

Gold-Backed Cryptocurrencies as Diversifiers and Hedging Instruments for NFTs, DeFi, and Traditional Cryptocurrencies: Insights from Dynamic GARCH-Copula Analysis

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Abstract

This study explores the role of gold-backed cryptocurrencies (PAXG and XAUT) as effective diversifiers, hedges, and safe havens for NFTs and DeFi assets, particularly during market crises such as the COVID-19 pandemic and the 2022 cryptocurrency crash. By employing a dynamic GARCH-copula approach, the research analyzes the interconnectedness and volatility spillovers between these digital asset classes, providing insights into their behavior during times of heightened uncertainty. We also compute the optimal hedge ratio for each gold-backed cryptocurrencies/stablecoins-NFT/DeFi/Traditional cryptocurrencies pair and evaluate their dynamic hedging effectiveness. The findings reveal that gold-backed cryptocurrencies offer superior hedging capabilities compared to stablecoins (USDT and BUSD), enhancing portfolio diversification and risk management. The results underscore the importance of incorporating gold-backed assets into digital portfolios to improve resilience and achieve better risk-adjusted returns during periods of market turmoil.

Keywords: *Gold-backed crypto, Dynamic effectiveness, Safe-haven, Global crises.*

Introduction

Over the past decade, cryptocurrencies have gained significant attention from the general public, media, investors, and policymakers. The rapid growth of blockchain technology and the introduction of various digital assets have increasingly attracted investors to financial markets. In this context, Decentralized Finance (DeFi) has emerged as a transformative system where financial assets and services are available on a public decentralized blockchain network. This innovation aims to eliminate intermediaries in financial transactions and enhance accessibility through the use of smart contracts (Schär, 2021; Corbet et al., 2022). DeFi relies on automated agreements and transactions, enabling self-execution and enforcement. By reducing dependence on traditional financial intermediaries, DeFi creates a financial ecosystem that is more accessible, transparent, and secure for individuals with internet access, regardless of their geographical or financial circumstances (Schär, 2021; Corbet et al., 2022). DeFi assets include a wide array of financial tools, ranging from cryptocurrencies like Bitcoin and Ethereum to stablecoins such as DAI and USDC, as well as decentralized platforms like exchanges (DEXs), lending and borrowing hubs (e.g., Aave, Compound), and insurance protocols (e.g., Nexus Mutual). These assets serve various functions, including facilitating lending and borrowing, engaging in speculation through derivatives, trading cryptocurrencies, hedging against risks, and earning interest through savings accounts (Dowling, 2021a,b; Ante, 2022; Alawadhi and Alshamli, 2022).

Non-Fungible Tokens (NFTs) represent unique virtual asset rights on the blockchain, encompassing distinct identities and information such as images, music, videos, coded virtual land, or trading cards (Schär, 2021; Dowling, 2021a,b; Ante, 2022; Alawadhi and Alshamli, 2022). Unlike conventional cryptocurrencies, NFTs are not interchangeable, with each token possessing a unique identity and characteristics (NFT Now, 2021; TechTarget, 2021). Their rapid rise in popularity is attributed to their ability to provide proof of ownership and authenticity for digital assets, thereby creating new opportunities for artists, musicians, and other creators to monetize their work (NFT Now, 2021; TechTarget, 2021). Despite being in its infancy, the NFT market has witnessed remarkable growth in trading volumes in recent years, often accompanied by significant profits (Karim et al., 2022; Corbet et al., 2022).

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From an academic perspective, research on NFTs and DeFi tokens remains limited. For instance, Aharon and Demir (2021) found that NFTs can offer diversification benefits during turbulent periods, such as the COVID-19 crisis and the market crash in March 2020. Dowling (2021a) documented a steady increase in NFT values, while Dowling (2021b) explored the correlation between NFT and cryptocurrency prices, revealing low volatility spillover effects. Juan et al. (2022) examined the relationship between DeFi token returns, traditional assets, and user-generated information, concluding that DeFi operates as a safe-haven asset. Karim et al. (2022) employed a quantile connectedness approach to investigate extreme risk transmission in blockchain markets, indicating that NFTs provide diverse channels for risk management. Ko et al. (2022) demonstrated that incorporating NFTs into traditional asset portfolios enhances the Sharpe ratio of both equally weighted and tangential portfolio strategies. As such, the diversification benefits of NFTs within traditional portfolios are well-established. Corbet et al. (2021) studied the presence of bubbles in DeFi-focused tokens, identifying key mechanisms that differentiate DeFi tokens from traditional cryptocurrencies. They concluded that the DeFi market represents a distinct asset class, advocating for the inclusion of DeFi assets in portfolios to enhance risk diversification. Yousaf and Yarovaya (2022a) calculated optimal weights, hedging ratios, and effectiveness for portfolios containing NFTs and DeFi assets, suggesting that investors should integrate these assets into traditional portfolios (e.g., gold, oil, and stock markets). Using the NARDL model, Zhang et al. (2022) examined the hedging and safe-haven capabilities of NFTs against traditional digital and financial assets, revealing that NFTs served as hedges prior to the COVID-19 pandemic and as safe havens during it.

Despite its rapid growth and market expansion, the prevalence of speculation and fraud in NFT trading is well-documented (Chalmers et al., 2022). Additionally, NFT pricing behavior appears to be susceptible to inconsistencies, bubbles, and sharp price fluctuations, which may be attributed to liquidity constraints inherent in the nascent NFT marketplaces (Horky et al., 2022). DeFi assets have similarly faced numerous instances of fraud and hacking (Grassi et al., 2022; Corbet et al., 2022). While Schär (2021) posits that DeFi can enhance the efficiency, transparency, and accessibility of financial infrastructure, various challenges—including risks related to smart contract execution, operational security, reliance on other protocols, and external data vulnerabilities—are also documented. Research by Maouchi et al. (2021), Corbet et al. (2021), and Wang et al. (2022) highlights the existence of financial bubbles in NFT and DeFi markets, while Xia et al. (2022) and Yousaf and Yarovaya (2022a) report significant volatility spillovers between NFT and DeFi tokens and traditional assets, particularly during crises.

Conversely, stablecoins can be viewed as alternatives to traditional cryptocurrencies (Wang et al., 2020). Unlike conventional cryptocurrencies, stablecoins aim to maintain a relatively stable value by pegging them to stable assets such as gold or the US Dollar. Gold-backed cryptocurrencies represent a prominent category of stablecoins. Researchers have examined these assets from an Islamic finance perspective (Alam et al., 2019; Adzimatunur et al., 2020; Aloui et al., 2021; Ncir et al., 2021; Ali et al., 2022). For instance, Díaz et al. (2023) explored stablecoins' ability to mitigate portfolio risk, demonstrating that both gold-backed and USD-backed stablecoins effectively diversify by reducing tail risk. Mnif et al. (2022) assessed the efficiency of gold-backed cryptocurrency markets, revealing that this market is the most efficient in the long term, while Bitcoin is only efficient in the short term. Ncir et al. (2021) found that gold-backed cryptocurrencies are less risky than Bitcoin and other stablecoins, exhibiting greater stability during the COVID-19 crisis. Wang et al. (2020) compared the diversification, hedging, and safe-haven attributes of stablecoins against conventional cryptocurrencies, suggesting that stablecoins may act as safe havens in certain scenarios and serve as efficient diversifiers in stable market conditions. However, gold-backed stablecoins underperformed USD-backed stablecoins as safe havens, although both assets surpassed their underlying assets in mitigating severe losses.

In reviewing the literature on cryptocurrencies, it becomes apparent that the dynamic analysis of relationships among NFTs, DeFi, and other asset classes requires further exploration to enhance understanding of these interconnections. This research seeks to address this knowledge gap by examining the interactions and diversification potential of stablecoins in relation to NFTs and DeFi assets. Specifically, it aims to determine whether gold-backed cryptocurrencies can assist investors in reducing portfolio volatility and hedging against bear markets. Gold-backed stablecoins differ notably from standard

cryptocurrencies, serving as efficient stores of value, reliable units of account, and mediums of exchange (Wang et al., 2020). This paper investigates the role of gold-backed cryptocurrency assets and/or stablecoins as diversifiers, hedges, and safe havens for NFT and DeFi tokens over the period from September, 2019, to September, 2023, which includes the disruptive phases of the COVID-19 pandemic, the escalating tensions of the Russia-Ukraine conflict, the Terra and Luna crash in May 2022, and the FTX collapse in November 2022. We first analyze the dynamic interconnectedness between gold-backed cryptocurrencies and NFT and DeFi assets using a dynamic GARCH-copula approach, followed by the calculation of optimal hedging ratios and effectiveness.

Our research contributes to the understanding of the cryptocurrency landscape in three significant ways. First, it explores the role of gold-backed cryptocurrencies as effective diversifiers, hedges, and safe havens for NFTs and DeFi assets, filling a notable gap in the existing literature. Second, by employing a dynamic GARCH-copula method, the study provides valuable insights into the interconnectedness and volatility spillovers between these digital asset classes during periods of market turmoil, thereby enhancing our comprehension of their behavior under stress. Lastly, the findings offer practical implications for investors, showcasing how the integration of gold-backed cryptocurrencies into portfolios can improve risk management and diversification strategies, ultimately leading to better risk-adjusted returns.

The analysis reveals that gold-backed cryptocurrencies (PAXG and XAUT) play a crucial role as effective hedging instruments for various digital assets, including NFTs and DeFi tokens, particularly during periods of market turbulence such as the COVID-19 pandemic and the 2022 cryptocurrency market crash. These assets provide a more stable and reliable hedge compared to stablecoins (USDT and BUSD), which, despite their consistent value, exhibit lower hedging capacity during crises. The findings indicate that PAXG and XAUT can significantly mitigate risks, making them strong safe-haven assets for portfolios in times of heightened market uncertainty, whereas stablecoins often show increased volatility and less effectiveness as protective instruments.

The remainder of the paper is structured as follows: Section 2 provides a literature review, while Section 3 outlines the methodology. Section 4 presents the data along with descriptive statistics. Empirical results are discussed in Section 5, followed by a discussion in Section 6, and the paper concludes in Section 7.

Literature Review

Numerous researchers have extensively explored the hedging and safe-haven characteristics of both emerging and traditional crypto-assets, such as Bitcoin and NFTs, when compared to other assets like stock indices and crude oil. For instance, Klein et al. (2018) analyzed and contrasted the conditional variance characteristics of gold, Bitcoin, and other assets, revealing significant differences between them. Utilizing a BEKK-GARCH model, they demonstrated that gold serves as a flight-to-quality asset in times of market turbulence. Conversely, they found Bitcoin to be positively correlated with declining markets. Similarly, Mensi et al. (2019) indicated that portfolios incorporating cryptocurrencies like Bitcoin, Monero, and Litecoin provide superior diversification benefits for investors and portfolio managers. Wang et al. (2019) concluded that while cryptocurrency can act as a safe haven, it generally does not function as a hedge for most stock markets, with this safe-haven trait being more evident in developed economies.

Le et al. (2021) explored the frequency-based dependency networks of financial assets, focusing on the tails of return distributions. Their findings show an increase in network density in both the upper and lower return distribution tails, with the Covid-19 pandemic amplifying these effects. Notably, they documented a heightened cross-asset tail-dependency between currency, equity, and commodity markets, particularly in the left tails, suggesting intensified contagion during downturns. Wang et al. (2020) investigated the safe-haven, hedging, and diversification properties of stablecoins versus conventional digital currencies, finding that USD-pegged stablecoins perform better than gold-pegged ones, especially in terms of risk reduction. Aloui et al. (2021) analyzed the impact of geopolitical risk on both conventional and Islamic gold-backed cryptocurrencies using an M-GARCH model, revealing distinct behavior in Islamic gold-backed cryptocurrencies and increased connectedness to gold's volatility and returns due to geopolitical tensions.

Further, Bouri et al. (2020) assessed the hedging and safe-haven roles of Bitcoin and gold relative to G7 stock markets, determining that gold offers more stable diversification benefits than Bitcoin across these indices, with Bitcoin only assuming such properties in the Canadian market. Jalan et al. (2021) evaluated the performance of five gold-backed stablecoins during the Covid-19 pandemic, comparing them to Bitcoin, Tether, and gold. They reported that gold-backed cryptocurrencies exhibited volatility akin to Bitcoin during the pandemic, with gold markets transmitting volatility to these assets. Wasiuzzaman and Rahman (2021) observed minimal increases in the returns of gold-backed cryptocurrencies during the Covid-19 crisis and the 2020 bear market, while PAX Gold showed heightened, though statistically insignificant, volatility during this period.

