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Shining in or fading out: Do precious metals sparkle for cryptocurrencies?

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ABSTRACT

Underlying volatility of cryptocurrency markets motivated this study to unveil the nexus with precious metals using multi-step analysis of GJR-GARCH, quantile connectedness, hedge ratios, hedge effectiveness, and conditional diversification benefits for the period spanning October 3, 2017, to October 27, 2021. Our analysis exhibits higher volatilities at extreme right and left tails, while network analysis demonstrates cryptocurrencies as net transmitters of spillovers and precious metals being the net recipients indicating diversification avenues of precious metals for cryptocurrencies. However, diversification features fade away at extreme tails as markets illustrate higher volatility. Meanwhile, platinum offers the greatest hedge effectiveness, whereas gold is the least effective hedge for cryptocurrencies. Our portfolio management analysis shows that precious metals outperform cryptocurrencies in terms of diversification, especially in times of crisis. This is consistent with research showing that precious metals offer investors a means of flight to safety when the financial markets are unstable. Our findings help cryptocurrency investors understand that precious metals should be considered when allocating weights to their risk portfolios. We devised multiple implications for policymakers, regulatory bodies, investors, and portfolio managers to apply effective risk management tools while investing in cryptocurrencies along with precious metals.

1. Introduction

The volatility of the financial markets is determined by their underlying mechanism of financial trade, exchange processes, integration of markets in the financial system, and exposure to external shocks. Cryptocurrencies and precious metals portray two different streams of investments that are of prime importance to financial economists, financial markets, investors, and portfolio designers due to their varying features in response to financial shocks and uncertainties. On the one hand, cryptocurrencies are ever-growing, with a market capitalization of USD 2.39 Trillion in 2021 compared to their accumulative worth of USD 302 Billion in 2019.[1] Literature posed that cryptocurrencies bear isolated features from the rest of the financial markets (Corbet et al., 2018a, b), where Bitcoin develops an emerging investment portfolio by offering Bitcoin futures contracts exceeding USD 3.4 Billion.[2] With this massive growth, cryptocurrencies have been in the limelight across the world's financial markets, raising serious concerns for risk-seeker and short-term investors (Rösch et al., 2021). In addition, the ten times higher volatility than conventional financial markets (Bariviera and Merediz-Solà, 2021), trading anonymity and bulk trading (Yue et al., 2021), vulnerability to manipulation (Gandal et al., 2018), and inherent price bubbles all are embarking the need of the current study to find an effective and

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[1] Please see: https://coinmarketcap.com/charts/.
[2] Please see: https://coinalyze.net/bitcoin/open-interest/.

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appropriate hedge and diversifier to mitigate the volatility of the cryptocurrencies.

On the other hand, precious metals are considered low risk bearing financial markets due to their ability to hedge and offset the risk of other financial markets. The extant literature (Akhtaruzzaman et al., 2021; Chemkha et al., 2021; Bredin et al., 2015) mainly relies on investigating the hedging capabilities of gold for other classes of financial markets and rarely consider other precious metals such as silver, platinum, and palladium to assess their diversification and hedging features. Since gold offers flight to safety avenues for the investors amid uncertainties of the financial markets (Foley et al., 2021), theoretically, our study provides insightful implications based on prospect theory (Kahneman and Tversky, 2013) who proposed that outcomes of investors' decisions in risky circumstances are subject to a reference point. For instance, investors exhibit risk-seeking behavior in the face of losses and are risk-averse when substantial gains from the investments. However, in the face of unexpected shocks, geopolitical risks, and global pandemics, investors cling to various overconfidence and over-optimism biases by falsely overestimating the accuracy of the information (Brooks and Byrne, 2008). Nonetheless, rational investors adopt the flight-to-safety route when exposed to unintended surmounted challenges to position their investments on a safer side. The current study contributes to this strand of literature by empirically examining the sparkling effect of precious metals on cryptocurrencies.

Several prior research studies have been carried out regarding the volatility and price fluctuations of cryptocurrency. There is a dearth of data in the literature that quantifies the value of precious metals as a hedge against cryptocurrencies and pinpoints the net risk givers and receivers at different tails in order to determine the underlying relationship between cryptocurrencies and precious metals. Methodologically, studies employed traditional connectedness approaches (Al-Yahyaee et al., 2020; Yousaf and Yarovaya, 2022; Yousaf et al., 2023a), quantile approaches (Iqbal et al., 2024; Shahzad et al., 2018), and hedge effectiveness techniques (Baur and Lucey, 2010; Ciner et al., 2013; Chemkha et al., 2021) in an independent manner by using the combination of different financial assets and markets. But unlike many other studies, like Arfaoui et al. (2023); Yousaf et al. (2023b); Hasan et al. (2021); Rehman (2020); and Rehman and Vo (2020), we provide a comprehensive analysis of both cryptocurrencies and precious metals simultaneously. We first used GJR-GARCH to evaluate the volatilities. Next, we computed the quantile connectivity of both financial markets to find risk spillovers at the median (50th), extreme lower (5th), and extreme higher (95th) quantiles. When the analysis is extended with right and left tails, quantile connectedness plays a crucial role in revealing the tail-dependence characteristics of specific financial markets, which in turn opens new tail-risk pathways between cryptocurrencies and precious metals that surpass mean-based metrics. Next, in order to determine an efficient hedge for cryptocurrencies, we computed hedge effectiveness and hedge ratios. By including precious metals in a portfolio of cryptocurrencies, we were ultimately able to classify the diversification paths and reap the benefits of conditional diversification.

