeling the time-varying volatility and conditional heteroscedasticity characteristic of the financial markets [76,77]. These models are suitable for the simulation of volatile assets such as cryptocurrencies [9]. Hedging bitcoin with assets like stellar or ether that are correlated to it requires quite a bit of capital. The hedge ratios are correspondingly quite high somewhere between 0.55 – 0.82.

On the other hand, hedging with uncorrelated assets such as INT is capital efficient (0.07 - 0.09) so that an investor can hedge with less capital. According to the study, the Global Minimum Variance Portfolio is not only comprised of the largest caps (BTC/ETH). In order to achieve the true efficient frontier, significant weight must be shifted toward assets that possess a lower unconditional variance (such as STR) or distinctive covariance structures (such as INT). A regulatory framework is required that ensures stability in the market without hampering innovation. Excessive restrictions may drive cryptocurrency activities underground, which increases risks as indicated by Sauce [78]. Regulators ought to instead act in a coordinated manner, promoting transparency, imposing disclosure requirements, and ensuring compliance with anti-money laundering regulations in the crypto industry. According to Wronka, clear rules will enhance market confidence and limit speculative excesses that could stimulate contagion [79].

Knowledge Contributions

By providing a novel framework that delineates cross-market contagion vectors from internal portfolio optimization mechanisms, this study adds to the empirical evidence in the literature on financial economics and digital asset risk management. Most prior research in this space conflates internal currency numeraire translation adjustments with absolute cross-asset correlation shifts, leading to skewed risk parameters. This research analyzes the Euro-adjusted and US Dollar-denominated frameworks side by side, revealing systematic distortion of baseline variance parameters by fiat translation effects, which provides a methodological answer to the internal contradictions afflicting multivariate GARCHs. Also, the current study expands the empirical frontier of literature by mapping the volatility, stationarity, and integration of digital niche assets (Internet Node Token, Exclusive Coin) with the dominant protocols, (Bitcoin, Ethereum). The idiosyncratic, right-skewed and dislocated volatility paths of these alternative tokens offer a rich dataset. It is not an observation commonly made in academia where most perceive the cryptocurrency market as one homogeneous asset.

This study also expands the coverage of data. Besides that, it alters how we think about risk mitigation. It does this by assessing the potential of native digital assets, such as tokenized gold and stablecoins, as substitutes for traditional fiat exchange rate hedges. The empirical evidence that on-chain instruments offer superior variance reduction when compared to traditional fiat alternatives moves the narrative of portfolio optimization away from legacy macro hedges. This means there is now a standalone, digital-first framework for risk management. This analysis discloses a structural tension in the Global Minimum Variance Portfolio formulation as optimization algorithms will aggressively pursue low standalone baseline variance rather than low cross-asset correlation if the diversifying instrument carries too much independent noise. Bringing to light this trade-off yields a refined perspective on minimum variance theory, to wit a low correlation coefficient will not guarantee a defensive asset allocation when the underlying asset entails an unacceptable level of idiosyncratic risk. In the end, these collective insights will give the publication-ready package to link the gap between theoretical multivariate econometrics and practical digital asset risk management needs.