Belguith et al. (2024) investigates whether gold-backed cryptocurrencies can serve as dynamic hedges and safe havens against decentralized finance (DeFi) and non-fungible token (NFT) assets. The study examines the potential of gold-backed cryptocurrencies to mitigate risks and provide stability in the face of high volatility and market stress in the DeFi and NFT markets. The main results indicate that gold-backed cryptocurrencies exhibit some hedging and safe-haven properties, particularly during periods of extreme volatility in the DeFi and NFT markets, providing potential diversification benefits to investors.

Jareno et al. (2021) explored the asymmetric and nonlinear interdependencies between cryptocurrencies and oil price shocks, highlighting that demand shocks significantly influence cryptocurrencies, particularly during turbulent times. Dowling (2022a) investigated the relationship between NFT and cryptocurrency prices, concluding that limited volatility transmission between these assets implies that NFTs may serve as low-correlation assets, distinct from traditional cryptocurrencies. Additionally, Bedowska-Sójka and Kliber (2022) demonstrated that stablecoins provide the best hedge against oil price declines but do not reduce investment volatility. Maouchi et al. (2022) identified overlapping financial bubbles in NFTs and DeFi tokens during the Covid-19 pandemic, with fewer high-magnitude bubbles compared to other crypto-assets. They also found that the frequency of bubbles increased with the onset of the pandemic.

Mokni et al. (2022) examined whether cryptocurrencies and gold served as safe havens or hedges against economic policy uncertainty before and during the Covid-19 crisis. They determined that neither gold nor cryptocurrencies fulfilled these roles during the pandemic. Dunbar and Owusu-Amoako (2022) found that equity returns influence cryptocurrency prices, and equities became more negatively correlated with cryptocurrencies during the pandemic, suggesting that equities could serve as a hedge against cryptocurrency risks. Using rolling window regressions, they showed that equity risk premiums reduced downside risks during crises like the Covid-19 pandemic. Gadi and Sicilia (2022) analyzed the safe-haven and diversification characteristics of cryptocurrencies in G7 and BRICS regions during the pandemic, concluding that stablecoins retained hedging properties, particularly in stock markets, while Bitcoin's investment characteristics shifted after the pandemic's onset. Shahzad et al. (2022) identified that the Japanese yen acts as an effective hedge for digital currencies, with the yen, euro, and yuan maintaining safe-haven properties during cryptocurrency market downturns.

Díaz et al. (2023) assessed the ability of stablecoins to mitigate downside risk in cryptocurrency portfolios, demonstrating that dollar-backed stablecoins function as effective hedges, with strong diversification potential. Khaki et al. (2023) revisited cryptocurrency portfolio diversification, concluding that adding more digital currencies only offers marginal benefits due to substantial co-movement among them. Finally, Nedved and Kristoufek (2023) revealed that stock markets generally move in tandem with Bitcoin, while gold and crude oil maintain their status as safe-haven assets, with gold being a particularly strong safe haven for Bitcoin.

From a methodological perspective, researchers have increasingly turned to advanced econometric models to examine the connections between cryptocurrencies and other assets. Burnie (2018) applied correlation network methods to identify factors influencing cryptocurrency price evolution, finding positive relationships among cryptocurrencies except for USD Tether. Ho et al. (2020) used network analysis to study the dynamic evolution of 120 cryptocurrencies from 2013 to 2020, showing increased cross-returns post-2016, particularly for cryptocurrencies used in blockchain applications. Giudici and Polinesi (2021) scrutinized the price dynamics of cryptocurrencies and their interactions with traditional assets, finding that

volatility in traditional assets influences, but does not directly affect, Bitcoin prices. Similarly, Nie (2022) employed network methods to analyze correlation dynamics in cryptocurrency markets, finding substantial fluctuations near significant events.

Caferra et al. (2022) used quantile-based approaches to predict Bitcoin returns, reporting the effectiveness of several connectivity measures in forecasting price spikes and downturns. Briola and Aste (2022) examined cross-correlations among 25 liquid cryptocurrencies at various time intervals, documenting decreasing correlations for shorter time resolutions and an increasing framework for coarser resolutions. Jing and Rocha (2023) employed network-based portfolios of cryptocurrencies and applied Markowitz's portfolio theory, showing that their portfolios, consisting of 46 cryptocurrencies, outperformed benchmarks for short-term investments. Ma et al. (2023) explored the potential of crypto tokens to enhance portfolio performance, noting that tokens with high Sharpe ratios but low centrality in network analysis can improve returns.

Borri (2019) estimated tail risk in cryptocurrency markets using CoVaR, showing that while cryptocurrency returns are highly correlated, idiosyncratic risks can be mitigated, resulting in superior risk-adjusted returns compared to individual cryptocurrencies. Canh et al. (2019) studied volatility spillovers in cryptocurrency markets, identifying structural breaks and shifts in market capitalization from smaller to larger cryptocurrencies. Opala et al. (2022) used extreme value theory to assess the risks of Ethereum, Bitcoin, and Litecoin, demonstrating that short time series may not fully capture highly volatile market phases. Ahn (2022) investigated tail dependence between cryptocurrencies and the S&P500, revealing that downward tail correlations are stronger than upward ones.

Finally, Umar et al. (2022) analyzed NFTs' hedging properties using CoVaR, indicating their potential in all market conditions, while Bouteska et al. (2023) examined the impact of the Covid-19 pandemic on cryptocurrency volatility, revealing return-volatility spillovers among Dash, Bitcoin, and Stellar, with Monero as the primary shock transmitter. Fang et al. (2023) used CoVaR and MES to forecast systemic risk in cryptocurrency markets, identifying specific cryptocurrencies that better predict systemic risk. Similarly, Jalan and Matkovskyy (2023) found that the cryptocurrency market exhibits little liquidity change during crises. Lastly, Borges and Neves (2020) applied machine learning methods to establish cryptocurrency trading strategies, outperforming traditional buy-and-hold strategies, while Ramkumar (2021) showed that cointegrated portfolio pairs maximize returns.

This review provides a comprehensive overview of recent methodologies and findings regarding the interconnections, hedging features, and portfolio diversification benefits of cryptocurrencies and related assets, particularly during the Covid-19 pandemic.

Research Design

Time-varying Student's t-copula

Let's consider a d dimensional distribution copula function C_t on $[0,1]^d$ with standard uniform marginal distribution. As an extension of Sklar's theorem, the bivariate conditional cumulative distribution function of random vectors $X = (X_1, \dots, X_d)$ is defined as:

$$C(u) = C(u_1, \dots, u_d) = F(F_1^{-1}(u_1), \dots, F_d^{-1}(u_d))$$

With F_i^{-1} is a quantile function of the margins. Among several types, two copulas have been used, in particular the Gaussian and t-Student. The latter was chosen for the reason that it allows for joint fat tails and an increased likelihood of joint extreme events.

The Student's t copula is written as

$$C(u, v | \rho, \nu) = \int_{-\infty}^{t_v^{-1}} \int_{-\infty}^{t_u^{-1}(\nu)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left\{ 1 + \frac{x^2 - 2\rho xy + y^2}{\nu(1-\rho^2)} \right\}^{-\frac{(\nu+2)}{2}}$$

with

ρ, ν : are the copula parameters

t_v^{-1} : is the inverse of the standard univariate student's t-distribution with ν is the freedom degrees.

u, v : are two random variables following the uniform distribution which obtained from the cumulative distribution of the two standardized residuals time series

Optimal hedging strategy

We investigate the hedging and safe-haven properties of Backed-gold and stable coins for the traditional cryptocurrencies, NFTs and DeFis. The time-varying dependency coefficients are used to calculate daily optimum weights, hedging ratios, and the efficacy of all portfolio mixes for proving how the traditional cryptocurrencies as well as NFTs and DeFIS-related risk can be effectively hedged. The optimal cryptocurrency portfolio weights at time t ($w_{C,H,t}$) is formulated according to Kroner and Ng (1998):

$$w_{C,H,t} = \frac{h_{H,t} - h_{C,H,t}}{h_{C,t} - 2h_{C,H,t} + h_{H,t}}$$

And 0; if $w_{C,H,t} < 0$

$$w_{C,H,t} = \begin{cases} w_{C,H,t}; & \text{if } 0 \leq w_{C,H,t} \leq 1 \\ 1; & \text{if } w_{C,H,t} > 0 \end{cases}$$

1; if $w_{C,H,t} > 0$

where $h_{H,t}$, $h_{C,t}$, and $h_{C,H,t}$ refer to the time-varying variance of the backed-gold cryptocurrencies (PAXG, XAUT) or stable coins (USDT, BUSD) returns, $h_{C,t}$ the time-varying variance of the traditional cryptocurrencies, NFTs and/or DeFis return, and the time-varying covariance between the portfolio digital cryptocurrencies. $h_{C,H,t}$. To reduce the risk of investing in traditional cryptocurrencies, the investor should take an acceptable position on the gold-backed cryptocurrencies/stable coins. The same steps are replicated for NFTs and DeFis. The long position (buying) of one dollar on the traditional cryptocurrencies, NFTs and DeFi assets (C) should be hedged by a short position (selling) of $\beta_{C,H,t}$ dollars on the gold-backed cryptocurrency or stable coins (H).

According to Kroner and Sultan (1993), the optimal hedge ratio is computed as the time-varying covariance between the returns of hedging assets and NFTs and DeFis assets $h_{C,H,t}$, to the variance of the returns of hedging assets, $h_{H,t}$, at time t:

$$\beta_{C,H,t} = \frac{h_{C,H,t}}{h_{H,t}}$$

We next assess each pair's hedging efficiency to help identify the hedging capabilities of gold-backed crypto assets. The hedging effectiveness (HE) index is defined as:

$$HE = \frac{\text{var}(unhedged) - \text{var}(hedged)}{\text{var}(unhedged)}$$

where $\text{var}(unhedged)$ and $\text{var}(hedged)$ refer to the variance of the hedged portfolio and the variance of the unhedged portfolio, respectively. A higher HE index indicates higher hedging effectiveness and a larger risk reduction.

Data

This section presents the dataset used, and the econometric methodology followed to analyse the financial properties of GBCs. Our empirical strategy can be summarized in three main steps: First, we extract the time-varying conditional volatility of each gold-backed cryptocurrency and each traditional cryptocurrency, DeFi token and NFT using multivariate GARCH-classes of models. Second, using time-varying Copula-GARCH approach, we estimate dynamic structure dependencies of each GBC/Stablecoins-Different crypto classes pair. Then, we follow Baur and McDermott (2010) and Baur and Lucey (2010) approaches to define and test the GBCs as well as the two stablecoins BUSD and USDT hedge, and safe haven properties against the three categories of digital assets, and consider the effect of different types of internal and external shocks to the digital assets markets on the GBCs' financial properties. Finally, we compute hedge ratios and evaluate hedging effectiveness (HE) across various Gold-Backed Cryptocurrencies (GBC), digital assets, and stablecoin pairs. Based on these findings, we offer strategic recommendations to investors and other market participants for optimizing portfolio risk management.

We collect closing prices over the period spanning from 29 September 2019 to 13 September 2023 for 17 crypto assets grouped into four categories:

- Two gold-backed cryptocurrencies (GBC): PAX Gold [PAXG], and Tether Gold Token [XAUT].
- Four traditional cryptocurrencies: Dogecoin [Doge], Internet Computer Protocol [ICP], Polkadot [DOT], and Baby Doge coin [BABYDOGE].
- Seven NFTs: Elon Doge [ELON], Shiba Inu [SHIB], Theta Network [THETA], Axie Infinity [AXS], Bored Ape [APE], The Sandbox [SAND], and Decentraland [MANA].
- Four DeFi tokens: ChainLink [LINK], Filecoin [FIL], Fantom [FTM], and The Graph [GRT].
- Two stablecoins: BUSD and USDT: USD and USDT are both stablecoins, but they are issued by different entities and have different underlying structures.

