



# Dependence structure between NFT, DeFi and cryptocurrencies in turbulent times: An Archimax copula approach

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## ABSTRACT

This paper investigates the connectedness among eighteen cryptocurrency assets including NFT, DeFi, gold-backed cryptocurrencies, and traditional cryptocurrencies. We also compute the Optimal hedge ratio for each pair of (gold-backed) cryptocurrency-NFT/DeFi and assess their hedge effectiveness. To this end, we use a combination of econometric methods. Our sample period goes from 01/11/2021 to 21/02/2023, making the empirical analysis insightful and interesting as it includes the Covid-19 health crisis and the Russia-Ukraine war. Our empirical findings highlight the dissimilarities between different cryptocurrencies in terms of connectedness with NFT/DeFi assets. They also reflect the diversification benefits generated by the inclusion of gold-backed cryptocurrencies into NFT/DeFi portfolios, in particular in times of unprecedented events. These findings could be useful for crypto-investors who search to diversify their portfolios.

## 1. Introduction

Cryptocurrencies have been subject to increasing scrutiny in the financial economics realm. This market experienced an explosive evolution, that departed from the original idea of Nakamoto (2009) of establishing a peer-to-peer payment system that could bypass the traditional banking system. In fact, this market has evolved into a complex cobweb of different but interrelated instruments such as plain cryptocurrencies, fungible tokens, non-fungible tokens (NFT), and Decentralized Finance projects (DeFi). Daily volume exceeds 60 USD billion, thus their importance in the investment strategy of many people cannot be ignored.

Bariviera and Merediz-Solà (2021) provide a comprehensive landscape of the scientific production around cryptocurrencies in the financial economics realm. Three closely related research lines emerge in the literature: assets' correlations, safe haven characteristics, and portfolio formation.

Regarding the first topic, Corbet et al. (2018) and Aslanidis et al. (2019) find that cryptocurrencies are relatively isolated from traditional assets (stocks, bonds, or gold), but they exhibit similar mean correlations among them. Additionally, Koutmos (2018) find that there is a bidirectional linkage between Bitcoin returns and transaction activity, whereas Giudici and Abu-Hashish (2019) report a strong price correlation of Bitcoin across different exchange markets. More recently, Aslanidis et al. (2022) uncover that cryptocurrency returns and volatilities are not linked to broad uncertainty indices (e.g. measured by Google Trends), but to market-specific uncertainty proxies. Consequently, the literature agrees that the different assets in the cryptocurrency market are correlated and that they do not comove with other financial assets.

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Regarding the second topic, the use of cryptocurrencies as a safe haven is controversial. [Bouri et al. \(2017\)](#) report that Bitcoin acts as a poor hedge and is more suitable for diversification purposes. However, according to [Urquhart and Zhang \(2019\)](#) it can be an intraday hedge against some fiat currencies, whereas it acts as a diversifier for other fiat currencies.

Finally, portfolio management seems to be an active research area involving cryptocurrencies. [Liu \(2019\)](#) use data from ten major cryptocurrencies, finding some diversification benefits. Similarly, [Platanakis and Urquhart \(2019\)](#) compares naïve diversification with more advanced portfolio models, finding that the latter yield superior risk-adjusted returns.

With the advent of Covid-19 pandemic, many researchers have endeavored to understand the impact of health crises on international financial markets and cross-market linkages ([Arouxet et al., 2022](#); [Bariviera et al., 2023](#); [Corbet et al., 2023](#); [Salisu & Vo, 2020](#); [Zhang et al., 2020](#)). Not only that, but they have also investigated the features of cryptocurrencies as hedge and safe haven against other assets ([Bedowska-Sójka & Kliber, 2022](#); [Yousaf & Yarovaya, 2022](#)). In this regard, an increasing number of papers focus on the connections between cryptocurrencies and traditional assets. Nevertheless, research on the potential roles of (gold-backed) cryptocurrencies in portfolios including NFT and DeFi still remains under-explored. Also, when comparing the large literature on Bitcoin and other cryptocurrencies, papers on DeFi and NFTs markets seem to be scanty ([Maouchi et al., 2022](#)). Very few issues related to such assets start to be under study such as NFTs pricing and relationship with other cryptocurrencies ([Dowling, 2022a](#)). Therefore, the empirical literature lacks evidence on the diversification advantages of different cryptocurrencies against new digital crypto assets.

Considering the relatively recent introduction of NFT and DeFi, the outbreak of stressing market situations (Covid-19 and Russia–Ukraine war), as well as the dynamic characteristics of this market, it is worth researching the linkage structure and hedge ratio of a set of representative crypto-assets during turbulent times.

In this sense, this paper studies a comprehensive sample of five NFTs, five DeFi projects, four traditional cryptocurrencies and tokens, and four gold-backed cryptocurrencies. Their interrelationship is not trivial, and investors would benefit from different hedging strategies, in order to reduce risks and generate the highest possible returns. In this paper, we use a sequential approach of quantitative methodologies, comprising Extreme Value Theory, and Archimax copula. The latter is a flexible class of copulas that have recently gained popularity in the field of finance. In particular, they are a type of copula that is based on the generalized extreme value distribution, which allows for the flexible modeling of tail dependence.

More precisely, the purpose of this study is two-fold. First, we investigate the dependence structure between gold-backed and traditional cryptocurrencies and tokens, and NFTs/DeFi assets through a four-step approach. Such a multi-step procedure allows us to examine and better understand the interdependence between new and traditional crypto-assets, specially at the tails of their distributions. Second, we also compute the hedge ratios and assess the hedge effectiveness which could further help to understand to what extent gold-backed and traditional crypto-assets could diminish the downside risk of NFT and DeFi crypto-portfolios. Then, we study the potential impact of the Covid-19 pandemic and the geopolitical risk. This could help cryptocurrency investors and portfolio managers to curb loss under extreme market conditions.

This study contributes to the literature in three key aspects. First, it expands the vast research on crypto-market linkages by considering the combination of gold-backed and plain cryptocurrencies and tokens with new digital currencies (DeFi and NFTs) in a portfolio, and assesses if (or to what extent) such dependence structure could offer further diversification benefits. Second, it contributes to the study of hedging, diversification, and safe-haven features between traditional versus new cryptocurrencies during turbulent economic conditions. In this regard, it provides a close look at the potential impact of geopolitical risk (and the derived economic uncertainty) on the (new/traditional) cryptocurrency connectedness. Particularly, we investigate if different digital currencies tend to exhibit (dis)similar connectedness reaction patterns to a political event. Third, this study offers some interesting information about the possibility of predicting NFTs/DeFi prices based on price formation from other cryptocurrencies' prices.

The remaining of the paper is organized as follows. Section 2 conducts a brief literature review. Section 3 explains the methodology. Section 4 describes the data. Sections 5 and 6 display the results and discuss the main empirical findings, respectively. Finally, Section 7 offers some concluding remarks.

## 2. Literature review

Many researchers have extensively investigated the hedging and safe-haven properties of new and traditional crypto-assets (e.g. Bitcoin and NFTs) against various assets (e.g. stock indices, crude oil). For instance, [Klein et al. \(2018\)](#) investigate and compare conditional variance features of gold, Bitcoin, and other assets, showing a discrepancy between them. Using a BEKK-GARCH model, they report that gold is relevant for stock markets as a flight-to-quality vehicle during turbulent times. They also reveal that Bitcoin could be correlated positively with downward markets. [Mensi et al. \(2019\)](#) show that forming different portfolios based on cryptocurrencies (e.g. Bitcoin, Monero, Litecoin, and Bitcoin) offers better diversification advantages for portfolio managers and investors. [Wang et al. \(2019\)](#) report that cryptocurrency could generally serve as a safe haven, but it is not a hedge for most stock markets. They also show that the safe-haven feature tends to be more pronounced in developed markets. [Le et al. \(2021\)](#) study the frequency-based dependency networks of different financial assets in the tails of return distributions. They report increases in the network density in both upper and lower regions of the distributions of asset returns. In particular, an asymmetric effect of the Covid-19 pandemic is well-documented. They also display that the cross-asset tail-dependency of currency, equity, and commodity markets raises significantly in the left tails, which implies a higher degree of tail contagion effects. [Wang et al. \(2020\)](#) investigate the safe-haven, hedging, and diversifying features of stablecoins against classical digital currencies. They show that USD-pegged (resp. gold-pegged) stablecoins tend to perform better (resp. worse) than their corresponding underlying assets. They afterward show that USD-pegged stablecoins perform better than gold-pegged stablecoins in extreme risk reductions. [Aloui et al. \(2021\)](#) evaluate

the effect of geopolitical risk on conventional and Islamic gold-backed gold cryptocurrencies using M-GARCH model. They reveal that Islamic gold-backed cryptocurrencies behave differently from their conventional counterparts. They show that geopolitical risk increases the connectedness of gold-backed cryptocurrencies to gold volatility and returns. [Bouri et al. \(2020\)](#) compare the hedging and safe-haven properties of Bitcoin and gold against the G7 stock markets. They show that gold can be considered a suitable hedge and safe-haven asset for many G7 stock indices, while Bitcoin takes such properties only for the Canadian stock market. They also report that gold provides many conditional diversification benefits and more stable linkage for the G7 stock markets compared to Bitcoin.