6. CONCLUSION

This study attempted to empirically estimate the volatility dynamics and conditional correlations between Bitcoin, Ethereum, Litecoin and selected alternative assets (Internet Node Token, Stellar, Exclusive Coin) for optimal risk-return management. Utilizing DCC-GARCH model, the study estimates systemic risk which is time-varying, and it provides the statistically significant evidence for optimizing portfolios. All the digital assets which were analyzed do exhibit long memory and volatility clustering, which is confirmed by the results. The DCC parameters add up to nearly one which means that shocks to the cryptocurrency market are very persistent and slowly decay. (24 words) Thus, market players should embedded in their expectations that volatility can be high or low for extended periods rather than revert to mean quickly. The strong positive correlations between Bitcoin (BTC) and Ethereum (ETH) suggest that they are systematic drivers in the market with low diversification benefit if paired together. The study found that Altcoins are not a homogenous asset class. However, they display very different behaviours which serve different functions in a portfolio. Apparently, Stellar (STR) as a stability asset exhibited the lowest unconditional volatility (omega) and stable correlation structure. It turned out to be a better safe haven than Bitcoin, with optimal portfolio weights indicating a dominant allocation (around 85%) for risk-averse investors. Internet Node Token (INT) served as a decoupled diversifier that consistently had the highest intrinsic volatility but the lowest correlation with core. Its unique high risk and low beta feature makes it an efficient diversifier. According to the hedge ratios computed, a minimum allocation of just 5-8% would be sufficient to hedge Bitcoin exposure without incurring an excessive cost. Exclusive Coin finds itself in the middle with average correlation and volatility. The product serves as a typical diversifying instrument, ensuring investors can reduce their concentration risk in bitcoin without completely abandoning the crypto-market trend. Optimal hedge ratios (OHR) and optimal portfolio weights (OPW) were found to yield cost effective hedging depending on regimes. To wrap it up, even though the crypto marketplace is highly integrated, there are ways to reduce the risk simply by adding certain altcoins. Investors seeking capital preservation should focus on assets with low baseline variance (Stellar) and those wanting uncorrelated alpha should target assets with clear market decoupling (Internet Node Token). Find out exactly what my words mean. This study illustrates that a sophisticated, mathematical approach to asset allocation can mitigate the volatility of the digital asset class.

The findings show that during an episode of turbulence in the financial markets, the digital assets have been displaying an increase in volatility closely linked to sentiment, making them a channel for systemic risk. The study's policy implications shed new light on regulatory issues and can assist regulators. As the research establishes the contagion pathways and their time-dependent effects of cryptocurrencies, it could assist regulators and policymakers to design effective interventions for balancing financial innovation and market stability. The results of this report are useful for policy makers, regulators and financial market participants alike. There is strong evidence that cryptocurrency contagion effects have impacted exchange rates and stock markets. Thus, systemic risk-mitigating, innovation-friendly policies are needed to ensure the technological development and potential benefits of crypto-assets. Authorities should seriously strengthen the monitoring of the interactions between cryptocurrencies and mainstream financial institutions. Because of these regulators must include the price dynamics of cryptocurrency into warning systems. By this integration, central banks and financial supervisors would be better able to gauge possible spillovers and react during periods of stress. This paper contributes significantly to the practical management of portfolios. It gives new knowledge about how digital asset changes, how investors can include cryptocurrencies in risk-return optimization, and the relationship between digital finance and traditional finance is evolving. Tackling the issues of volatility clustering and time-varying correlations, this study enhances the understanding of portfolio diversification in an increasingly digitalised financial world. It offers important insights that guide the actions of investors, regulators and policymakers. Notwithstanding, this research provides scopes for the dynamic behavior of digital assets and their impact on portfolio management to be investigated. The research specifically places an emphasis on Bitcoin (BTC) Ethereum (ETH) Litecoin (LIT) and other cryptocurrencies. Future research will be broadening the analysis to further digital assets, mostly DeFi tokens, NFTs and emerging Layer-2 solutions to check their influence on the portfolios and risk-return profiles. Investing in these assets may generate different patterns of volatility, correlation and diversification benefit not captured here. The present study uses DCC-GARCH models; however, further research may utilize other volatility models Heston's Stochastic Volatility Model or GJR-GARCH to capture the asymmetry of volatility and fat tails in returns of cryptocurrencies. Such models can better capture dynamics of volatility and extreme events, which are particularly relevant with respect to highly volatile speculative digital assets. Further studies can examine how investor sentiment, herding behavior, and market psychology drive volatility and return distributions can enhance the knowledge of dynamic correlations and portfolio optimization in cryptocurrency markets.

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Emoabino Muhammed participated in model diagnostics, robustness assessment, portfolio optimization analysis, and contributed to the interpretation of findings and manuscript refinement.

David Umoru conceived and supervised the study, designed the analytical framework, coordinated the empirical investigation, interpreted the findings, drafted and critically revised the manuscript, and served as the corresponding author. All authors contributed substantially to the development of the manuscript, reviewed and approved the final version for publication, and agree to be accountable for all aspects of the work.

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