BUSD, or Binance USD, is a stablecoin issued by Binance, one of the largest cryptocurrency exchanges in the world. It is pegged to the value of the US dollar on a 1:1 basis, meaning that 1 BUSD is intended to always be worth 1 US dollar. BUSD is built on the Binance Chain and the BEP-2 token standard. USDT, or Tether, is also a stablecoin that is pegged to the US dollar. It is issued by Tether Limited, a company closely associated with the Bitfinex exchange. USDT is one of the most widely used stablecoins in the cryptocurrency ecosystem and is available on several different blockchains, including Ethereum (ERC-20), Tron (TRC-20), and others. While both BUSD and USDT serve the purpose of providing a stable value in the volatile cryptocurrency market, some users may have preferences for one over the other based on factors such as issuer reputation, blockchain compatibility, and availability on different exchanges. The data has been retrieved from coinmarketcap.com. The selection of the coins and tokens is based on the market capitalization by class category and data availability. We refer the reader to Table A2 for more details on the selected coins and categories. For GBC, the PAXG is ranked 82 in market cap and XAUT 212. We estimate GARCH-ADCC class of models on the return series calculated as the first difference of the logarithmic prices, (formule), where p_{it} is the price of the digital assets i at time t . Our sample period allows us to explore the financial properties of GBCs and their evolution...

The provided table summarizes key statistical measures such as mean, variance, skewness, kurtosis, Jarque-Bera, ERS, Q(20), and Q²(20) for various cryptocurrencies, while the figure illustrates the return series over time for these assets, spanning different periods. From a financial perspective, we observe that several cryptocurrencies (such as ELON, SHIB, and DOGE) exhibit significant volatility, as shown by their high variance values (e.g., 47.290 for ELON and 31.757 for DOGE). This reflects the erratic price movements of these assets in recent years, driven by market sentiment and speculative trading.

Table 1: Descriptive statistics

	Mean	Variance	Skewness	Kurtosis	Jarque-Bera	ERS	Q(20)	Q ² (20)
ELON	-0.180	47.290***	1.057***	9.330***	1266.110***	-7.271***	16.046*	22.929***
SHIB	-0.165	29.766***	0.123	7.808***	844.111***	-8.151***	29.812***	33.989***
APE	-0.001	0.007***	-0.241*	6.666***	617.852***	-0.497	19.836**	57.676***
AXS	-0.005	0.004***	0.354***	4.862***	333.948***	-8.534***	20.095**	11.732
THETA	-0.003	0.003***	-0.794***	3.525***	206.800***	-5.406***	31.302***	71.542***
SAND	-0.005	0.003***	-0.292**	3.289***	154.321***	-7.804***	19.406**	49.050***
MANA	-0.004	0.004***	0.324**	8.138***	922.013***	-8.704***	17.380*	125.049***
DOGE	-0.105	31.757***	0.354***	8.135***	922.451***	-5.584***	30.430***	25.922***
ICP	-0.003	0.003***	-0.706***	6.269***	571.285***	-5.779***	31.009***	61.027***
DOT	-0.003	0.002***	-0.664***	3.580***	201.673***	-7.162***	25.647***	92.499***
BABYD OGE	0.001	0.003***	-0.006	6.897***	658.077***	-6.492***	24.132***	85.213***
GRT	-0.003	0.005***	-0.200	13.348***	2467.004***	-8.337***	8.810	25.901***
FIL	-0.004	0.004***	-0.382***	5.516***	428.942***	-7.402***	20.733**	7.442
LINK	-0.002	0.002***	-0.718***	2.354***	105.206***	-4.088***	15.759*	99.643***
FTM	-0.003	0.005***	-1.664***	11.922***	2119.311***	-4.846***	15.618*	16.121*

Many assets display significant skewness and kurtosis, with high kurtosis values suggesting heavy tails in their return distributions. For example, ELON's kurtosis of 9.330 and SHIB's kurtosis of 7.808 indicate that extreme returns are more likely than in a normal distribution. The skewness measures also highlight asymmetry in the distribution of returns—cryptos like THETA and ICP exhibit negative skewness, implying more frequent large negative returns, which is consistent with market corrections or sell-offs.

The Jarque-Bera test values are highly significant for almost all assets, further confirming that the return distributions deviate from normality, with heavy-tailed behavior and potential implications for risk management strategies. In terms of autocorrelation, the Q(20) and Q2(20) statistics reveal persistence in both the return levels and squared returns, particularly in assets like MANA and FIL, implying that past volatility may influence future volatility—a characteristic often seen in speculative assets.

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LINK	-0.002	0.002***	-0.718***	2.354***	105.206***	-4.088***	15.759*	99.643***
FTM	-0.003	0.005***	-1.664***	11.922***	2119.311***	-4.846***	15.618*	16.121*

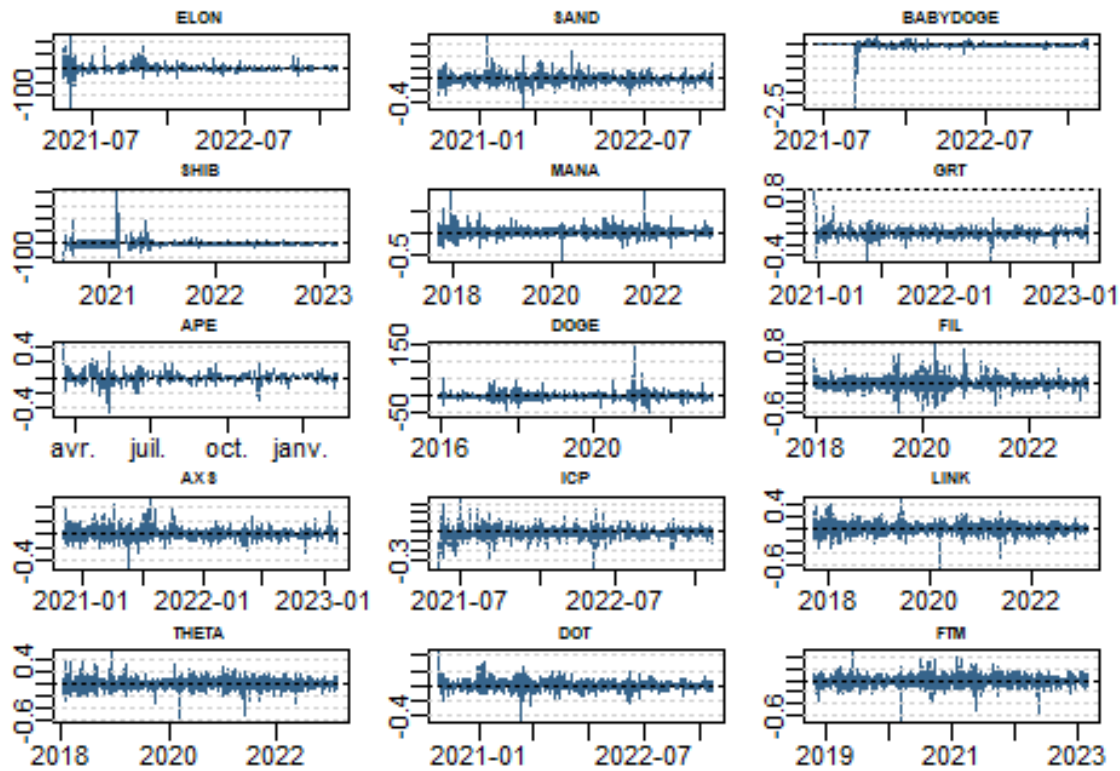


Figure 1. Time Path Graphs of Return Series

In line with the figure, these statistical properties align with the visual patterns of volatility clusters observed across most cryptocurrencies. Assets like ELON and DOGE, which have experienced periods of extreme price fluctuations, demonstrate sharp spikes in returns over time, reinforcing the idea of volatility clustering. Other assets, like FIL and LINK, exhibit more consistent, albeit volatile, return patterns, indicative of broader market dynamics influenced by underlying fundamentals, technological developments, or macroeconomic factors.

Empirical Results

Before investigating the dependence between commodity return series and stock market return series, it is crucial to account for autocorrelation and heteroscedasticity in the marginal series. Therefore, we propose utilizing different specifications for the mean equation, specifically ARFIMA (p, dm, q), and for the variance equation, FIGARCH (k, dv, l). The empirical findings from the estimation of ARFIMA (p, dm, q) and FIGARCH (k, dv, l) are presented in table 2.

GARCH-models estimation results

Table 2: ARFIMA-GARCH models results

Model	A	AR(1)	C	ARCH (1)	GARCH (1)	Fraction	Par. (1)	Par. (2)	Lg(HY)
Non-Fungible Token NFT									
ELON	IGARCH	-0.00015	-0.254***	8.351171	0.43559**	0.62583***			
SHIB	IGARCH	-0.15015	-0.124***	4.651271	0.287166**	0.712834***	-	-	-

APE	IGARCH	-0.00128	-0.09324	7.711562	0.424753*	0.575247***	-	-	-	-
THETA	GARCH	0.000655	-0.126***	3.6444***	0.131103***	0.816934***	-	-	-	-
MANA	FIAPARCH	-0.00061	-0.00724	1444.7497***	-0.65779***	-0.58152***	0.386510***	-0.1294***	1.3575***	-
AXS	FIGARCH	-0.00280	-	0.421211	-0.55548***	-0.319831	0.626022***	-	-	-
			0.05673**							
SAND	IGARCH	-0.00116	-0.04088	0.003449	0.431472*	0.568528	-	-	-	-
Conv. Cryptocurrencies										
DOGE	HYGARCH	-0.13***	-0.134***	0.914802	0.514280***	0.608235***	0.5200***	-	-	0.6243**
ICP	FIGARCH	-0.00212	-	667.765841***	-0.005966	0.484015***	0.604733***	-	-	-
			0.0764***							
DOT	IGARCH	0.000047	-	0.754274**	0.099834***	0.900166***	-	-	-	-
			0.0709***							
BABYDOGE	IGARCH	-0.00071	0.056335	1.459758**	0.239937***	0.760063***	-	-	-	-
Decentralized Finance										
GRT	FIGARCH	-0.00110	-0.047653	1729.631332***	-0.50029***	-0.139635	0.584144***	-	-	-
FIL	FIGARCH	-0.002**	-	670.620654***	0.263143***	0.463316***	0.496164***	-	-	-
			0.1764***							
LINK	FIGARCH	0.000724	-0.059143	0.033671	0.295086	0.861011***	0.740414***	-	-	-
FTM	FIAPARCH	-0.00016	-0.040624	0.026294**	0.265891***	0.568099***	0.4349 ***	-0.2582***	1.780567***	-
Gold-Backed Cryptocurrencies										
PAXG	EGARCH	0.027524	-	0.351832	-0.483279**	0.972038***	-	0.079615**	0.345113***	-
			0.0945***							
XAUT	FIGARCH	0.000240	-0.015276	1056.974101***	0.645718***	0.810942***	0.411475***	-	-	-

The table provides an overview of the results derived from the application of various GARCH-type models, capturing the volatility dynamics for cryptocurrency. To ensure the most accurate model was selected, a sequential multi-model approach was employed. First, different GARCH-type models—such as GARCH, EGARCH, TGARCH, and FIGARCH—were estimated for each asset. Information criteria, such as AIC and BIC, were used to identify the best-fitting model for each asset. Based on the lowest values of these criteria, the appropriate model was selected.

For instance, SHIB and APE were best modeled using an IGARCH approach, reflecting high volatility persistence, while THETA required a GARCH model due to its significant asymmetric shock effects. More sophisticated models, such as FIAPARCH and FIGARCH, were applied to assets like MANA and GRT, indicating the importance of both leverage effects and long memory persistence in their volatility. For gold-backed cryptocurrencies like PAXG and XAUT, EGARCH and FIGARCH models were selected, showcasing lower volatility but significant asymmetry and persistence, typical of assets that serve as hedging instruments. This comprehensive approach ensures that the unique volatility characteristics of each asset are captured, leading to more accurate estimations of risk and return for investors.

However, prior to estimating the copula for each pair of series, it is crucial to assess the correct specification of the residual series from the ARFIMA-FIGARCH models. To evaluate the assumptions of independence and identically distributed (i.i.d.) residuals as well as uniformity, we first conducted residual diagnostic tests (results not reported) that indicate the specifications have successfully mitigated the issues of autocorrelation and heteroscedasticity in the original data. The specified residuals are, then, transformed into uniform values in accordance with the methodology outlined by Diebold et al. (1998), which posits

that if the marginal distributions are correctly specified, then the Probability Integral Transform (PIT) series should be independent and identically distributed (i.i.d.) uniform (0,1).