[\(Jalan et al., 2021\)](#) investigate the performance of five gold-backed stablecoins during the Covid-19 pandemic and compare them to Bitcoin, Tether, and gold. They show that gold-backed cryptocurrencies seem to be susceptible to volatility transmitted from gold markets during the Covid-19 pandemic period. They also report that the volatility of such assets is similar to that of Bitcoin. [Wasiuzzaman and Rahman \(2021\)](#) study the performance of gold-backed cryptocurrencies during the Covid-19 pandemic and the bear market of 2020. They record that the mean returns of such assets rise insignificantly during crisis periods. They also reveal that PAX Gold displays increased volatility over the Covid-19 pandemic and the bear market, but its increase can be insignificant. [Jareno et al. \(2021\)](#) study potential asymmetric and nonlinear interdependencies between cryptocurrencies and oil price shocks over the period 20/11/2018-30/06/2020. Using the NARDL model, they also analyze the connectedness between cryptocurrencies and crude oil. They afterward report that demand shocks display the highest association with cryptocurrencies. The long and short-run analysis proves a strong connection between cryptocurrencies and oil during turbulent times. [Dowling \(2022a\)](#) examines the relationship between NFT pricing and cryptocurrency pricing. The empirical results show limited volatility transmission between NFTs and other crypto-assets, given the value of the spillover index. This seems to indicate that cryptocurrency pricing behavior can help to recognize NFT pricing patterns. Nevertheless, the low volatility transmission reveals that NFTs could be considered as low-correlation assets, and different from traditional cryptocurrencies. [Bedowska-Sójka and Kliber \(2022\)](#) investigate the hedging potential of cryptocurrencies against Brent crude oil during the period 10/02/2020-10/02/2022. In this context, the advent of the Covid-19 pandemic has increasingly impacted oil prices by raising the economic uncertainty and mobility factor. They clearly display that stablecoins constitute the best hedge against downward fluctuations in oil prices, but do not decrease investment volatility. [Maouchi et al. \(2022\)](#) analyze digital financial bubbles during the Covid-19 pandemic period using Bitcoin, Ethereum, nine DeFi tokens, and three NFTs. They identify many overlapping bubbles. In particular, they detect NFT and DeFi bubbles, which tend to be less recurrent with high magnitude than the other crypto-assets. The outbreak of the Covid-19 pandemic increased bubble occurrences. [Mokni et al. \(2022\)](#) examine if cryptocurrencies and gold tend to be safe-haven assets and hedge against economic policy uncertainty (EPU) before and during the health crisis. They disclose that cryptocurrencies and gold cannot act as safe haven or hedge against EPU before and during the health crisis. [Dunbar and Owusu-Amoako \(2022\)](#) indicate that causality seems to flow from equity returns to cryptocurrencies. They afterward show that equities tend to be more inversely related to cryptocurrencies during the Covid-19 pandemic period. This suggests that equities could be a suitable hedge against cryptocurrency risks. Based on rolling window regressions, they display that the equity risk premium decreases downside risk during a substantial crisis event (e.g. the Covid-19 pandemic). [Gadi and Sicilia \(2022\)](#) investigate the safe-haven, hedging, and diversifying abilities of cryptocurrencies against stock indices in G7 and BRICS regions during the period 01/01/2018-30/09/2022. Based on the Baur and McDermott model, they show that blockchain technology pre/during the Covid-19 pandemic period could play a crucial role in the safe-haven, hedging, and diversifying features linked to such assets. More precisely, stablecoins tend to sustain hedging features in most stock markets before and during the health crisis. Nevertheless, Bitcoin investment features tend to change after the beginning of such a crisis. [Shahzad, Bouri, Ahmad, and Naeem \(2022\)](#) study the safe-haven and hedging properties of traditional currencies for Bitcoin, Litecoin, Ethereum, and Ripple. They report that the Japanese yen is an effective hedge for digital currencies, followed by the British pound, and the Chinese yuan. The safe-haven proprieties for the yen, euro, and yuan are maintained during the adverse explosiveness periods of the cryptocurrency market. [Díaz et al. \(2023\)](#) evaluate the capacity of stablecoins to reduce the downside risk of a traditional cryptocurrency portfolio. They detail the low conditional correlations between dollar-backed stablecoins and cryptocurrency portfolios, clearly showing that they can be considered as hedges for cryptocurrencies. They also report that all stablecoins tend to have great diversification abilities by decreasing portfolio tail risk. [Khaki et al. \(2023\)](#) re-examine the portfolio diversification properties of cryptocurrencies, using mean-variance and higher-order moments optimization techniques. They conclude that expanding the set of digital currencies can achieve only marginal advantages given the substantial comovements between cryptocurrencies. Finally, [Nedved and Kristoufek \(2023\)](#) show that stock markets tend to move along with Bitcoin, whereas gold and crude oil could be considered safe havens. In particular, gold tends to be a strong safe haven for Bitcoin.

From a methodological standpoint, many researchers have increasingly tried to use advanced econometric models to better understand interconnections between cryptocurrencies and other assets ([Burnie, 2018](#); [Caferri et al., 2022](#); [Giudici & Polinesi, 2021](#)), analyze the tail risk of cryptocurrency prices ([Ahelegbey et al., 2021](#); [Bouteska et al., 2023](#)) and construct portfolios using machine learning models ([Babaei et al., 2022](#); [Jiang & Liang, 2016](#)). For instance, [Burnie \(2018\)](#) uses the correlation networks method to identify features that highly affect the evolution of cryptocurrency prices. They show a positive relationship among different cryptocurrencies, except for USD Tether. [Ho et al. \(2020\)](#) study the features and dynamic evolution of 120 cryptocurrencies during the period 2013–2020 by performing network analysis. They show that the cross-returns between cryptocurrencies are decreasing during 2013–2016 and increased after that period. They also display that cryptocurrencies used for transaction payment tend to be dominant in the market until mid-2016, followed by those developed for applications based on Blockchain. Using the correlation networks method, [Giudici and Polinesi \(2021\)](#) scrutinize the dynamics of cryptocurrencies' prices and how price information is conveyed between the different Bitcoin exchanges and between Bitcoin markets and traditional ones. They reveal that Bitcoin exchange prices tend to be positively linked to each other. They also report that traditional asset volatilities (resp. prices) affect

(resp. cannot influence) Bitcoin prices with adverse and lagged effects. Nie (2022) examines the evolution of correlations in the cryptocurrency market by using a network method. Such a method is also employed to detect critical events in the correlation dynamics of cryptocurrencies. The empirical results show great fluctuations in the market index near such events. This indicates the existence of a relationship between the correlation matrix dynamics and market states. The empirical findings also display a synchronization among changes in correlation and changes in network structures. Caferra et al. (2022) study if and how cryptocurrency ecosystem network connectivity could predict Bitcoin returns through quantiles of the return distribution. They show the effectiveness of many connectivity measures in predicting both price downfalls and spikes, but in a different way before and during the Covid-19 pandemic. Briola and Aste (2022) analyze cross-correlations of 25 liquid cryptocurrencies at various time horizons. Using the network, they show that a decrease in correlation among pairs of cryptocurrencies for finer time sampling resolutions is well-documented. They also display a growing framework for coarser resolutions, indicating multiple changes in the hierarchical reference role played by cryptocurrencies. Jing and Rocha (2023) employ network methods to choose cryptocurrencies and the Markowitz Portfolio Theory to establish portfolios that are agnostic for further market behavior. They show that the performance of their network-based portfolios tends to be optimal with 46 cryptocurrencies and higher to benchmarks for short-term investments, achieving up to mean expected returns within 1 day. Ma et al. (2023) try to explore if crypto tokens could improve portfolio performance and how crypto tokens could be interesting alternatives for portfolio diversification. Using correlation-based networks, they report tokens with great Sharp ratios but low centrality could boost the portfolio performance. They also report that the market is dominated by tokens from GameFi sectors, DeFi, and Blockchain infrastructure.

Borri (2019) estimate the conditional tail-risk in the cryptocurrency markets (Ripple, Litecoin, Bitcoin, and Ether) by employing CoVaR. The empirical results show that even though cryptocurrency returns tend to be greatly linked one to another, idiosyncratic risk could be substantially decreased and cryptocurrency portfolios provide better conditional and risk-adjusted returns than individual cryptocurrencies. Canh et al. (2019) study the structural breaks and volatility spillovers in different cryptocurrencies. They use the Granger Causality test, LM test for ARCH and Dynamic conditional correlation MGARCH model, and Cumulative sum test for parameter stability. They report that structural breaks exist in many cryptocurrencies. They also show the shifts from smaller cryptocurrencies to larger ones in terms of market capitalization. Opala et al. (2022) study the risk measurement of Ethereum, Bitcoin, and Litecoin using different models such as the extreme value theory. They report that the extreme value theory with the peaks-over-threshold method shows satisfactory backtesting results at a 99% confidence level. They show that the greatly volatile market phases may not be observed from the short time series. Ahn (2022) examines extreme tail dependence between cryptocurrencies and the S&P500 index using a model-free approach. The empirical results show that any symmetric model cannot succeed in explaining the correlation framework in major cryptocurrency returns. The sample upward tail correlations among digital currencies and the equity market are lower than the downward tail ones. Ahelegbey et al. (2021) study the links between market assets during turbulent times using the extreme downside hedge and the extreme downside correlation. They show that crypto-assets could be divided into two sets: technical assets (e.g. Ethereum) which are receivers of tail contagion whereas speculative assets are transmitters of contagion.

Umar et al. (2022) analyze tail dependence of higher-order moments and portfolio features using NFTs and other assets. Using Conditional Value-at-Risk (CoVaR) and  $\Delta$ CoVaRs along with different copula functions, they show that NFTs have beneficial investment and hedging features under all market conditions. Bouteska et al. (2023) analyze the interconnections among the cryptocurrency volatilities, the US equity and bond markets' volatility, and the effects of Covid-19 pandemic. They also explore the potential presence of structural breaks in the volatility of Dash, Monero, Bitcoin, and Stellar. They use GARCH models and Inclán and Tiao (1994) Cumulative Sums of Squares algorithm and Simultaneous Equation Model. They report the presence of return-volatility spillovers among Dash, Bitcoin, and Stellar while Monero is the main transmitter of shocks. Fang et al. (2023) employ  $\Delta$ CoVaR and MES to forecast the systemic risk in the cryptocurrency markets. They display that EOS, Aoen, and Sinacoin tend to better forecast systemic risk. Jalan and Matkovskyy (2023) show the lack of substantial decreases and increases in liquidity and systemic risk, respectively.