In summary, the analysis of residuals and goodness-of-fit tests demonstrate that the marginal distribution models are adequately and correctly specified. This confirms that the copula models can effectively capture the dependence between each pair of commodity and stock market return series.

Copula estimation results

The selection of the copula is informed by prior research that evaluated various information criteria after estimating both Gaussian and Student's t-copulas, with the latter being identified as more suitable (Gregoire et al., 2008). The Student's t-copula accommodates heavier tails than the Gaussian distribution, thereby assigning a higher probability to extreme events (Embrechts et al., 2002). Additionally, it provides enhanced flexibility for capturing tail dependence in financial returns, making it particularly effective for modeling essential stylized facts such as volatility clustering, time-varying volatility, and both short- and long-term dependence behaviors (Patton, 2006).

Furthermore, employing the Student's t-distribution aids in estimating residuals that approximate independence and identical distribution (i.i.d.), which is critical for subsequent statistical analyses (Gregoire et al., 2008). The dependence structure of the Student's t-copula also facilitates the modeling of joint extreme movements, irrespective of the marginal behavior of individual assets. By transforming the standardized residuals from the ARIMA-GARCH model using the cumulative distribution function, we generate uniformly distributed random variables, which are vital for the application of the copula model (Chollete et al., 2009). This approach bolsters the robustness of our findings, particularly in the context of financial data that exhibit fat tails and extreme dependencies.

The time-varying behaviour of the copula-dependency parameter

The analysis of time-varying dependence between NFT/DeFi/Conv.cryptocurrencies and GBC/USD1/BUSD utilizes the Student-t copula, which is chosen based on information criteria after comparing it to the Gaussian copula. The Student-t copula model is preferred because it accounts for heavier tails, giving more weight to extreme events compared to the normal distribution. This is particularly important for capturing dynamic volatility, tail dependencies, and volatility clustering, which are common in financial markets. The use of the Student-t distribution also enhances the estimation of residuals, making them suitable for further analysis due to their approximate independence and identical distribution. By transforming the cumulative distribution of standardized residuals, the model captures joint extreme movements between asset pairs, offering a robust framework for analyzing dependencies under extreme market conditions. Figure 2 illustrates the dependence between NFTs and GBC/Stablecoins comparatively.

Kendall's tau measures the co-dependence between two assets. A lower or negative dependency suggests that the two assets are less likely to move together, which is beneficial for portfolio diversification (Baur & Lucey, 2010). Conversely, a higher positive dependency implies that the assets tend to move in sync, reducing diversification benefits.

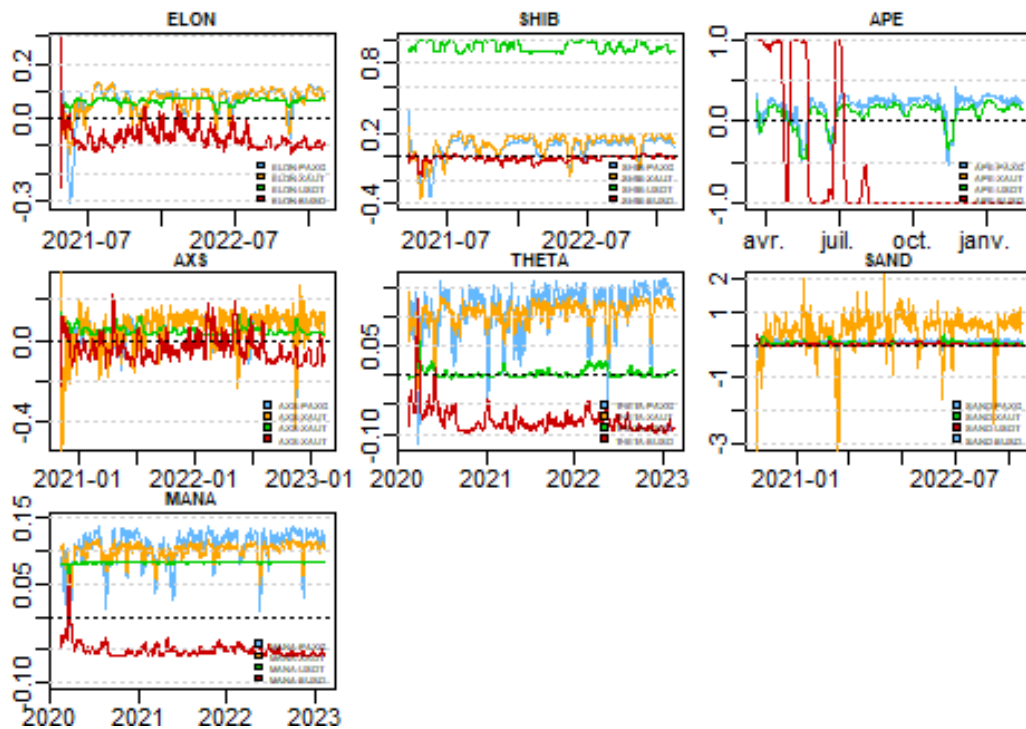


Figure 2: Time-varying dependence parameter from the Student-t copula for the pairs of 7 NFTs–PAXG/XAUT/USDT/BUSD

The figure illustrates the time-varying dependence parameters derived from a Student-t copula model for pairs of seven NFTs (ELON, SHIB, APE, AXS, THETA, SAND, MANA) with Gold-Backed Cryptocurrencies (PAXG, XAUT) and stablecoins (USDT, BUSD). The yellow and blue lines represent NFT-GBC pairs, while the red and green lines correspond to NFT-stablecoin pairs. Significant volatility and fluctuation are observed, especially during major market crises such as the COVID-19 pandemic and geopolitical events like the Russia-Ukraine conflict. For instance, during the early pandemic (2020), pairs involving stablecoins display heightened dependency, possibly reflecting a flight to safer assets. The correlation between gold-backed cryptocurrencies and NFTs seems to fluctuate between positive and negative values. This suggests the diversification and hedging abilities of these digital gold assets compared to stablecoins.

The Kendall copula parameters for almost NFTs with the gold-backed cryptocurrencies are relatively positive, indicating a steady dependency over time, during normal periods. This suggests that PAXG and XAUT are good diversifiers for almost NFTs, providing reliable risk management. However, it can be considered as a strong safe-haven asset only for the SAND and AXS during post-COVID-19 period (early 2021) and the 2022 bear market, particularly during the Terra-USD (USDT) collapse in May 2022 and the cryptocurrency market crash in November 2022. This confirms the negative and significant tail dependence coefficients (β_3 and β_4) shown in table 2.

Figure 2 displays that BUSD mainly acts as a hedging tool only for THETA, MANA, and ELON. The safe haven ability of BUSD is considered only for APE during both crises and for PLAY at the end of 2022. Regarding USDT/BUSD-ELON pairs, higher volatility in the copula parameter is observed, particularly during stressful periods, suggests that the dependency is less stable with stablecoins, making them less reliable as hedging instruments. Thus, PAXG/XAUT serve as better diversifiers for ELON, especially during market stress, compared to USDT/BUSD.

On the other hand, the post-crisis recovery phase exhibits more stability in the parameters, particularly for assets like AXS and MANA. These empirical results suggest that Gold-Backed Cryptos offered better hedging opportunities during turbulent times, while stablecoins provided a mixed level of protection.

Overall, the dynamic nature of these dependencies highlights the importance of tailoring portfolio strategies to prevailing market conditions to optimize risk management.

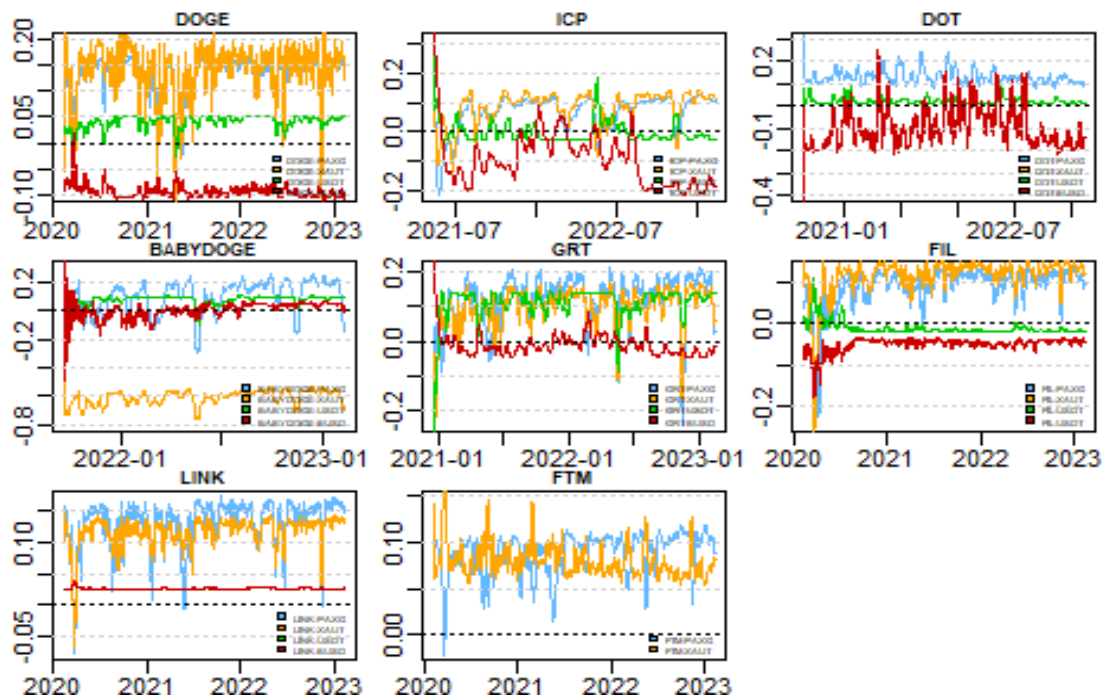


Figure 3: Time-varying dependence parameter (Kendall's tau) from the Student-t copula for the pairs of 4 Defis/ 4 Conv.Crypto – PAXG/XAUT/USDT/BUSD

Significant fluctuations across different periods can be observed (Figure 3), likely influenced by market conditions and macroeconomic events such as the COVID-19 pandemic, financial market shifts, and geopolitical tensions. Across all four cryptocurrencies (DOGE, DOT, ICP, BABYDOGE), XAUT consistently shows lower dependency (Kendall's tau) compared to PAXG, making it the better diversifier overall. Especially during crisis periods (such as the COVID-19 pandemic and the 2022 crypto market downturn), XAUT seems to offer better risk mitigation, highlighting its suitability for enhancing portfolio diversification. For instance, ICP and DOT exhibit a similar pattern, where their dependency on PAXG and XAUT remains generally low throughout the study period. However, their connection with stablecoins (red and green lines) tends to increase, particularly during downturns, reflecting higher liquidity needs and stronger co-movements with stable assets. BABYDOGE demonstrates one of the lowest dependencies on both PAXG/XAUT and USDT/BUSD, particularly in 2022, which aligns with its volatile and speculative nature. This suggests that during times of high volatility, BABYDOGE exhibits very limited co-movement with more stable assets, such as gold-backed currencies and stablecoins.

In line with results of copula parameters estimation (Table 2) indicate that XAUT a more crucial role in mitigating the risk of conv.crypto portfolios than PAXG. The results display a negative (w) coefficient of XAUT's copula contribution for almost conv.crypto, as well as a negative and significant tail dependence coefficient (β_3 and β_4). Hence, XAUT serves as a strong safe haven for these crypto during bear markets for DOGE and DOT, and its hedging feature during normal times is observed for ICP and BABYDOGE.

DOGECOIN (DOGE) and CHAINLINK (LINK) charts show noticeable dependency shifts during late 2020 and 2021, coinciding with high market volatility due to the pandemic and subsequent economic recovery efforts. Particularly, during the COVID-19 crisis in 2020 and early 2021, there's an increase in the dependency on gold-backed assets, notably observed with DOGE and LINK. FIL show relatively low dependence on PAXG and XAUT (yellow and blue lines). This is especially evident during periods of high market uncertainty, where their correlation with gold-backed cryptocurrencies dips to near-zero levels,

suggesting that these assets tend to decouple from gold-backed assets during crises. However, their dependency on stablecoins (USDT and BUSD) is stronger and more consistent, especially during volatile periods like the 2021–2022 market shocks. Similarly observed in table 2, results display a negative (w) coefficient of Stablecoin’s copula contribution for this Defi’s asset, as well as a negative and significant tail dependence coefficient (beta3 and beta4). Namely, BUSD serves as a strong safe haven for FIL crypto during bear markets compared to USDT.