Jiang and Liang (2016) employ a convolutional neural network with historic prices of cryptocurrencies to provide forecasts. They provide interesting results for portfolio management. Borges and Neves (2020) develop a system using machine learning methods to establish an investment strategy to trade cryptocurrency exchange markets. They show that all learning algorithms tend to outperform the buy-and-hold strategy in most markets. Using ARIMA, convolutional neural network, and long/short-run memory methods, Ramkumar (2021) attempts to forecast the cryptocurrency prices. The empirical results display that multiple portfolios are established using equal-weighted portfolios, modern portfolio theory, cointegrated pairs, Kelly criterion, and risk parity. They show that a portfolio constructed using a cointegrated pair has outperformed and the annualized returns are maximized based on a pair trading strategy. Sebastiao and Godinho (2021) analyze the predictability of three cryptocurrencies (Bitcoin, Ethereum and Litecoin) and the profitability of trading strategies using machine learning techniques during the period 15/08/2015-03/03/2019. Overall, they report that machine learning methods offer robust results concerning the predictability of cryptocurrencies. Babaei et al. (2022) propose an explainable portfolio management approach for cryptocurrencies using a machine learning model. Using such an approach they are able to understand what is behind the chosen portfolio weights, providing useful hints for portfolio managers (better risk adjustment) and policymakers (implementation of better financial regulation).

### 3. Methodology

This paper investigates the dependence structure and optimal hedge ratios between NFT, DeFi, and traditional and gold-backed cryptocurrencies. To do so, a four-step approach is used. First, we filter residuals using an AR(1)-FIEGARCH(1,  $d$ , 1) model. Second, we employ the Extreme Values Theory (EVT) to identify extreme events (e.g. the Covid-19 pandemic and the Russia–Ukraine war). We particularly adopt the Peaks Over Thresholds (POT) method. Before estimating the GEV distribution parameters of extreme values, we choose 30% of the observations; 15% of them are related to the large-value (resp. small-value) observations. Finally, we employ the copula method to estimate the extreme series interdependence structures.

We employ a FIEGARCH( $p, d, q$ ) model to deal with autocorrelations, shock asymmetry, and shock persistence of the time series. Such a model also enables us to take into consideration both ARCH and long-memory effects. Developed by [Bollerslev and Mikkelsen \(1996\)](#), the model is given as follows:

$$\ln(h_t) = \omega + \phi(L)^{-1}(1 - L)^{-d}[1 + \alpha(L)]g(z_{t-1}) \tag{1}$$

with  $g(z_t) = \gamma_1 z_t + \gamma_2 [|z_t| - E|z_t|]$

The FIEGARCH( $p, d, q$ ) model can be transformed into an EGARCH model (resp. an integrated EGARCH) when  $d = 0$  (resp.  $d = 1$ ). Analogous to the ARFIMA model,  $\{\ln(h_t)\}$  is covariance-stationary and invertible for  $d \in [-0.5, 0.5]$  ([Bollerslev & Mikkelsen, 1996](#)). Additionally, the long-memory feature dissipates for all the values of  $d < 1$ . We thereafter assume that the return equation is given as follows :

$$r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \tag{2}$$

where  $r_t$  (resp.  $r_{t-1}$ ) denotes the return index at time  $t$  (resp.  $t - 1$ ), and  $\alpha_0, \alpha_1$  are parameters.

Needless to say, analyzing the cross-market linkages among several assets requires information regarding the underlying dependence associations. To do so, a flexible copula framework is selected. Following the [Sklar \(1959\)](#) theorem, the joint distributions of two continuous random variables  $X$  and  $Y$ ,  $F_{XY}(x, y)$ , with marginal functions  $F_X(x)$  and  $F_Y(y)$ , are described using the following copula function  $C$ :

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)) \tag{3}$$

There is a critical issue related to multivariate distribution modeling. To obviate any complexity, one might use the bivariate distribution copula method to model the dependence relationship among two variables. In particular, the Archimax copulas developed by [Capéraà et al. \(2000\)](#) are used in this study. Indeed, they combine the Extreme Value Theory and Archimedean copula classes into a single class. Extreme value theory is a branch of the theory of order statistics, which dates back to the pioneering works by [Fisher and Tippett \(1928\)](#). Extreme value theory is concerned with the asymptotic distribution of standardized maxima from a series of i.i.d random variables. Extreme Value Theory provides a strong framework to formally analyze the behavior of extreme observations ([Marimoutou et al., 2009](#)). Essentially, there are two main methods to apply the EVT, i.e. to model extreme values of a random variable. First, we have the Block Maxima Method (BMM); it divides the time horizon into periods (i.e. blocs) in which the maximum values of the variable in each period are retained. These observations are considered as extreme events. However, taking into account merely the maximum return in each period induces the exclusion of many data points from the analysis. Hence, the BMM does not allow enough study of the volatility clustering. Second, to overcome such shortcomings, the so-called Peak-Over Threshold (POT) method was developed. This method takes into consideration all the values above a given (high) threshold.

The Archimax copulas are given by:

$$C(u, v) = \varphi^{-1} \left[ (\varphi(x) + \varphi(y)) A \left( \frac{\varphi(u)}{\varphi(u) + \varphi(v)} \right) \right] \tag{4}$$

where  $A(t)$  is a valid dependence function, and  $\varphi$  is a valid Archimedean generator. Archimax copulas reduce to Archimedean copulas for  $A(t) = 1$  and to EV copulas for  $\varphi(t) = -\ln(t)$ .

In this context, the BB4 Archimax copula with

$$\varphi(t) = t - \theta - 1 \text{ and } A(t) = 1 - (t^{-\delta} + (1 - t)^{-\delta})^{-1/\delta} \tag{5}$$

is called the BB4 copula and is given by the following formula:

$$C(u, v) = \left( u^{-\theta} + v^{-\theta} - 1 - [(u^{-\theta} - 1)^{-\delta} + (v^{-\theta} - 1)^{-\delta}]^{-1/\delta} \right)^{-1/\theta} \tag{6}$$

with  $\theta \geq 0$  and  $\delta > 0$ .

Afterward, the dependence coefficient could be used to compute the optimal hedge ratios. In this way, investors could learn how NFT and DeFi can be effectively hedged by other assets (i.e. plain and gold-backed cryptocurrencies and tokens).

To illustrate, let an investor want to hedge his/her portfolio position against cryptocurrency market price fluctuations. From a portfolio perspective, the investor wants to minimize the portfolio risk without diminishing the expected returns. Following [Kroner and Sultan \(1993\)](#), the optimal hedge ratio of his/her portfolio is determined as follows:

$$\beta_t^{SO} = \frac{h_t^{SO}}{h_t^S} \tag{7}$$

where:

- $\beta_t$  refers to the risk-minimizing hedge ratio about assets.
- $h_t^s$  refers to the conditional variances of the assets.
- $h_t^{s'o}$  corresponds to the conditional covariance between digital assets at time  $t$ .

Hedging strategies can be used to reduce market risk by offsetting losses in one asset with gains in another. In this study, we investigate the effectiveness of hedging plain and gold-backed cryptocurrencies with NFT and DeFi tokens. We find that the optimal hedge ratio, which is the amount of NFT and DeFi tokens to sell ( $\beta$ ) for every dollar invested in plain and gold-backed cryptocurrencies, varies depending on the specific cryptocurrency. We then use the hedge effectiveness (HE) index to assess the performance of various optimal hedge ratios.

Following [Ku et al. \(2007\)](#) and [Chang et al. \(2011\)](#), the HE index is computed as follows:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \quad (8)$$

#### 4. Data

This paper uses daily data from 01/11/2021 to 21/02/2023 of eighteen digital assets<sup>1</sup>:

- five NFTs: Metaverse NFT index (PLAY), Unicy CryptoPunks Collection (UPUNK), Sandbox (SAND), NFTLaunch (NFTL), and xNFT Protocol (xNFT).
- five DeFi projects: DeFi Pulse Index (DPI), Terra Classic (LUNC), Avalanche (AVAX), Wrapped Bitcoin (WBTC), and Chainlink (UNK).
- four plain cryptocurrencies and tokens: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), and FTX Token (FTT).
- four gold-backed cryptocurrencies: Pax Gold (PAXG), Tether Gold (XAUT), Perth Mint Gold Token (PMGT), and Digix Global (DGX).

Data were downloaded from [www.coinmarketcap.com](http://www.coinmarketcap.com). Thus, the sample has 477 daily observations.

The rationale behind choosing (five) NFTs, (five) DeFi and (four) cryptocurrencies, and (four) gold-backed cryptocurrencies is based on two criteria: the availability of the data and the market capitalization. According to [Karim et al. \(2022\)](#), such cryptocurrencies, seem to be mature and have strong market capitalization whereas DeFis and NFTs remain emerging and show different market capitalization. We also chose four gold-backed cryptocurrencies as stablecoins which are different from those used by [Díaz et al. \(2023\)](#) to better understand and assess the ability of such assets against new digital assets in terms of portfolio diversification.

All the price series are transformed into logreturns as  $R_{i,t} = \log(P_{i,t}) - \log(P_{i,t-1})$ , where  $P_{i,t}$  (resp.  $P_{i,t-1}$ ) corresponds to the asset  $i$  closing price at time  $t$  (resp.  $t - 1$ ).

[Table 1](#) reports the sample statistics for assets under consideration. It is worth mentioning that the highest (resp. the lowest) mean return is recorded for LUNC (resp. PAXG and PMGT) which is equal to 0.0317 (resp. 0). All the mean values of assets are positive whereas median of some assets presents negative values such as LINK and BNB. We also report that the highest standard deviation is recorded for LUNC (0.3888) whereas the lowest one is for PAXG (0.0080). The results of the Jarque–Bera test reject the null hypothesis of normal distribution for returns.

[Fig. 1](#) illustrates the daily return movements over the period 01/11/2021-30/11/2022. From [Fig. 1](#), all daily return series seem to fluctuate over time, indicating the existence of some turning points. All daily returns series tend to show a volatility clustering behavior.

[Fig. 2](#) illustrates the correlation among different assets. Recall that the diagonal elements of the matrix correspond to the variances (dark blue color) whereas the off-diagonal elements refer to the covariances between all potential pairs of assets. At first sight, the pairwise correlations between assets tend to be positive and vary from 0 and 0.9. Some dissimilarities in the correlation framework are well-documented. Indeed, some correlations are low whereas other ones are high. For instance, the pairs ETH/DPI, BTC/WBTC, and XAU/PAXG are highly and positively related, with a value of about 0.8. However, SAN/UPUNK, FTT/PLAY are weakly and positively linked, with a value of around 0.1.

<sup>1</sup> [Díaz et al. \(2023\)](#) show that three stablecoins (Tether, USD coins and Digix Gold) are characterized by higher diversifying and hedging potential against traditional cryptocurrencies (Bitcoin, Ethereum, Ripple, Cardano and Litecoin). Many researchers have studied the hedging, diversifying, and safe-haven features of different assets against cryptocurrencies ([Dunbar & Owusu-Amoako, 2022](#); [Nekhili & Sultan, 2022](#); [Shahzad, Bouri, Ahmad, & Naeem, 2022](#); [Shahzad, Bouri, Rehman, & Roubaud, 2022](#)). In our paper, we analyze the interrelatedness of NFTs and DeFi to evaluate the ability of different asset classes (gold-backed cryptocurrencies and traditional cryptocurrencies). Four gold-backed cryptocurrencies (i.e. Pax Gold, Tether Gold, Perth Mint Gold Token, and Digix Gold) which are stablecoins are used in our study. Among them, Digix Gold has already been used as a stablecoin by [Díaz et al. \(2023\)](#). We also chose four gold-backed cryptocurrencies as stablecoins which are different from those used by [Díaz et al. \(2023\)](#) to better understand and assess the ability of such assets against new digital assets in terms of portfolio diversification.

**Table 1**  
Descriptive statistics.

Asset	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque–Bera	Q(16)	Q2(16)
PLAY	-0.524	0.000	83.509	-81.830	13.584	0.236	21.069	6493.27***	123.720***	136.640***
UPUNK	-0.253	-0.039	28.137	-27.455	5.506	-0.568	9.942	983.51***	38.694***	114.790***
SAND	-0.208	-0.170	37.499	-28.576	6.615	0.503	7.137	360.23***	19.719	47.402***
NFTL	-0.319	-1.127	58.159	-53.078	9.172	1.460	14.546	2819.04***	12.960	56.737***
XNFT	-0.788	-0.663	57.812	-53.957	8.811	1.451	17.586	4395.61***	20.599	22.675
DPI	-0.293	-0.014	18.914	-25.108	4.967	-0.521	5.800	177.44***	14.591	43.585***
LUNC	-2.618	-0.376	150.364	-554.678	35.408	-11.186	157.847	486502.50***	155.430***	174.190***
AVAX	-0.238	-0.078	22.299	-36.414	6.038	-0.497	6.213	224.87***	22.200	40.545***
WBTC	-0.192	-0.013	13.548	-17.460	3.275	-0.574	7.187	374.69***	18.562	17.642
LINK	-0.297	0.000	14.770	-21.502	5.100	-0.545	4.429	64.15***	23.356	112.530***
BTC	-0.192	-0.111	13.576	-17.405	3.271	-0.536	7.180	370.17***	18.978	16.890
ETH	-0.201	-0.138	16.648	-19.185	4.305	-0.404	5.904	180.57***	23.367	46.347***
BNB	-0.104	0.179	20.546	-19.376	3.878	-0.604	7.994	524.80***	11.171	86.481***
FTT	-0.747	-0.202	42.555	-194.000	10.935	-11.482	207.091	838337.40***	33.920***	2.219
PAXG	0.002	0.001	3.000	-3.068	0.774	-0.054	5.129	90.34***	29.133**	35.551***
XAUT	0.005	0.011	2.745	-2.848	0.700	-0.148	5.126	91.55***	24.645*	17.793
PMGT	0.005	0.000	11.365	-13.226	1.325	-0.783	33.707	18789.63***	30.865***	106.290***
DGX	0.009	-0.141	186.727	-151.260	16.542	1.994	59.993	64873.88***	61.472***	43.946***

**Table 2**  
FIEGARCH estimation results.

	C	AR(1)	A	GARCH(1)	ARCH(1)	LEV(1)	Fraction
PLAY	0.0112***	-0.1183***	-0.1088***	0.6318	0.3104***	0.2312***	0.8743***
UPUNK	0.0072***	-0.0829**	-0.4273**	0.8638***	0.1473***	-0.1832	0.4402**
SAND	0.0039*	0.0125	-0.3582***	0.3528*	0.2743***	0.0482**	0.5703***
NFTL	0.0072***	-0.0765**	-0.9752***	0.1122	0.4219***	0.1983***	0.4038***
XNFT	0.0032	-0.1214***	-1.8732***	0.7148*	0.1993***	0.2438***	0.1183**
DPI	0.0082*	0.0195	-0.4478**	0.7153**	0.1473**	0.2731***	0.3274**
LUNC	0.0061**	-0.0406*	-0.7532***	0.7012***	0.2842***	0.1704***	0.0329
AVAX	0.0033**	0.0337	-0.7632**	0.6731***	0.3422***	0.1392***	0.3521
WBTC	0.0044**	0.0041	-0.6429	0.6662*	0.1288**	0.2231***	0.1099
LINK	0.0021	0.0039	-0.8652	0.6991***	0.2626***	0.0904**	0.0438
BTC	0.0043**	-0.0019	-15.095	0.5723*	0.1629**	0.2520***	0.1275
ETH	0.006	0.0308	-17.753	0.7629***	0.1852***	0.2187***	0.0184
BNB	0.0023	0.0886**	-0.7459**	0.6982***	0.1399**	0.2762***	0.2067*
FTT	0.0011	-0.0773*	0.0195	0.6421***	0.2862***	0.7896***	0.4208***
PAXG	0.0002	0.0028	-11.642	0.8751***	0.0847*	-0.0628**	0.4401**
XAUT	0.0001	0.0209	-12.406	0.8621***	0.0642	-0.1382***	0.4502**
PMGT	-0.0002	-0.2127***	-14.175	0.7230***	0.1851*	-0.1421**	0.3217
DGX	0.0113**	-0.1578***	-0.4652***	0.9261***	0.0632***	-0.6413***	0.1982

Note: \*, \*\* and \*\*\* denote significance at 10%, 5%, and 1%, respectively.

## 5. Results and discussion

### 5.1. FIEGARCH model

Since ours is a sequential multi-model approach, it is important to select the more appropriate model at each stage. Thus, we first estimate different GARCH-type models (i.e. GARCH, EGARCH, TGARCH and FIGARCH), with their corresponding information criteria, which allow us to choose the best model. Table 4 in the Appendix reports the results from the calculation of the usual information criteria. The lowest values of different information criteria clearly show the FIEGARCH model is preferred, indicating that this model offers the best fit for our data.

As aforementioned, the AR(1)-FIEGARCH(1,  $d$ , 1) model allows us to evaluate the asymmetric shock effect on volatility (i.e. the leverage effect) and the long memory persistence. Table 2 reports the estimation results.

Table 2 reveals that the leverage effect coefficient LEV(1) is significant for all assets. That is, all time series show significant and positive leverage effects whereas gold-backed cryptocurrencies show significant and negative effects. Indeed, a negative leverage effect indicates that negative shocks raise volatility less than positive ones. Such empirical results confirm those reported by Jeribi and Fakhfekh (2021), Choi and Shin (2022), and Fakhfekh et al. (2016) for financial time series. According to Wang (1993) and Gajurel and Chawla (2022) an (in)decrease in volatility can be attributed to the behavior of (un)informed investors. The price changes due to the presence of uninformed market participants will be reversed, raising volatility by more than those attributed to informed ones (Avramov et al., 2006; Gajurel & Chawla, 2022). In particular, for NFT, DeFi, and plain and gold-backed cryptocurrencies, the invested asymmetric effect can be attributed to the herding (resp. the contrarian behavior) of uninformed