These findings highlight the varying degrees of co-movement between cryptocurrencies, NFTs, DeFis, and traditional or stable assets during periods of market uncertainty, with stablecoins typically showing stronger dependencies than gold-backed cryptocurrencies across different digital assets. Specifically, results suggest that portfolio managers aiming for long-term diversification benefits might find XAUT to be a more reliable hedge in these conventional cryptocurrency portfolios. These results will be further supported with optimal hedging strategies results.

Table 3: Copula parameters

Panel A: PAXG												
	W1		Beta1		Beta2		W2		Beta3		Beta4	
	Est.	P-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.	Est.	p-val.
Elon Doge	0.0726	0.367	1.492** *	0.005	-0.068	0.318	-1.017	0.735	-0.012	0.935	-0.892	0.352
Doge	0.401	0.314	-0.305	0.876	-0.173	0.451	-0.617	0.212	-0.047	0.730	2.453	0.311
Shib	0.103	0.134	1.478** *	0.000	-0.108	0.112	-0.988** *	0.024	-0.236***	0.019	-0.725** *	0.011
Theta	0.469	0.129	-0.666	0.665	-0.308	0.244	2.302	0.780	0.013	0.908	-2.458	0.510
AXS	0.336***	0.043	0.000	0.000	-0.404	0.000	-0.032	0.000	-0.087***	0.000	-0.404** *	0.000
APE	1.310*** *	0.000	-1.559** *	0.000	-1.125** *	0.000	-1.021** *	0.024	-0.090***	0.000	0.716	0.385
GRT	0.465	0.176	0.016	0.993	-0.400**	0.088	0.004	0.987	-0.062***	0.000	0.017	0.979
ICP	0.032**	0.076	1.826** *	0.000	-0.034** *	0.042	-2.195	0.274	-0.100	0.738	-0.342	0.364
FIL	0.279***	0.000	0.109** *	0.000	-0.210** *	0.000	-0.565** *	0.000	-0.149***	0.000	-0.682** *	0.000
LINK	0.383**	0.059	-0.126** *	0.043	-0.189** *	0.023	-1.153** *	0.017	-0.120***	0.017	0.264**	0.087

SAND	0.516***	0.018	-0.965	0.148	-0.559** *	0.027	0.811	0.710	-0.058***	0.026	-0.559	0.625
DOT	0.036	0.631	1.370** *	0.026	0.08	0.486	1.259	0.613	-0.053	0.207	-4.576	0.112
Baby Doge	0.252*	0.092	1.214** *	0.012	-0.322** *	0.072	-1.632**	0.078	-0.093**	0.072	1.178	0.110
FTM	0.069	0.521	1.463	0.156	-0.039	0.436	0.008	0.999	4.492***	0.000	0.059	0.999
MANA	0.293	0.920	-0.027	0.790	-0.134	0.530	-0.163	0.814	-0.077	0.710	-0.224	0.830
Panel B: XAUT												
	W1		Beta1		Beta2		W2		Beta3		Beta4	
	Est.	P-val.	Est.	P-val.	Est.	p-val.	Est.	P-val.	Est.	P-val.	Est.	P-val.
Elon Doge	0.197	0.238	0.583	0.534	-0.194	0.276	0.320	0.552	2.623** *	0.000	0.223	0.999
Doge	0.756***	0.000	-1.642** *	0.000	-0.453** *	0.043	0.834** *	0.022	-0.047** *	0.010	-2.044***	0.001
Shib	0.124	0.126	1.535** *	0.000	-0.131	0.110	-0.034	0.971	-0.109** *	0.045	-1.108	0.109
Theta	0.284	0.912	0.011	0.995	-0.127	0.914	0.003** *	0.000	0.061** *	0.000	0.009***	0.000
AXS	0.672***	0.000	-1.888** *	0.000	-0.802** *	0.000	5.000** *	0.015	0.127	0.320	0.627	0.422
APE	0.365	0.258	0.772	0.462	-0.436	0.215	1.284** *	0.012	-0.091** *	0.000	2.642***	0.036
GRT	0.380	0.149	0.049	0.974	-0.338	0.120	0.0514* *	0.060	-0.061	0.150	-0.000	0.225
ICP	0.064	0.156	1.682** *	0.000	-0.063** *	0.010	-3.752** *	0.000	0.045** *	0.000	0.607***	0.000
FIL	0.325***	0.015	0.060	0.230	-0.166	0.817	-0.631** *	0.000	-0.085** *	0.000	0.308	0.311
LINK	0.298	0.474	0.008	0.997	-0.121	0.593	-0.621** *	0.000	-0.148** *	0.000	-0.619	0.000

SAND	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
DOT	- 1.356***	0.000	0.021** *	0.00 0	1.341** *	0.000	-5.000	0.99 2	-5.00**	0.09 2	-5.000**	0.09 1
Baby Doge	- 0.588***	0.000	1.082** *	0.00 0	- 0.320** *	0.000	-0.838	0.95 2	5.000	0.99 9	1.409***	0.00 0
FTM	0.080	0.543	0.406	0.82 3	0.087	0.564	3.245**	0.08 6	- 0.031** *	0.02 6	5.000	0.68 0
MAN A	0.250	0.272	-0.070	0.96 7	-0.073	0.580	- 1.705** *	0.00 0	- 0.103** *	0.00 0	0.875	0.41 0
Panel C: USDT												
	W1		Beta1		Beta2		W2		Beta3		Beta4	
	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	p-val.
Elon Doge	0.112	0.511	0.412	0.67 3	-0.030	0.802	- 4.416** *	0.00 0	0.049** *	0.00 0	2.817** *	0.002
Doge	0.104	0.611	-0.011	0.22 3	- 0.074***	0.000	-0.104	0.83 7	-0.084	0.00 0	0.426	0.470
SHIB	2.507***	0.000	0.315	0.55 1	2.882***	0.000	5.000** *	0.00 0	- 5.000** *	0.00 0	5.000** *	0.000
Theta	-0.009	0.903	0.115	0.90 8	0.030	0.574	- 0.280** *	0.00 0	0.037** *	0.00 0	- 1.070** *	0.000
AXS	0.049	0.360	0.446	0.53 0	0.066	0.530	- 3.135** *	0.00 0	0.054** *	0.00 0	0.482** *	0.000
APE	0.640	0.431	-0.897	0.73 5	0.001	0.996	- 1.863** *	0.02 9	-0.365	0.13 5	-0.730	0.578
GRT	0.347	0.357	-0.409	0.82 5	-0.153	0.487	- 0.197** *	0.00 0	- 0.091** *	0.00 0	- 0.312** *	0.000
ICP	-0.041	0.710	0.482	0.19 0	0.089	0.334	0.118** *	0.01 0	- 0.109** *	0.00 0	- 0.569** *	0.001
FIL	-0.04**	0.062	-0.337	0.90 4	0.062	0.443	- 0.340** *	0.00 0	- 0.120** *	0.00 0	- 0.429** *	0.000

LINK	0.049	0.446	-0.007	0.78 0	0.006	0.879	0.005** *	0.00 0	- 0.006** *	0.00 0	- 0.038** *	0.000
SAND	0.035	0.670	0.162	0.43 0	0.155	0.222	-0.116	0.72 0	- 0.083** *	0.00 0	- 0.472** *	0.000
DOT	0.017	0.741	0.270	0.20 9	0.051	0.463	- 0.855** *	0.00 0	- 0.146** *	0.00 0	- 0.612** *	0.000
Baby Doge	0.229	0.999	-0.298	0.54 0	-0.117	0.550	0.114	0.92 2	- 0.104** *	0.00 0	-0.623	0.503
FTM	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
MAN A	0.177	0.347	-0.115	0.95 6	- 0.007***	0.000	0.464** *	0.00 0	- 0.07***	0.00 0	- 1.331** *	0.000

Panel D: BUSD

	W1		Beta1		Beta2		W2		Beta3		Beta4	
	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	P- val.	Est.	P- val.
Elon Doge	-0.407	0.229	- 1.555** *	0.00 3	0.353	0.383	0.424	0.99 9	2.334	0.84 4	0.791	0.98 1
Doge	0.389***	0.018	- 1.718** *	0.00 0	0.106	0.512	- 5.000** *	0.00 0	0.075** *	0.00 0	3.014***	0.00 0
SHIB	- 0.389***	0.018	- 1.718** *	0.00 0	0.106	0.511	- 5.000** *	0.00 0	0.071** *	0.00 0	3.014***	0.00 0
Theta	-0.159	0.205	0.359	0.74 7	0.069	0.358	-0.438	0.85 7	-0.063	0.62 4	-0.511	0.35 8
AXS	-0.332	0.178	-0.718	0.41 2	0.544	0.148	-5.000	0.51 3	0.859	0.87 7	-5.000	0.39 0
APE	-4.195	0.280	4.130	0.31 1	5.000	0.340	-2.890	0.18 0	-0.687	0.52 7	1.549	0.99 5
GRT	-0.036	0.563	1.256** *	0.02 0	0.056	0.521	- 4.226** *	0.00 0	0.043	0.22 5	4.586	0.28 3
ICP	-0.047	0.492	1.829** *	0.00 0	0.062	0.415	0.027** *	0.00 0	0.415** *	0.00 0	0.002***	0.00 0
FIL	- 0.131***	0.033	- 1.552** *	0.00 2	-0.107	0.424	-0.081	0.91 8	- 0.190** *	0.01 3	- 0.822***	0.02 2

LINK	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
SAND	-0.039	0.706	0.567	0.61 1	0.131	0.466	5.000	0.83 1	0.443	0.68 6	-4.156	0.68 1
DOT	-0.624	0.317	-1.134	0.19 7	0.764	0.551	0.499	0.99 9	2.915	0.99 9	0.048	0.39 8
Baby Doge	0.217	0.591	- 1.858** *	0.00 0	-0.460	0.323	0.305	0.64 0	2.757	0.72 0	0.244	0.43 3
FTM	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR	NR
MAN A	0.115	0.560	0.086	0.97 5	0.043	0.642	-1.816	0.72 6	0.049	0.15 6	-0.701	0.43 0

*NR: No copula results for these pairs

The time-varying hedge ratio

The hedge ratio represents the number of units of stablecoins or gold-backed crypto in a short position required to hedge one unit of a conventional cryptocurrency or NFT or DeFi tokens in a long position. A higher hedge ratio suggests better portfolio diversification, indicating that more hedging asset is needed per unit of the cryptocurrencies, which implies a lower potential for risk-adjusted returns. Essentially, as the hedge ratio increases, it reflects greater market dependency, pointing to reduced volatility in the overall portfolio.

Figure 4 displays dynamic hedge ratios for seven NFT-based cryptocurrencies (ELON, SHIB, APE, AXS, THETA, SAND, and MANA) against both gold-backed assets (PAXG/XAUT) and stablecoins (USDT/BUSD).

Results analysis highlights significant differences in hedging behavior. Across all NFTs, the hedge ratios with PAXG and XAUT demonstrate greater stability and consistency, especially during periods of market turbulence. For example, ELON and SHIB exhibit low volatility in their hedge ratios with PAXG and XAUT, suggesting that gold-backed cryptocurrencies provide a more reliable hedge. In contrast, the hedge ratios with USDT and BUSD are more volatile, particularly during crises, indicating less stable hedging potential.

In assets like APE and THETA, while both gold-backed and stablecoin hedges show occasional spikes, PAXG/XAUT maintains relatively better consistency compared to the pronounced fluctuations in USDT/BUSD. This trend is observed across most of the NFTs, with PAXG/XAUT emerging as the preferred hedge during periods of market instability, as stablecoin hedging tends to fluctuate sharply.

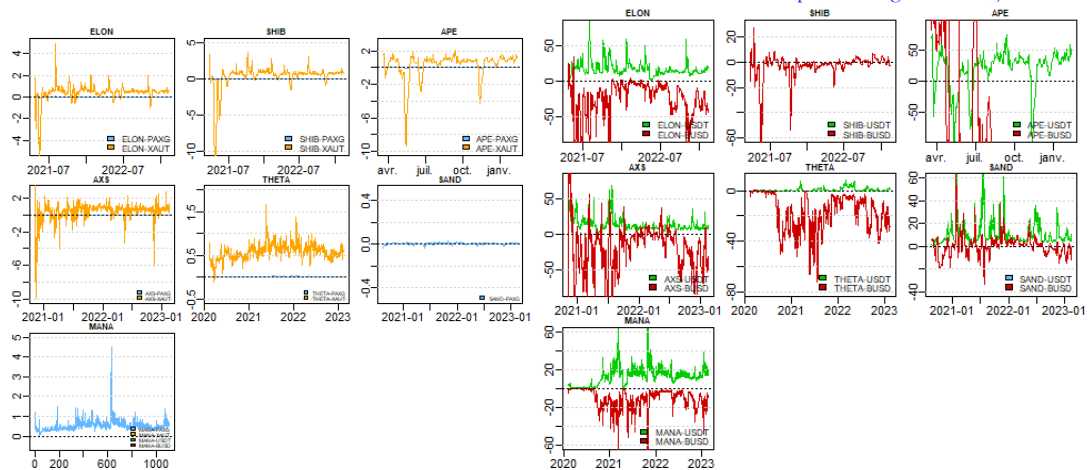


Figure 4: Time-varying Hedge Ratio (Beta) from the Student-t copula for the pairs of 7 NFTs—PAXG/XAUT/USDT/BUSD

From a managerial perspective, these findings suggest that managers and investors should prioritize gold-backed cryptocurrencies over stablecoins for hedging NFT assets, particularly in volatile market conditions. Stablecoins, although traditionally considered stable, display less reliability as hedgers in this context. Consequently, a dynamic and flexible hedging strategy, particularly involving PAXG/XAUT, may provide better risk management and portfolio stability when dealing with NFT-based cryptocurrencies.

To conclude, in times of heightened market volatility, incorporating gold-backed cryptocurrencies (PAXG/XAUT) in the same direction (long/long; short/short) as NFT-based assets could enhance diversification and stability, confirming the gold-backed’s role as a reliable hedge during market turbulence. In contrast, stablecoins (USDT/BUSD) display greater variability in their hedge ratios, making them less effective as stable hedging instruments in these conditions. For instance, during periods of significant market stress, relying on gold-backed assets proves to be a more stable and consistent strategy compared to using stablecoins. This dynamic approach underscores the importance of integrating gold-backed cryptocurrencies into hedging strategies for improved risk management and portfolio stability.

Figure 5 displays dynamic hedge ratios for DeFis (GRT, FIL, LINK and FTM) against both gold-backed assets (PAXG/XAUT) and stablecoins (USDT/BUSD).

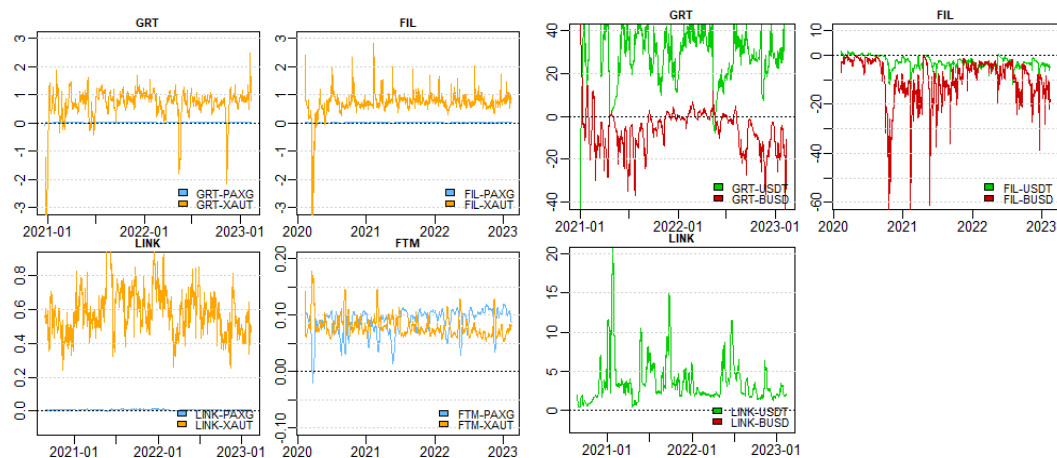


Figure 5: Time-varying Hedge Ratio (Beta) from the Student-t copula for the pairs of 4 DeFis – PAXG/XAUT/USDT/BUSD

Starting with the figure of the hedge ratios of DeFi tokens (GRT, FIL, LINK, and FTM) against gold-backed crypto. Overall, this figure demonstrates that while both PAXG and XAUT provide hedging capabilities for these DeFi tokens, PAXG generally requires larger hedge ratios but offers more dynamic hedging, while XAUT tends to provide weaker but more stable hedging across most tokens. GRT and FIL exhibit the highest variability in hedge ratios, indicating more volatile behavior, which requires larger and more dynamic hedging adjustments. FTM shows the most consistent hedge ratios, requiring the smallest positions in either gold-backed asset to mitigate risk. The general takeaway is that PAXG appears to be a more active hedge, with greater variability but higher responsiveness, whereas XAUT tends to provide more subdued and stable hedging, albeit sometimes less effective. For instance, for GRT, the hedge ratio with PAXG fluctuates significantly, often exceeding 1, indicating that a long position on PAXG was needed to hedge GRT's volatility. The hedge ratio with XAUT is more stable, staying close to zero, suggesting weaker but more predictable hedging.

Regarding the dynamic hedge ratios of USDT and BUSD as hedging assets for three DeFi tokens: GRT, FIL, and LINK. The results show that GRT has high volatility in its hedge ratios with both USDT and BUSD, making them inconsistent hedges. FIL has a relatively stable hedge ratio with USDT, indicating moderate effectiveness, though BUSD's role as a hedge fluctuates during market stress. LINK demonstrates moderate fluctuations, suggesting USDT and BUSD provide a more stable hedge compared to the other assets, though still impacted by market volatility. In summary, this figure reveals that USDT and BUSD display varying degrees of effectiveness as hedging assets for these DeFi assets. While USDT appears slightly more stable in its hedging role, particularly with FIL and LINK, both stablecoins experience limitations when dealing with the high volatility of DeFi assets like GRT. This analysis underscores the challenges in using stablecoins as reliable hedging instruments for DeFi assets, with effectiveness influenced by the unique volatility and market dynamics of each asset.

Figure 6 displays the Hedge Ratio from the Student-t copula for the pairs of 4 crypto–PAXG/XAUT/USDT/BUSD. Regarding results of the figure at the left (PAXG or XAUT), overall results suggest that portfolio managers should prioritize PAXG over XAUT when seeking hedging instruments for highly speculative cryptos, while XAUT may be better suited for less volatile assets requiring stable risk management.

From the figures, the empirical findings indicate that the hedge ratios for portfolios containing PAXG and XAUT with the four conventional cryptocurrencies (DOGE, ICP, DOT, BABYDOGE) exhibit time-varying behavior, which suggests changing levels of risk mitigation over time. When considering a short position in the cryptocurrency and a long position in either PAXG or XAUT, we see that PAXG's hedge ratios fluctuate more widely. This indicates that PAXG can offer significant hedging benefits in certain periods but may also expose the portfolio to greater risk in others, as seen when its hedge ratios turn negative during periods of heightened market uncertainty (e.g., during the Ukraine-Russia war).

For example, during times of market distress, like the 2022 crypto market downturn, PAXG's hedge ratio sometimes becomes negative, implying that a long position in PAXG and a short position in DOGE or BABYDOGE could introduce more risk into the portfolio rather than mitigate it. In contrast, XAUT typically maintains positive hedge ratios, indicating that a long position in XAUT coupled with a short position in any of the four cryptocurrencies provides more consistent hedging benefits and portfolio stability.

This highlights that XAUT is generally a more reliable hedging instrument over the long term, offering steadier protection against the volatility of these cryptocurrencies. In contrast, PAXG, due to its volatility, may be better suited for investors willing to take on higher short-term risk for potential gains during specific market shocks. For instance, during the SVB collapse, XAUT's stability would have provided a safer hedge, whereas PAXG could have been more suitable for short-term tactical adjustments.

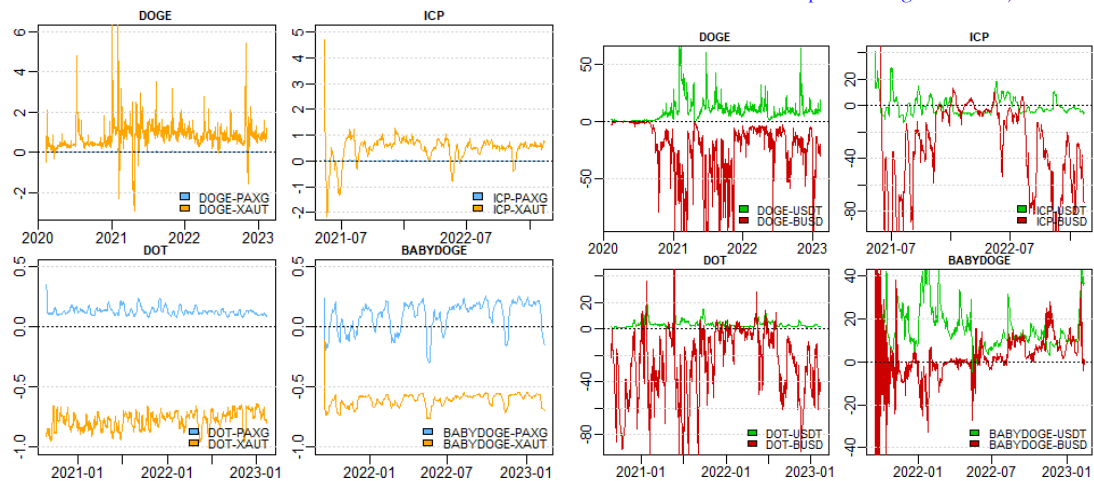


Figure 6: Time-varying Hedge Ratio (Beta) from the Student-t copula for the pairs of 4 crypto-PAXG/XAUT/USDT/BUSD

For the Conv.crypto/Stablecoins pairs, results reveal that generally USDT shows somewhat more stable hedge ratios, particularly for ICP, suggesting a modest hedging capability in mitigating volatility. However, BUSD displays greater fluctuations across all four assets, with especially high volatility when paired with DOGE, DOT, and BABYDOGE. These volatile hedge ratios imply that BUSD may be less reliable as a hedge asset for these cryptocurrencies, particularly during global market crises, such as the 2021 bull run and subsequent corrections. In essence, while neither USDT nor BUSD consistently stabilizes these assets, USDT appears marginally more effective, particularly in managing ICP's volatility.

The time-varying behaviour of Hedging effectiveness (HE)

Across various periods, PAXG and XAUT, both gold-backed cryptocurrencies, show superior hedging capacity, especially during major crises such as the COVID-19 pandemic, the crypto market crash (2021-2022), and the FTX collapse (late 2022). These assets provide robust protection in times of heightened market stress, particularly for volatile NFTs like APE, SAND, and AXS. In contrast, USDT and BUSD, while offering consistent hedging, generally exhibit lower effectiveness during crises, making them reliable for stable but less dynamic hedging. Overall, gold-backed cryptocurrencies emerge as stronger hedging tools compared to stablecoins, particularly during market downturns.