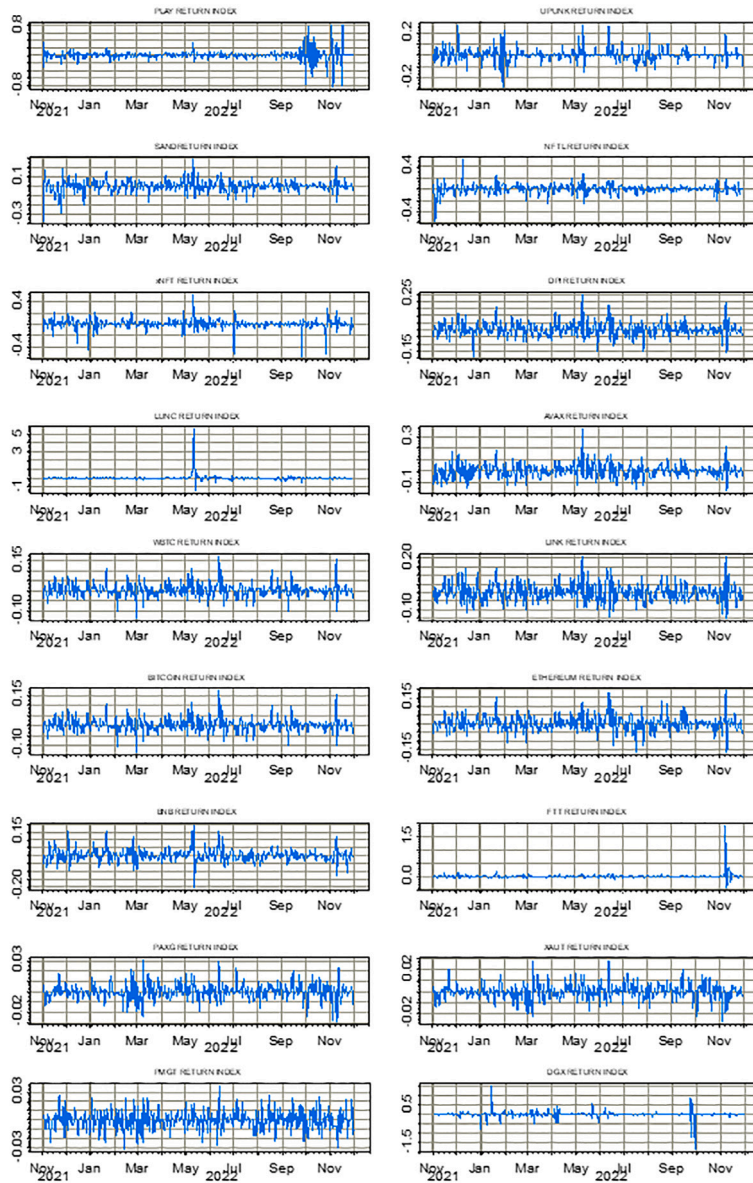


Fig. 1. Daily Return of the different assets in the sample.

investors (resp. informed investors) when assets' prices increase (resp. decrease). Such finding seems to be in line with [Fakhfekh and Jeribi \(2020\)](#) and [Charfeddine et al. \(2020\)](#).

The positive (inverted) asymmetric volatility effect is well-documented for NFT, DeFi, and cryptocurrencies. As mentioned, both NFT series (i.e. PLAY and SAND) exhibit the persistence of volatility shocks, given that the persistence degree  $d$  is greater than 0.5. This situation shows a strong persistence and might be explained by the structural changes in the variance process ([Lamoureux & Lastrapes, 1990](#)). In addition, PLAY reveals a strong persistence, implying that the effect of the shock on the volatility of this asset is long-lasting. However, the shock impact on the rest of return volatilities seems to exhibit transitory persistence of volatility shocks.

### 5.2. Extreme value theory

Once the FIEGARCH model is estimated, the estimation results are used to identify extreme losses based on the Extreme Value Theory. In this study 30% of the residuals series are considered as outliers (i.e. 15% represent the highest values and 15% the lowest ones). Using Generalized Pareto Distribution (GPD), the upper and lower tails' estimations are displayed in [Table 3](#). The POT method is performed through the GPD for tail estimation while accounting for 30% of the sample residuals. It can be observed in

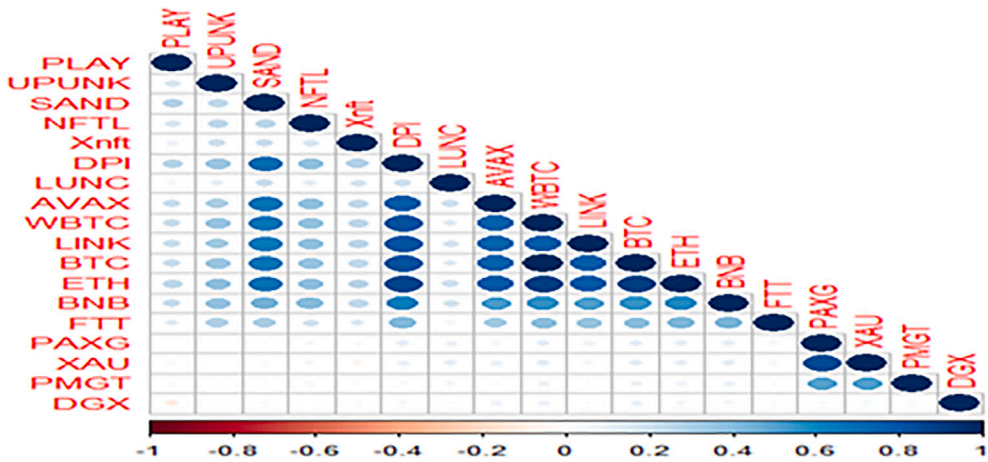


Fig. 2. Correlation Matrix among time series.

Table 3  
EVT estimation results.

		Upper tail	Lower tail
PLAY	$\xi$	0.327	0.0294
	$\beta$	0.4378	0.6643
UPUNK	$\xi$	0.0742	-0.2696
	$\beta$	0.8962	1.2843
SAND	$\xi$	-0.0724	0.2038
	$\beta$	0.7534	0.7083
NFTL	$\xi$	-0.0908	0.1628
	$\beta$	0.7962	0.6843
XNFT	$\xi$	-0.0352	0.3099
	$\beta$	0.5973	0.4473
DPI	$\xi$	-0.2861	-0.0632
	$\beta$	0.8633	0.7039
LUNC	$\xi$	0.0799	-0.7392
	$\beta$	0.6621	0.7382
AVAX	$\xi$	-0.1853	-0.4281
	$\beta$	0.8963	0.6643
WBTC	$\xi$	-0.3907	-0.0125
	$\beta$	1.0842	0.5944
LINK	$\xi$	-0.3536	-0.1782
	$\beta$	0.7952	0.5399
BTC	$\xi$	-0.4399	-0.0639
	$\beta$	1.1974	0.6224
ETH	$\xi$	-0.3082	-0.0108
	$\beta$	0.8236	0.6482
BNB	$\xi$	-0.1904	-0.231
	$\beta$	1.1774	0.6284
FTX	$\xi$	0.5538	0.0799
	$\beta$	0.4293	0.3298
PAXG	$\xi$	-0.2744	-0.0432
	$\beta$	0.9071	0.6674
XAUT	$\xi$	-0.5457	-0.1264
	$\beta$	1.1823	0.8094
PMGT	$\xi$	-0.4632	-0.4263
	$\beta$	0.796	0.8894
DGX	$\xi$	0.904	0.4092
	$\beta$	0.2742	0.4483

Note: Coefficients  $\beta$  and  $\xi$  are, respectively, the shape and scale parameters of the fitted generalized Pareto distribution (GPD)

Table 3 that, regarding the upper tail, all time series show a short-tailed feature. As a matter of fact,  $\xi$  values are negative, except for PLAY, UPUNK, LUNC, FTX and DGX, which exhibit long-tailedness. Regarding the lower tail, it can be noticed that only PLAY, SAND, NFTL, XNFT, FTX, and DGX show long-tail features.



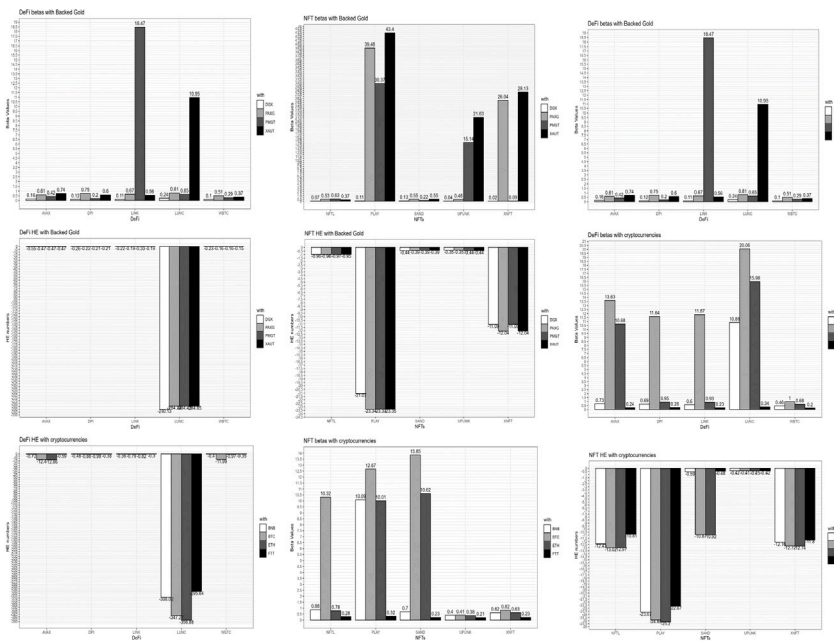


Fig. 4. Overview of hedging strategies.

assets are the best hedging instruments compared to those of cryptocurrencies. Indeed, investors could use these assets to hedge their portfolios and reduce their likely risk.

Overall, the empirical findings display that gold-backed cryptocurrencies seem to show more effectiveness in portfolio diversification efficiency. So, they can be considered as hedging tools. Such findings can provide insightful information for several reasons. First and foremost, they help investors for effective decision-making regarding optimal portfolio choices. This can be achieved using the nonlinear dependence framework among NFT/DeFi-gold-backed cryptocurrencies. Afterward, they may help portfolio managers adjust their strategies and grasp better opportunities. In this regard, the conditional EVT approach (i.e. the FIEGARCH-EVT-Coula method) seems to be an interesting econometric tool to diminish financial losses and curb portfolio risk.

## 6. Discussion

Hedging the extreme risk in cryptocurrency is a crucial issue for risk-averse investors and portfolio managers during episodes of turbulent market conditions, which are frequent in this market. Such a situation justifies the interest of the literature in the hedging and safe-haven features of cryptocurrencies (e.g. Conlon and McGee 2020, Goodell and Goutte 2021), which gain relevance as an emerging asset class (Dunbar & Owusu-Amoako, 2022). For instance, Charfeddine et al. (2020) examine the diversification and hedging abilities of cryptocurrencies under different economic and political situations. They show that cryptocurrencies could be used for portfolio diversification. However, this market is in continuous evolution. In addition to plain cryptocurrencies and tokens, other new digital assets emerged. For instance, gold-backed cryptocurrencies (whose value is pegged to the value of gold), NFTs, and DeFi projects have increasingly attracted investors' attention and media coverage (Aloui et al., 2021; Maouchi et al., 2022). In particular, the prompt evolution of DeFi and NFTs was contemporaneous with the upsurge of the health crisis (Maouchi et al., 2022) and was characterized by the bubble formation in such markets (Kyriazis et al., 2020).

Intending to contribute to the ongoing aforementioned literature, this study investigates the dependence structure among NFT/DeFi assets and plain/gold-backed cryptocurrencies and evaluates hedge effectiveness based on a multi-method approach during the geopolitical event.

Our empirical findings clearly show dissimilarities in the dependence structure among different crypto-asset classes during the period 01/11/2021-05/10/2023. This period was crossed by the Covid-19 pandemic and by the war in Ukraine. Afterward, a short position of  $\beta$  in NFT and DeFi could hedge a long position of one dollar in the four plain and gold-backed cryptocurrencies. However, some discrepancies among different couples of NFT/DeFi-traditional/gold-backed cryptocurrencies in terms of hedge ratio values are clearly reported. In particular, the pairs of SAND/other cryptocurrencies and AVAX/other cryptocurrencies tend to be less than 1. As far as the hedging effectiveness is concerned, portfolios including PLAY and DGX or UPUNK and DGX outperform the other ones. This shows that greater hedge effectiveness and higher portfolio risk diminution could offer interesting benefits for investors and portfolio managers when including DGX index as a hedging instrument for an NFT portfolio. The PMGT index can be also considered an effective hedging instrument for SAND, AVAX, XNFT, and DPI; whereas the XAUT index is an effective hedging instrument and successfully can diminish the NFT portfolio risk. From the foregoing, gold-backed assets seem to be the best hedging

assets in comparison to traditional cryptocurrencies and show more effectiveness in portfolio diversification. This finding indicates that adding such an asset class contributes to decreasing the downside risk during crucial crisis events, such as the Covid-19 pandemic and the Ukraine-Russia war. Even though the relationship between NFT/DeFi and other asset classes remains under-explored (Umar et al., 2022) and despite their distinguishable features such as the non-fungibility (Corbet et al., 2023; Nadini et al., 2021), our results confirm recent findings by Díaz et al. (2023), who report the added value of stablecoins and gold-backed cryptocurrencies to systematically reduce the tail risk of portfolios composed by traditional cryptocurrencies. Moreover, they confirm findings reported by Wasiuzzaman and Rahman (2021), who argue that gold-backed cryptocurrencies could serve as safe-haven investments during crisis periods. Nevertheless, Bitcoin fails somewhat to be a useful hedging asset. They are also in line with findings found by some researchers who have shown that the prices of NFTs could be influenced by Ethereum and Bitcoin (Ante, 2023) and that there are low spillovers among cryptocurrency and NFT markets (Dowling, 2022b).

## 7. Conclusions

Overall, DeFi and NFTs price dynamics and their increased demand have attracted individual and institutional investors. In this regard, the current study examines the dependence structure of such new digital assets and gold-backed cryptocurrencies with the traditional ones. We also compute the optimal hedge ratio for different pairs and assess the portfolio hedge effectiveness. With this aim, this study applies a multi-method approach to the returns of five NFTs, five DeFi projects, four plain cryptocurrencies, and four gold-backed cryptocurrencies.

Overwhelmingly, the findings show different behavior displayed by various dependence structures, which greatly depends on the currency pair under consideration. We also report that plain cryptocurrencies (particularly, Bitcoin) could not offer portfolio diversification benefits during some periods. Nevertheless, gold-backed cryptocurrencies exhibit more effective portfolio diversification efficiency during geopolitical and health crises. Such findings could lay the foundations for future discussion about the issue of safe-haven features of gold-backed/traditional cryptocurrencies from a dynamic perspective during extreme events.

Our empirical findings are important for investors and traders as they shed light upon the (dis)similarities of gold-backed/plain cryptocurrencies with respect to DeFi/NFT. They show suitable investment strategies by comparing the potential diversification benefits of portfolios composed of gold-backed/plain cryptocurrencies, NFT, and DeFi portfolios during the outbreak of extreme events. Our results offer DeFi and NFTs investors a better understanding of the connectedness with other asset classes during unforeseeable and disrupting events.

Some limitations of this study correspond to the small period, given that the purpose of our paper is to assess the ability of gold-backed cryptocurrencies and traditional cryptocurrencies *vis-à-vis* NFTs/DeFis. So, a future extension of our study would be to extend the sample backward and forward to better apprehend the nature of the correlation structure between assets. Another limitation of this study refers to the static nature of volatilities and correlation structure which leads to static optimal hedging ratios. Therefore, an interesting extension would be to take into account the time-varying nature of volatility and correlation structures which would allow us to analyze the dynamic behavior of the optimal hedge ratio by using the three models. This implies varying costs for hedging risk and a demand for frequent portfolio rebalancing.

## CRedit authorship contribution statement

**Mohamed Fakhfekh:** Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Azza Bejaoui:** Data curation, Formal analysis, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. **Aurelio F. Bariviera:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing. **Ahmed Jeribi:** Conceptualization, Formal analysis, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Appendix

See Tables 4–6.