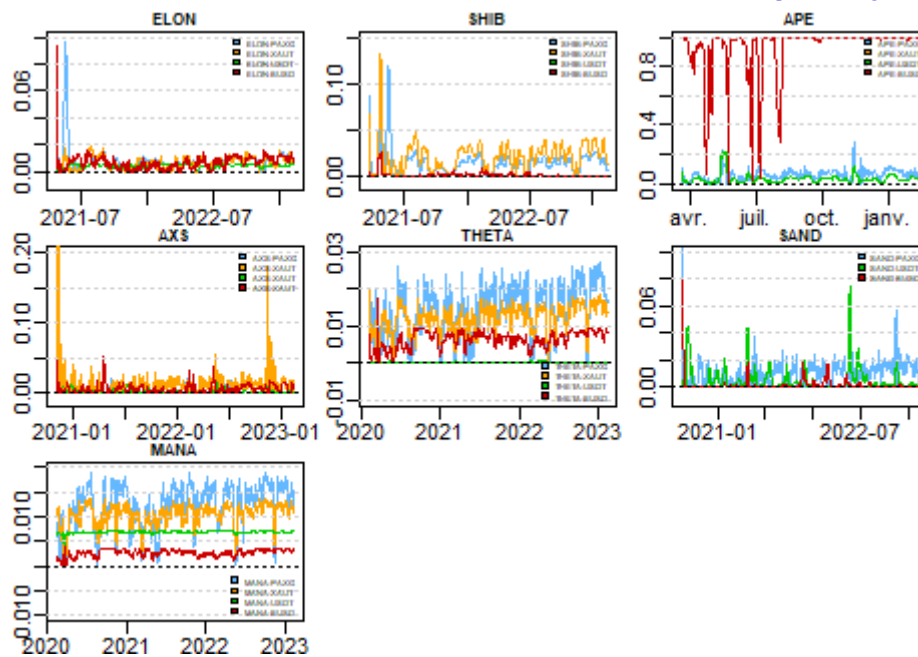


Figure 7: Time-varying HE (Hedging Effectiveness) from the Student-t copula for the pairs of 7 NFTs—PAXG/XAUT/USDT/BUSD

The figure presents the hedging effectiveness of PAXG, XAUT, USDT, and BUSD against four DeFi (DOGE, ICP, DOT, BABYDOGE) and four classic cryptocurrencies (GRT, FIL, LINK, FTM) from 2020 to 2023. Similar to the results seen in NFT hedging, gold-backed cryptocurrencies (PAXG and XAUT) demonstrate stronger and more stable hedging effectiveness during major crises, including the COVID-19 pandemic, crypto crashes (2021-2022), and the FTX collapse. The hedging effectiveness for assets like FIL, DOT, and LINK is particularly pronounced during periods of high volatility. PAXG and XAUT consistently outperform USDT and BUSD, providing greater protection during downturns, especially for more volatile DeFi assets like DOGE and BABYDOGE. USDT and BUSD, being stablecoins, offer relatively constant but lower hedging capacity compared to gold-backed assets. While stablecoins provide useful diversification, they fall short in offering the same level of crisis protection as PAXG and XAUT, especially in moments of extreme market stress. Therefore, gold-backed cryptocurrencies demonstrate superior hedging abilities, especially in environments marked by heightened uncertainty, whereas stablecoins are better suited for more consistent, low-risk scenarios.

In conclusion, for both DeFi and traditional cryptocurrencies, gold-backed assets remain the stronger hedging tool, particularly during stressful periods.

Table 4 presents detailed results on the hedging effectiveness (HE) of four assets: PAXG, XAUT, USDT, and BUSD, against various cryptocurrencies, including 7 NFTs (Elon, Doge, SHIB, Theta, AXS, APE, and SAND) and 4 DeFi tokens (Doge, Baby Doge, GRT, and ICP), as well as more traditional cryptocurrencies like LINK and FIL. Overall results suggest that gold-backed cryptocurrencies (PAXG and XAUT) outperform stablecoins (USDT and BUSD) in terms of hedging effectiveness, particularly during periods of heightened market stress. While USDT and BUSD offer stable value, they lack the robust hedging capacity of gold-backed assets during crises. Investors looking for protection against volatility in NFT and DeFi markets would benefit from the superior hedging capabilities of PAXG and XAUT, especially in times of financial turbulence between 2019 and 2023.

The median and mean values for beta and hedging effectiveness are displayed, allowing for a comprehensive comparison of the assets' performance across different periods. For instance, in the case of Elon Doge, the PAXG median HE value is 0.00627, with a slightly higher mean of 0.00558, suggesting relatively stable hedging performance. This contrasts with USDT's HE, where the median is significantly higher at 0.50308,

and its mean follows closely at 0.42026, highlighting USDT's stronger but more volatile hedging capacity against Elon Doge. In contrast, BUSD exhibits a notable negative hedging effectiveness with values as low as -17.1424, which indicates its inefficacy in hedging against this particular NFT. This pattern repeats with other cryptocurrencies, for example, in the case of Doge, where BUSD again shows negative HE (-12.18848 median), while USDT consistently outperforms with a median of 0.75671 and a mean of 0.83282. This shows that USDT and, to a lesser extent, PAXG and XAUT are stronger hedging instruments, while BUSD tends to underperform or even act as a liability in certain cases.

Table 4: Hedging and Hedging Effectiveness

	PAXG				XAUT				USDT				BUSD			
	Beta		He		Beta		He		Beta		He		Beta		He	
	Me di an	Me an	Me di an	Me an	Me di an	Me an	Me di an	Me an	Me di an	Me an	Me di an	Me an	Me di an	Me an	Me di an	Me an
Elon Doge	0.0 06 27	0.0 05 58	0.0 07 59	0.0 08 58	0.5 030 8	0.4 20 26	0.0 063 4	0.0 064 6	14. 612 79	17. 527 7	0. 00 45	0. 00 40	- 17. 142	- 25. 350	0.0 06 10	0.0 064 66
Doge	0.0 07 93	0.0 09 42	0.0 19 61	0.0 18 24	0.7 567 1	0.8 32 82	0.0 227 7	0.0 216 09	1.4 270 8	5.0 277 9	0. 00 17	0. 00 16	- 12. 188	- 21. 120	0.0 08 85	0.0 089 34
SHIB	0.0 06 45	0.0 03 08	0.0 12 79	0.0 14 37	0.7 198 9	0.3 55 97	0.0 204 2	0.0 202 6	174 .57 7	210 .49 0	0. 88 38	0. 88 20	- 1.1 474	- 2.7 753	0.0 00 15	0.0 008 5
Theta	0.0 06 39	0.0 06 85	0.0 15 34	0.1 41 79	0.5 849 6	0.5 74 55	0.0 128 4	0.0 118 5	0.0 182 3	0.3 909	0. 00 00	0. 00 01	- 10. 361	- 14. 857	0.0 06 71	0.0 063 18
AXS	0.0 07 25	0.0 04 80	0.0 07 67	0.0 09 03	0.6 239 1	0.4 00 48	0.0 080 3	0.0 116 1	11. 631 6	14. 864 6	0. 00 17	0. 00 29	- 11. 341	- 17. 861	0.0 03 29	0.0 052 4
APE	0.0 14 73	0.0 10 77	0.0 57 27	0.0 58 69	0.7 923 2	0.3 41 51	0.0 248 7	0.0 299 6	28. 609 84	18. 177 1	0. 02 48	0. 02 99	- 192 .22	- 188 .87	0.0 00 02	0.0 006 54
GRT	0.0 11 48	0.0 10 39	0.0 20 68	0.0 20 00	0.7 786 5	0.6 60 47	0.0 131 2	0.0 131 1	30. 197 18	28. 470 83	0. 01 64	0. 01 50	- 4.0 744	- 2.6 012	0.0 00 51	0.0 012 16
ICP	0.0 06 01	0.0 04 76	0.0 06 97	0.0 08 34	0.5 749 3	0.4 117 78	0.1 117 7	0.0 102 1	- - 2.4	- - 0.6	0. 00 00	0. 00 00	- - 19.	- - 27.	0.0 12 26	0.0 167 68

*NR:

						48			531	945	06	12	828	238			
						8			8	3	2	5	43	75			
FIL	0.0 06 73	0.0 06 13	0.0 10 62	0.0 10 06	0.7 227 3	0.7 10 79	0.0 168 6	0.0 159 1	- 0.3 318	- 1.6 131	0. 00 02	0. 00 03	- 6.7 829	- 9.2 421	0.0 02 22	0.0 031 7	
LINK	0.0 06 92	0.0 07 02	0.0 20 45	0.0 18 04	0.5 512 8	0.5 53 36	0.0 148 2	0.0 138 2	0.5 971 4	2.1 206 9	0. 00 06	0. 00 07	NR				
SAND	0.0 06 63	0.0 05 62	0.0 09 26	0.0 09 61	NR				7.5 293 8	10. 929 1	0. 00 14	0. 00 48	0.7 032 5	0.6 026 5	0.0 00 30	0.0 015 0	
DOT	0.0 07 57	0.0 08 35	0.0 15 39	0.0 17 51	- 3.8 472	- 4.3 02 97	0.5 860 6	0.6 080 6	2.6 956 3	3.5 353 1	0. 00 03	0. 00 08	- 19. 910	- 25. 864	0.0 13 99	0.0 160 3	
Baby Doge	0.0 06 51	0.0 04 27	0.0 21 67	0.0 23 00	- 2.8 991 9	- 3.7 27 08	0.3 510 0	0.3 725 8	12. 169 5	15. 176 6	0. 00 84	0. 00 69	1.4 475 0	1.6 699 1	0.0 01 38	0.0 042 10	
FTM	0.0 06 32	0.0 06 86	0.0 09 19	0.0 08 64	0.5 062 8	0.5 73 91	0.0 058 0	0.0 068 0	NR								
MAN A	0.0 05 83	0.0 06 36	0.0 13 16	0.1 20 7	0.4 867 3	0.5 31 67	0.0 108 1	0.0 102 6	2.1 371 0	7.5 304 2	0. 00 67	0. 00 66	- 6.3 944	- 9.6 708	0.0 02 72	0.0 026 37	

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SHIB presents a similar scenario, with USDT again exhibiting strong hedging capacity, reflected in a median HE of 0.71989, although it has a large discrepancy between its median and mean, indicating periods of volatility. Theta displays much closer values across PAXG, XAUT, and USDT, all staying within a narrow range in their hedging effectiveness. However, APE shows distinct behavior with extremely low hedging effectiveness for all assets, particularly BUSD, which shows a massive negative HE (-192.225), meaning it performs worse than simply holding APE unhedged. Similarly, AXS presents better performance for gold-backed tokens like PAXG, with a median HE of 0.00725, while BUSD again proves inefficient with consistently negative values.

For DeFi tokens, the performance trends continue in a similar vein. GRT, for instance, shows strong hedging from USDT with a median HE of 0.77865, outperforming both PAXG and XAUT. Meanwhile, ICP demonstrates volatility, especially for XAUT, where the hedging effectiveness fluctuates between a median of 0.57493 and a higher mean of 0.478488, suggesting that XAUT's hedging capacity is subject to varying market conditions. FIL continues to show strong support for USDT (0.72273 median), while LINK shows better hedging with XAUT. SAND appears as an outlier with consistently weaker hedging effectiveness across most assets, further emphasizing the variability of performance in NFTs and DeFi tokens when compared to classic cryptocurrencies like DOT and LINK.

In terms of broader observations, it is clear that USDT offers the most robust hedging across the majority of assets, often outperforming both gold-backed tokens and BUSD in terms of both median and mean values. PAXG and XAUT generally provide stable performance, particularly against less volatile assets, but their effectiveness tends to weaken when applied to highly speculative or nascent assets like APE and Baby Doge. BUSD, on the other hand, shows frequent negative hedging effectiveness, suggesting that it often acts as a poor hedging instrument, particularly in the NFT and DeFi space. This overall analysis demonstrates that while stablecoins like USDT offer consistent protection, the performance of gold-backed assets is more asset-specific, and the negative performance of BUSD indicates that investors must be cautious when using it as a hedging tool, particularly in volatile markets.

Conclusion

Overall, the price dynamics of DeFi and NFTs, along with their growing demand, have attracted both individual and institutional investors. In this context, the current study investigates the dependence structure between these new digital assets and gold-backed cryptocurrencies in relation to traditional assets. Additionally, we calculate the optimal hedge ratios for various pairs and evaluate the effectiveness of portfolio hedging. To achieve this, the study employs a multi-method approach, analyzing the returns of five NFTs, five DeFi projects, four traditional cryptocurrencies, and four gold-backed cryptocurrencies.

Overall, the findings indicate that different dependence structures exhibit distinct behaviors, heavily influenced by the specific currency pair being analyzed. In conclusion, this study highlights the superior hedging capabilities of gold-backed cryptocurrencies (PAXG and XAUT) compared to stablecoins (USDT and BUSD) during periods of heightened market volatility, particularly amidst significant crises such as the COVID-19 pandemic and the 2021-2022 cryptocurrency downturn. The empirical analysis demonstrates that PAXG and XAUT provide more reliable protection against market fluctuations for both NFTs and DeFi tokens, enhancing portfolio diversification and risk management. Conversely, stablecoins, while offering stable value, exhibit inconsistent hedging effectiveness, particularly during turbulent market conditions. These findings underscore the importance of incorporating gold-backed assets into hedging strategies for better resilience against market uncertainties.