**Table 4**  
Information criteria results of the best GARCH models' estimations.

Asset	Information Criterion	GARCH	FIEGARCH	EGARCH	TGARCH	FIGARCH
BTC	Akaike	5.0229	<b>5.0121</b>	5.0233	5.0230	5.0135
	Bayesian	5.0448	<b>5.0376</b>	5.0421	5.0486	5.0426
	Shibata	5.0229	<b>5.0121</b>	5.0231	5.0230	5.0134
	Hannan-Quinn	5.0311	<b>5.0216</b>	5.0342	5.0326	5.0243
ETH	Akaike	5.5716	<b>5.5602</b>	5.5762	5.5726	5.5608
	Bayesian	5.5935	<b>5.5857</b>	5.5862	5.5981	5.5899
	Shibata	5.5716	<b>5.5602</b>	5.5731	5.5725	5.5607
	Hannan-Quinn	5.5798	<b>5.5697</b>	5.5749	5.5821	5.5717
BNB	Akaike	5.4668	<b>5.4528</b>	5.4631	5.4670	5.4669
	Bayesian	5.4887	<b>5.4783</b>	5.4832	5.4925	5.4960
	Shibata	5.4668	<b>5.4527</b>	5.4603	5.4670	5.4668
	Hannan-Quinn	5.4750	<b>5.4623</b>	5.4732	5.4765	5.4778
FTT	Akaike	6.9305	<b>6.9045</b>	6.9193	6.9184	6.9059
	Bayesian	6.9524	<b>6.9300</b>	6.9431	6.9439	6.9350
	Shibata	6.9305	<b>6.9045</b>	6.9264	6.9183	6.9058
	Hannan-Quinn	6.9387	<b>6.9140</b>	6.9235	6.9279	6.9168
PAXG	Akaike	2.4836	<b>2.4743</b>	2.4781	2.4829	2.4793
	Bayesian	2.5055	<b>2.4998</b>	2.5036	2.5084	2.5085
	Shibata	2.4836	<b>2.4743</b>	2.4781	2.4829	2.4793
	Hannan-Quinn	2.4918	<b>2.4839</b>	2.4876	2.4924	2.4902
XAUT	Akaike	5.4890	<b>5.4357</b>	5.4899	5.4843	5.4366
	Bayesian	5.5109	<b>5.4632</b>	5.5154	5.5098	5.4658
	Shibata	5.4889	<b>5.4374</b>	5.4899	5.4842	5.4376
	Hannan-Quinn	5.4971	<b>5.4472</b>	5.4994	5.4938	5.4475
PMGT	Akaike	6.2848	<b>6.2730</b>	6.2793	6.2767	6.2744
	Bayesian	6.3067	<b>6.2985</b>	6.3048	6.3023	6.3035
	Shibata	6.2848	<b>6.2729</b>	6.2793	6.2767	6.2743
	Hannan-Quinn	6.2930	<b>6.2825</b>	6.2888	6.2863	6.2852
DGX	Akaike	6.2650	<b>6.2452</b>	6.2653	6.2585	6.2598
	Bayesian	6.2869	<b>6.2708</b>	6.2909	6.2840	6.2890
	Shibata	6.2650	<b>6.2452</b>	6.2653	6.2584	6.2598
	Hannan-Quinn	6.2732	<b>6.2548</b>	6.2749	6.2680	6.2707
PLAY	Akaike	6.2543	<b>6.2384</b>	6.2514	6.2446	6.2396
	Bayesian	6.2762	<b>6.2639</b>	6.2770	6.2701	6.2688
	Shibata	6.2543	<b>6.2384</b>	6.2514	6.2446	6.2396
	Hannan-Quinn	6.2625	<b>6.2479</b>	6.2610	6.2541	6.2505
UPUNK	Akaike	6.2497	<b>6.2438</b>	6.2504	6.2491	6.2451
	Bayesian	6.2716	<b>6.2693</b>	6.2759	6.2746	6.2743
	Shibata	6.2497	<b>6.2437</b>	6.2503	6.2491	6.2451
	Hannan-Quinn	6.2579	<b>6.2533</b>	6.2599	6.2586	6.2560
SAND	Akaike	6.1262	<b>6.1216</b>	6.1272	6.1271	6.1265
	Bayesian	6.1480	<b>6.1471</b>	6.1527	6.1526	6.1557
	Shibata	6.1261	<b>6.1215</b>	6.1272	6.1271	6.1265
	Hannan-Quinn	6.1343	<b>6.1311</b>	6.1367	6.1366	6.1374
NFTL	Akaike	5.9806	<b>5.9728</b>	5.9784	5.9809	5.9740
	Bayesian	6.0025	<b>5.9983</b>	6.0040	6.0064	6.0032
	Shibata	5.9806	<b>5.9727</b>	5.9784	5.9809	5.9740
	Hannan-Quinn	5.9888	<b>5.9823</b>	5.9880	5.9904	5.9849
XNFT	Akaike	6.6156	<b>6.6101</b>	6.6168	6.6176	6.6113
	Bayesian	6.6374	<b>6.6356</b>	6.6424	6.6431	6.6405
	Shibata	6.6155	<b>6.6101</b>	6.6168	6.6176	6.6112
	Hannan-Quinn	6.6237	<b>6.6196</b>	6.6264	6.6271	6.6222
DPI	Akaike	6.7381	<b>6.7293</b>	6.7357	6.7312	6.7321
	Bayesian	6.7599	<b>6.7548</b>	6.7612	6.7567	6.7613
	Shibata	6.7380	<b>6.7292</b>	6.7357	6.7312	6.7321
	Hannan-Quinn	6.7462	<b>6.7388</b>	6.7453	6.7407	6.7430
LUNC	Akaike	5.0240	<b>5.0121</b>	5.0121	5.0128	5.0243
	Bayesian	5.0495	<b>5.0376</b>	5.0413	5.0456	5.0498
	Shibata	5.0240	<b>5.0120</b>	5.0121	5.0128	5.0242
	Hannan-Quinn	5.0335	<b>5.0216</b>	5.0230	5.0251	5.0338
AVAX	Akaike	5.5726	<b>5.5597</b>	5.5618	5.5622	5.5723
	Bayesian	5.5981	<b>5.5852</b>	5.5909	5.5950	5.5978
	Shibata	5.5725	<b>5.5596</b>	5.5617	5.5621	5.5722
	Hannan-Quinn	5.5821	<b>5.5692</b>	5.5726	5.5744	5.5818
WBTC	Akaike	5.4677	<b>5.4657</b>	5.4657	5.4670	5.4681
	Bayesian	5.4932	<b>5.4912</b>	5.4949	5.4998	5.4936
	Shibata	5.4677	<b>5.4657</b>	5.4657	5.4670	5.4680
	Hannan-Quinn	5.4772	<b>5.4752</b>	5.4766	5.4793	5.4776
LINK	Akaike	6.9093	<b>6.9052</b>	6.9173	6.9066	6.9289
	Bayesian	6.9348	<b>6.9343</b>	6.9428	6.9394	6.9544
	Shibata	6.9093	<b>6.9051</b>	6.9173	6.9065	6.9288
	Hannan-Quinn	6.9188	<b>6.9161</b>	6.9268	6.9188	6.9384

**Table 5**  
Archimax copula estimation results.

	Copula		Kendall's Tau	Spearman's Rho		Copula		Kendall's Tau	Spearman's Rho
	Parameter	Value				Parameter	Value		
PLAY/BTC	$\theta$	0.1768	0.2461	0.3591	DPI/BTC	$\theta$	0.1975	0.5687	0.7577
	$\delta$	0.4708				$\delta$	1.3959		
PLAY/ETH	$\theta$	0.1904	0.2594	0.3777	DPI/ETH	$\theta$	0.2655	0.6372	0.8238
	$\delta$	0.487				$\delta$	1.7209		
PLAY/BNB	$\theta$	0.0737	0.2056	0.3021	DPI/BNB	$\theta$	0.0000***	0.3321	0.4768
	$\delta$	0.4655				$\delta$	0.7713		
PLAY/FTT	$\theta$	0.0693	0.1877	0.2766	DPI/FTT	$\theta$	0	0.2912	0.4217
	$\delta$	0.4374				$\delta$	0.6805		
PLAY/PAXG	$\theta$	0.0753	0.1572	0.2676	DPI/PAXG	$\theta$	0.1123	0.0747	0.1116
	$\delta$	0.3972				$\delta$	0.1976		
PLAY/XAUT	$\theta$	0.0642	0.1684	0.2636	DPI/XAUT	$\theta$	0.1177	0.0556	0.0833
	$\delta$	0.4001				$\delta$	0.0287		
PLAY/PMGT	$\theta$	0.0597	0.1498	0.2852	DPI /PMGT	$\theta$	0.0353	0.0267	0.04
	$\delta$	0.4153				$\delta$	0.1584		
PLAY/DGX	$\theta$	0	0.0788	0.1177	DPI /DGX	$\theta$	0.1354	0.1679	0.2481
	$\delta$	0.305				$\delta$	0.359		
UPUNK/BTC	$\theta$	0.1623	0.1514	0.2241	LUNC/BTC	$\theta$	0.0367	0.3217	0.4628
	$\delta$	0.3112				$\delta$	0.7194		
UPUNK/ETH	$\theta$	0.2284	0.1868	-0.1879	LUNC/ETH	$\theta$	0	0.3574	0.5101
	$\delta$	0.3301				$\delta$	0.8326		
UPUNK/BNB	$\theta$	0.0218	0.1594	0.2359	LUNC/BNB	$\theta$	0	0.2007	0.2955
	$\delta$	0.4219				$\delta$	0.5076		
UPUNK/FTT	$\theta$	0.1322	0.1864	0.2438	LUNC/FTT	$\theta$	0	0.1537	0.2277
	$\delta$	0.3541				$\delta$	0.4277		
UPUNK /PAXG	$\theta$	0.035	0.0414	0.062	LUNC/PAXG	$\theta$	0	0.0269	0.0403
	$\delta$	0.2022				$\delta$	0.2075		
UPUNK/XAUT	$\theta$	0.1513	0.1652	0.2486	LUNC/XAUT	$\theta$	0	0.0341	0.051
	$\delta$	0.3354				$\delta$	0.2233		
UPUNK/PMGT	$\theta$	0.1494	0.176	0.2597	LUNC/PMGT	$\theta$	0	0.0293	0.0438
	$\delta$	0.3635				$\delta$	0.2128		
UPUNK/DGX	$\theta$	0.0403	0.0454	0.0679	LUNC /DGX	$\theta$	0	0.1024	0.1525
	$\delta$	0.2057				$\delta$	0.3439		
SAND/BTC	$\theta$	0.098	0.53	0.7171	AVAX/BTC	$\theta$	0.1645	0.5465	0.7346
	$\delta$	1.3135				$\delta$	1.3225		
SAND/ETH	$\theta$	0.0308	0.5416	0.7297	AVAX/ETH	$\theta$	0.3388	0.5799	0.7689
	$\delta$	1.4348				$\delta$	1.3212		
SAND/BNB	$\theta$	0	0.2643	0.3848	AVAX/BNB	$\theta$	0	0.289	0.4188
	$\delta$	0.6256				$\delta$	0.676		
SAND/FTT	$\theta$	0	0.1963	0.2891	AVAX/FTT	$\theta$	0	0.2209	0.3241
	$\delta$	0.4997				$\delta$	0.5436		
SAND/PAXG	$\theta$	0.0922	0.044	0.066	AVAX/PAXG	$\theta$	0.089	0.0501	0.0749
	$\delta$	0.0267				$\delta$	0.1513		
SAND/XAUT	$\theta$	0.0855	0.0409	0.0614	AVAX/XAUT	$\theta$	0.0904	0.0568	0.0849
	$\delta$	0.0281				$\delta$	0.174		
SAND/PMGT	$\theta$	0.0478	0.0233	0.035	AVAX/PMGT	$\theta$	0.096	0.0458	0.0686
	$\delta$	0.0252***				$\delta$	0.0274***		
SAND/DGX	$\theta$	0.064	0.1564	0.2315	AVAX/DGX	$\theta$	0.1376	0.1901	0.2799
	$\delta$	0.4457				$\delta$	0.396		
NFTL/BTC	$\theta$	0.0976	0.2899	0.4196	WBTC/BTC	$\theta$	1.0819	0.9388	0.9945
	$\delta$	0.6079				$\delta$	9.8921		
NFTL/ETH	$\theta$	0.1159	0.2919	0.4223	WBTC/ETH	$\theta$	0.2735	0.6994	0.8762
	$\delta$	0.5994				$\delta$	2.2157		
NFTL/BNB	$\theta$	0.0414	0.2641	0.3843	WBTC/BNB	$\theta$	0	0.3243	0.4664
	$\delta$	0.5956				$\delta$	0.7532		
NFTL/FTT	$\theta$	0	0.1919	0.2828	WBTC/FTT	$\theta$	0	0.3218	0.4631
	$\delta$	0.4922				$\delta$	0.7475		
NFTL/PAXG	$\theta$	0.0206	0.034	0.0509	WBTC/PAXG	$\theta$	0.0907	0.0756	0.1129
	$\delta$	0.2007				$\delta$	0.2225		
NFTL/XAUT	$\theta$	0.0451	0.0221	0.0331	WBTC/XAUT	$\theta$	0.1001	0.0502	0.0752
	$\delta$	0.0303***				$\delta$	0.1227		
NFTL/PMGT	$\theta$	0.0963	0.0535	0.0801	WBTC/PMGT	$\theta$	0.0622	0.056	0.0838
	$\delta$	0.152				$\delta$	0.2069		
NFTL/DGX	$\theta$	0.0000***	0.0622	0.093	WBTC/DGX	$\theta$	0.2382	0.2166	-0.1344
	$\delta$	0.2766				$\delta$	0.3779		
XNFT/BTC	$\theta$	0.0261	0.1869	0.2755	LINK/BTC	$\theta$	0.088	0.5342	0.7216
	$\delta$	0.4654				$\delta$	1.3416		
XNFT/ETH	$\theta$	0.064	0.1904	0.2805	LINK/ETH	$\theta$	0.1317	0.5627	0.7516
	$\delta$	0.4457				$\delta$	1.4316		
XNFT/BNB	$\theta$	0	0.1517	0.2247	LINK/BNB	$\theta$	0	0.2654	0.3864
	$\delta$	0.4243				$\delta$	0.6279		
XNFT/FTT	$\theta$	0	0.1279	0.2137	LINK/FTT	$\theta$	0	0.2338	0.3423
	$\delta$	0.4214				$\delta$	0.5412		
XNFT/PAXG	$\theta$	0	0.1401	0.2351	LINK/PAXG	$\theta$	0.1058	0.0627	0.0938
	$\delta$	0.4417				$\delta$	0.1708		
XNFT/XAUT	$\theta$	0	0.1502	0.2019	LINK/XAUT	$\theta$	0.0857	0.0485	0.0726
	$\delta$	0.4532				$\delta$	0.1509		
XNFT/PMGT	$\theta$	0	0.0061	0.0091	LINK/PMGT	$\theta$	0	0.2217	0.3321
	$\delta$	0.1435				$\delta$	0.5021		
XNFT/DGX	$\theta$	0	0.0149	0.0225	LINK/DGX	$\theta$	0.0917	0.1535	0.2272
	$\delta$	0.1765				$\delta$	0.364		