Our empirical findings are significant for investors and traders, as they highlight the similarities and differences between gold-backed and traditional cryptocurrencies in relation to DeFi and NFTs. They provide insights into effective investment strategies by comparing the potential diversification benefits of portfolios that include gold-backed and traditional cryptocurrencies alongside NFT and DeFi assets during periods of extreme market events. Additionally, our results enhance the understanding for DeFi and NFT investors regarding their interconnectedness with other asset classes during unpredictable and disruptive occurrences.

Some limitations of this study stem from the relatively short time frame, as our aim is to evaluate the performance of gold-backed cryptocurrencies compared to traditional cryptocurrencies, NFTs, and DeFi assets. A future extension of this research could involve expanding the sample period both backward and forward to gain a more comprehensive understanding of the correlation structure between these assets. Another limitation of this research is that its implications primarily apply to investors holding only digital portfolios. Future research could explore portfolios that include both digital assets and non-digital assets, such as index stocks, commodities, and others.

In this regard, future researchers could investigate the dynamics of portfolios that integrate digital assets alongside traditional assets, such as equities and commodities. This would allow for a more comprehensive understanding of the interplay between digital and non-digital investments, particularly in terms of risk management and diversification strategies during periods of market volatility. Additionally, exploring different asset classes could provide insights into how hybrid portfolios respond to extreme market events, further enhancing investment strategies in an evolving financial landscape.

References

- Adzimatunur, F., Manalu, V.G., & Rahimi, F. (2020). The sharia compliance of gold-backed-cryptocurrency: analysis of volatility and risk. Proceedings of the 1st Universitas Kuningan International Conference on Social Science, Environment and Technology, UNiSET 2020, 12 December 2020, Kuningan, West Java, Indonesia.
- Ahn, Y. (2022). Asymmetric tail dependence in cryptocurrency markets: A model-free approach. *Finance Research Letters*, 47, Article 102746.
- Alam, N., Gupta, L., Zameni, A. (2019). *Cryptocurrency and Islamic Finance*. Fintech and Islamic Finance. Palgrave Macmillan, Cham, pp. 99–118. https://doi.org/10.1007/978-3-030-24666-2_6.
- Aloui, C., ben Hamida, H., & Yarovaya, L. (2021). Are Islamic gold-backed cryptocurrencies different? *Finance Research Letters*, 39, Article 101615. <https://doi.org/10.1016/j.frl.2020.101615>.
- Ali, F., Elie, B., Nader, N., Syed, J. Shahzad, H., & Mohammad, A.A. (2022). An Examination of Whether Gold-Backed Islamic Cryptocurrencies Are Safe Havens for International Islamic Equity Markets. *Research in International Business and Finance* 63, 101768. <https://doi.org/10.1016/j.ribaf.2022.101768>.
- Aharon, D.Y., Demir, E. (2021). NFTs and asset class spillovers: lessons from the period around the COVID-19 pandemic. *Finance Research Letters*, 102515.
- Alawadhi, K.M., & Alshamali, N. (2022). NFTs Emergence in Financial Markets and their Correlation with DeFis and Cryptocurrencies. *Applied Economics and Finance*, 9(1), ISSN 2332-7294. <https://doi.org/10.11114/aef.v9i1.5444>.
- Baur, D.G., Lucey, B.M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *The Financial Review*, 45 (2), 217–229. <https://dx.doi.org/10.2139/ssrn.952289>.
- Baur, D.G., & McDermott, T.K. (2010). Is gold a safe-haven? International evidence. *Journal of Banking & Finance*, 34, 1886–1898. <https://doi.org/10.1016/j.jbankfin.2009.12.008>.
- Belguith, R., Manzli, Y.S., Bejaoui, A., Jeribi, A., (2024). Can gold-backed cryptocurrencies have dynamic hedging and safe-haven abilities against DeFi and NFT assets? *Digital Business*, 4, 2, 100077. <https://doi.org/10.1016/j.digbus.2024.100077>.
- Ante, L. (2022). The Non-Fungible Token (NFT) Market and Its Relationship with Bitcoin and Ethereum. *FinTech*, 1, 216–224. <https://doi.org/10.3390/fintech1030017>.
- Ante, L. (2023). Non-fungible token (NFT) markets on the Ethereum blockchain: temporal development, cointegration and interrelations. *Economics of Innovation and New Technology*, 32(8), 1216–1234.
- Bedowska-Sójka, B., & Kliber, A. (2022). Can cryptocurrencies hedge oil price fluctuations? A pandemic perspective. *Energy Economics*, 115, Article 106360.
- Borges, T. A., & Neves, R. F. (2020). Ensemble of machine learning algorithms for cryptocurrency investment with different data resampling methods. *Applied Soft Computing*, 90, Article 106187.
- Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, 50, 1–19.
- Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, 77, 156–164.
- Bouteska, A., Sharif, T., & Abedin, M. Z. (2023). Volatility spillovers and other dynamics between cryptocurrencies and the energy and bond markets. *The Quarterly Review of Economics and Finance*, 92, 1–13.
- Briola, A., & Aste, T. (2022). Dependency structures in cryptocurrency market from high to low frequency. *Entropy*, 24(11).
- Burnie, A. (2018). Exploring the interconnectedness of cryptocurrencies using correlation networks: Papers 1806.06632, arXiv.org.
- Caferra, R., Morone, A., & Potì, V. (2022). Crypto-environment network connectivity and Bitcoin returns distribution tail behaviour. *Economics Letters*, 218, Article 110734.
- Canh, N. P., Wongchoti, U., Thanh, S. D., & Thong, N. T. (2019). Systematic risk in cryptocurrency market: Evidence from DCC-MGARCH model. *Finance Research Letters*, 29, 90–100.
- Chalmers, D., Christian, F., Russell, M., William, Q., and Jan, R. (2022). Beyond the bubble: Will NFTs and digital proof of ownership empower creative industry entrepreneurs? *Journal of Business Venturing Insights*, 17: e00309.
- Corbet, S., Goodell, J., Gunay, S., & Kaskaloglu, K. (2021). Are DeFi tokens a separate asset class from conventional cryptocurrencies? Available at: <https://ssrn.com/abstract=3810599>.
- Corbet, S., Goodell, J., Gunay, S. (2022). What drives DeFi prices? Investigating the effects of investor attention. *Finance Research Letters*, 48, 102883. <https://doi.org/10.1016/j.frl.2022.102883>.
- Dowling, M. (2021a). Fertile land: pricing non-fungible tokens. *Finance Res. Lett.*, 102096.
- Dowling, M. (2021b). Is non-fungible token pricing driven by cryptocurrencies? *Finance Res. Lett.*, 102097.
- Grassi, L., Lanfranchi, D., Faes, A., & Renga, F. M. (2022). Do we still need financial intermediation? The case of decentralized finance–DeFi. *Qualitative Research in Accounting & Management*. Vol. 19 No. 3, pp. 323–347.
- Díaz, A., Esparcia, C., & Huélamo, D. (2023). Stablecoins as a tool to mitigate the downside risk of cryptocurrency portfolios. *North American Journal of Economics and Finance*. 64: 101838.
- Juan, P.C., Angeles, M.L.C., Aleksander, S., Isaac, G.L. (2022). A preliminary assessment of the performance of DeFi cryptocurrencies in relation to other financial assets, volatility, and user-generated content. *Technological Forecasting & Social Change*, 181, 121740.
- Jalan, Akanksha & Matkovskyy, Roman, (2023). "Systemic risks in the cryptocurrency market: Evidence from the FTX collapse," *Finance Research Letters*. Vol. 53(C). <https://doi.org/10.1016/j.frl.2023.103670>

- Jalan, A., Matkovskyy, R., & Yarovaya, L. (2021). "Shiny" crypto assets: A systemic look at gold-backed cryptocurrencies during the COVID-19 pandemic. *International Review of Financial Analysis*, 78: 101958.
- Horky, F., Rachel, C., & Fidrmuc, J. (2022). Price determinants of non-fungible tokens in the digital art market. *Finance Research Letters*, 48, 103007.
- Kroner, K.F., & Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *The Journal of Financial and Quantitative Analysis*, 28, 535–551. <https://doi.org/10.2307/2331164>.
- Kroner, K.F., & Ng, V.K. (1998). Modelling asymmetric co-movements of asset returns. *Review of Financial Studies*, 11, 817–844. <http://dx.doi.org/10.1093/rfs/11.4.817>.
- Karim, S., Lucey, B.M., Naeem, M.A. & Uddin, G.S. (2022). Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies. *Finance Research Letters*. 47: 102696.
- Maouchi, Y., Lanouar, C., & Ghassen, E.M. (2021). Understanding Digital Bubbles amidst the COVID-19 Pandemic: Evidence from DeFi and NFTs. *Finance Research Letters*, 1544-6123. <https://doi.org/10.1016/j.frl.2021.102584>.
- Mnif, E., Salhi, B., Trabelsi, L., & Jarboui, A. (2022). Efficiency and Herding analysis in gold-backed cryptocurrencies. *Heliyon*. <https://doi.org/10.1016/j.heliyon.2022.e11982>.
- Ncir, C.E.B., Jarboui, A., & Alyoubi, B. (2021). A wavelet analysis approach to study the volatility risk of Islamic cryptocurrencies and its comparison with stable and non-stable coins: special emphasis on the COVID-19 crisis. *Research Support Program in Islamic Finance (Saudi Central Bank)*.
- Patton, A.J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review*, 47(2).
- Schär, F. (2021). Decentralized Finance: On Blockchain- and Smart Contract-Based Financial Markets. *FRB of St. Louis Review*, <http://dx.doi.org/10.20955/r.103.153-74>.
- Schaar, L., & Kampakis, S. (2022). Non-Fungible Tokens as an alternative investment: evidence from CryptoPunks. *Peer Reviewed Research*, 2516-3957. [https://doi.org/10.31585/jbba-5-1-\(2\)2022](https://doi.org/10.31585/jbba-5-1-(2)2022).
- umUmar, Z., Abrar, A., Zaremba, A., Teplova, T., Vo, X.V. (2022). The Return and Volatility Connectedness of NFT Segments and Media Coverage: Fresh Evidence Based on News About the COVID-19 Pandemic. *Finance Research Letters*, 49, 103031. <https://doi.org/10.1016/j.frl.2022.103031>.
- Wang, G.J., Ma, X.Y., Wu, H.Y. (2020). Are stablecoins truly diversifiers, hedges, or safe havens against traditional cryptocurrencies as their name suggests? *Res. Int. Bus. Financ.* 54, 101225. <https://doi.org/10.1016/j.ribaf.2020.101225>.
- Wang, Y., Horky, F., Baals, L.J., Lucey, B.M., & Vigne, S.A. (2022). Bubbles all the way down? Detecting and stamping bubble behaviors in NFT and DeFi markets. *Journal of Chinese Economic and Business Studies*, 20(4), 415–436. <https://doi.org/10.1080/14765284.2022.2138161>.
- Wasiuzzaman, S., Azwan, A.N.M., & Nordin, A.N.H. (2022). Performance of gold-backed cryptocurrencies during the COVID-19 crisis. *Finance Research Letters*. <https://doi.org/10.1016/j.frl.2021.101958>
- Xia, Y., Li, J., & Fu, Y. (2022). Are non-fungible tokens (NFTs) different asset classes? Evidence from quantile connectedness approach. *Finance Research Letters*. 49: 103156.
- Yousaf, I., Yarovaya, L. (2022a). Static and dynamic connectedness between NFTs, Defi and other assets: Portfolio implication. *Global Finance Journal*, 1044-0283. <https://doi.org/10.1016/j.gfj.2022.100719>.
- Yousaf, I., and Yarovaya, L. (2022b). Spillovers between the Islamic Gold-Backed Cryptocurrencies and Equity Markets during the COVID-19: A Sectorial Analysis. *Pacific-Basin Finance Journal*, 71, 101705. <https://doi.org/10.1016/j.pacfin.2021.101705>.
- Yousaf, I., Nekhili, R., Gubareva, M. (2022). Linkages between DeFi assets and conventional currencies: Evidence from the COVID-19 pandemic. *International Review of Financial Analysis*, 81,102082. <https://doi.org/10.1016/j.irfa.2022.102082>.
- Zhang, Z., Sun, Q., & Ma, Y. (2022). The hedge and safe haven properties of non-fungible tokens (NFTs): Evidence from the nonlinear autoregressive distributed lag (NARDL) model. *Finance Research Letters*, 50, 103315. <https://doi.org/10.1016/j.frl.2022.103315>.