Note: \*,\*\* and \*\*\* denote statistical significance at 10%, 5%, and 1% level.

**Table 6**  
Hedging strategy results estimation.

	$\beta$	mean	var	corr	HE		$\beta$	mean	var	corr	HE
PLAY/BTC	1.2670	0.0029	0.0192	0.3770	-2.4875	DPI /BTC	1.1636	0.0004	0.0041	0.7791	-0.8824
PLAY/ETH	1.0014	0.0039	0.0194	0.3963	-2.5195	DPI/ETH	0.9465	0.0013	0.0043	0.8419	-0.9750
PLAY/BNB	1.0089	0.0060	0.0185	0.3174	-2.3669	DPI /BNB	0.6898	0.0023	0.0032	0.4984	-0.4792
PLAY/FTT	0.3187	0.0014	0.0180	0.2906	-2.2671	DPI /FTT	0.2618	0.0019	0.0030	0.4416	-0.3829
PLAY/PAXG	3.9484	0.0076	0.0183	0.2906	-2.3344	DPI /PAXG	0.7533	0.0041	0.0027	0.1171	-0.2211
PLAY/XAUT	4.3396	0.0072	0.0183	0.2906	-2.3349	DPI /XAUT	0.6044	0.0041	0.0026	0.0872	-0.2139
PLAY/PMGT	3.0370	0.0077	0.0183	0.2906	-2.3333	DPI /PMGT	0.2038	0.0042	0.0026	0.0420	-0.2070
PLAY/DGX	0.1146	0.0067	0.0171	0.1235	-2.1065	DPI /DGX	0.1150	0.0043	0.0027	0.2608	-0.2576
UPUNK/BTC	0.4128	0.0024	0.0037	0.2355	-0.4141	LUNC /BTC	2.0064	0.0292	0.1697	0.4841	-34.7269
UPUNK/ETH	0.3826	0.0028	0.0038	0.2892	-0.4469	LUNC /ETH	1.5984	0.0257	0.1742	0.5325	-35.6876
UPUNK /BNB	0.4030	0.0033	0.0037	0.2478	-0.4208	LUNC /BNB	1.0880	0.0338	0.1510	0.3102	-30.8018
UPUNK/FTT	0.2068	0.0024	0.0037	0.2730	-0.4234	LUNC /FTT	0.3419	0.0311	0.1451	0.2391	-29.5643
UPUNK/PAXG	0.4803	0.0037	0.0035	0.0650	-0.3502	LUNC /PAXG	0.8106	0.0306	0.1398	0.0422	-28.4340
UPUNK/XAUT	2.1627	0.0037	0.0038	0.2730	-0.4434	LUNC /XAUT	1.0952	0.0305	0.1399	0.0535	-28.4653
UPUNK /PMGT	1.5144	0.0040	0.0038	0.2730	-0.4428	LUNC /PMGT	0.6519	0.0308	0.1398	0.0459	-28.4431
UPUNK /DGX	0.0361	0.0037	0.0035	0.0712	-0.3491	LUNC /DGX	0.2391	0.0328	0.1425	0.1601	-29.0128
SAND/BTC	1.3849	-0.0017	0.0063	0.7397	-1.0874	AVAX /BTC	1.3634	-0.0003	0.0061	0.7568	-1.2397
SAND/ETH	1.0618	-0.0002	0.0063	0.7518	-1.0924	AVAX /ETH	1.0684	0.0007	0.0063	0.7901	-1.2864
SAND/BNB	0.6990	0.0023	0.0048	0.4033	-0.5910	AVAX /BNB	0.7277	0.0027	0.0047	0.4386	-0.7208
SAND/FTT	0.2265	0.0016	0.0045	0.3034	-0.4810	AVAX /FTT	0.2433	0.0021	0.0044	0.3401	-0.5911
SAND/PAXG	0.5534	0.0032	0.0042	0.0691	-0.3906	AVAX /PAXG	0.6100	0.0040	0.0040	0.0786	-0.4722
SAND/XAUT	0.5536	0.0032	0.0042	0.0643	-0.3897	AVAX /XAUT	0.7450	0.0040	0.0040	0.0891	-0.4748
SAND/PMGT	0.2210	0.0033	0.0042	0.0367	-0.3859	AVAX /PMGT	0.4213	0.0041	0.0040	0.0719	-0.4707
SAND/DGX	0.1336	0.0033	0.0043	0.2433	-0.4384	AVAX /DGX	0.1570	0.0042	0.0042	0.2942	-0.5480
NFTL/BTC	1.0320	0.0035	0.0091	0.4398	-1.3018	WBTC /BTC	0.9978	0.0000	0.0022	0.9954	-1.1990
NFTL/ETH	0.7848	0.0043	0.0091	0.4426	-1.2970	WBTC /ETH	0.6763	0.0013	0.0020	0.8906	-0.9682
NFTL/BNB	0.8776	0.0053	0.0089	0.4030	-1.2426	WBTC /BNB	0.4588	0.0020	0.0014	0.4877	-0.3979
NFTL/FTT	0.2796	0.0047	0.0082	0.2969	-1.0815	WBTC /FTT	0.1957	0.0015	0.0014	0.4843	-0.3521
NFTL/PAXG	0.5347	0.0068	0.0078	0.0534	-0.9573	WBTC /PAXG	0.5127	0.0032	0.0012	0.1186	-0.1631
NFTL/XAUT	0.3745	0.0068	0.0077	0.0347	-0.9541	WBTC /XAUT	0.3674	0.0032	0.0012	0.0788	-0.1543
NFTL/PMGT	0.6349	0.0069	0.0078	0.0840	-0.9653	WBTC /PMGT	0.2872	0.0033	0.0012	0.0879	-0.1559
NFTL/DGX	0.0665	0.0069	0.0078	0.0976	-0.9645	WBTC /DGX	0.0994	0.0033	0.0013	0.3337	-0.2288
XNFT/BTC	0.8164	0.0077	0.0138	0.2894	-1.2718	LINK /BTC	1.1869	-0.0007	0.0044	0.7440	-0.7879
XNFT/ETH	0.6296	0.0082	0.0138	0.2947	-1.2736	LINK /ETH	0.9271	0.0001	0.0045	0.7732	-0.8190
XNFT /BNB	0.6217	0.0090	0.0134	0.2360	-1.2161	LINK /BNB	0.6001	0.0024	0.0034	0.4050	-0.3592
XNFT/FTT	0.2291	0.0086	0.0132	0.2149	-1.1796	LINK /FTT	0.2311	0.0016	0.0032	0.3591	-0.2971
XNFT/PAXG	2.6036	0.0104	0.0134	0.2149	-1.2044	LINK /PAXG	0.6682	0.0036	0.0030	0.0984	-0.1925
XNFT/XAUT	2.8130	0.0099	0.0134	0.2149	-1.2045	LINK /XAUT	0.5586	0.0036	0.0030	0.0761	-0.1880
XNFT/PMGT	0.0873	0.0099	0.0128	0.0096	-1.1087	LINK /PMGT	1.8474	0.0040	0.0033	0.3591	-0.3304
XNFT/DGX	0.0195	0.0100	0.0128	0.0235	-1.1092	LINK /DGX	0.1108	0.0037	0.0030	0.2388	-0.2244

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