In light of the aforementioned insights, our contribution to the current body of literature is multifaceted. First off, the question of whether precious metals are valuable for cryptocurrencies has never been investigated in prior study. Second, we conducted a multi-step analysis on our collection of financial markets to uncover every possible relationship at quantiles, the effectiveness of our hedges, and the benefits of conditional diversification. Third, we have acknowledged previous theories' support for the flight-to-safety mechanism in asymmetrical circumstances by carefully examining them. However, we offered useful ramifications for risk-seeker investors by enhancing the magnitude of their returns in the face of higher risk. Fourth, the current study is unique in that it emphasizes the hedging and diversification capabilities of cryptocurrencies in volatile markets by utilizing two well-known shock events—the COVID-19 pandemic and the burst of the cryptocurrency price bubble. Finally, we proposed beneficial implications for policymakers, regulation bodies, financial markets, investors, and portfolio managers.

The results of our multi-step analysis displayed that higher volatilities prevail between precious metals and cryptocurrencies at extreme left and right tails, signifying asymmetric volatility arrangement between two streams of financial markets. Network connectedness analysis indicates that precious metals act as a diversifier for cryptocurrencies, and there is a disconnection between precious metals and cryptocurrencies at extreme lower and median quantiles. In addition, at extreme higher quantile, the connectedness increases during volatility periods reducing the diversification avenues of precious metals for cryptocurrencies. Regarding hedge effectiveness, platinum is considered an effective hedge for cryptocurrencies following the hedge effectiveness of silver, palladium, and gold. Our results concerning conditional diversification benefit reveal that greater diversification benefits can be achieved against cryptocurrencies using precious metals, particularly during a crisis period. Similarly, the portfolio management analysis substantiates that cryptocurrency investors must include precious metals in their assets combinations while weighting their risk and evaluating the periods of economic turmoil. We designed various implications for policymakers, regulatory bodies, financial markets, investors, and portfolio managers by reflecting the strong diversification potential and hedging effectiveness of precious metals for cryptocurrencies.

The rest of the study proceeds as follows: A review of the literature is presented in Section 2, the methodology is covered in Section 3, the empirical results are presented in Section 4, and the study's conclusions and potential implications are discussed in Section 5.

2. Literature review

The purpose of this literature review is to provide a solid basis for our research. To do this, we will look at some of the most recent, relevant papers that have been published in the empirical literature on our subject. The main objective of this part is to review the existing literature with a focus on the mechanics of cryptocurrencies and metals and explore the relationships between the two. Understanding the relationship between cryptocurrencies and metals, as well as whether precious metals can serve as diversifiers or havens for the volatile nature of cryptocurrencies, is the primary objective of our research. The current financial literature has two relevant research strands that are relevant to this study. The first is the connectivity research strand, which focuses on traditional cryptocurrencies. Studies by Yousaf et al. (2023b), Pagnottoni (2023), Díaz et al. (2023), Bejaoui et al. (2023), and Alam et al. (2023) are some examples of this strand. The second strand focuses on the relationship between cryptocurrencies and metals including Rehman and Vo (2020), Fasanya et al. (2021, 2022), Ali et al. (2023), and Yousaf et al. (2023b). Below, we will discuss some of the studies mentioned here.

Fasanya et al. (2021) conducted a study to look at the relationship between US economic policy uncertainty (EPU) and the effects on the bitcoin and precious metals markets. The study demonstrated a strong link between bitcoin and precious metals using TVP-VAR and non-parametric causality-in-quantiles approaches. The results indicate that the strongest correlation between these markets and EPU is found in the higher and median quantiles. Additionally, the investigation found that the relationship between bitcoin, precious metals, and EPU exhibited non-linear behaviour.

Alam et al. (2023) examine volatility spillovers and connectivity across REITs, NFTs, cryptocurrencies, and other assets from January 2019 to November 2022, with a focus on both cryptocurrencies and NFTs. Using a variety of connectedness techniques, the authors discover that during the COVID-19 epidemic and the military war between Russia and Ukraine, there is an increase in total return and volatility connection. Furthermore, they note that while NFTs represent a new form of portfolio diversifier, REITs only partially retain their historical independence from shocks from other assets. Their findings suggest that during times of financial shocks and crises, investors can utilize REITs or a combination of NFTs, gold, oil, and REITs with other assets as a hedge against volatile assets. Similarly, Bejaoui et al. (2023) examine the relationships between DeFi, NFT, gold, emerging stock markets, and cryptocurrencies using wavelet analysis. The authors discover that there is a tendency for the connectivity between different asset classes to change over time and to get stronger during political and health crises. Furthermore, the authors draw the conclusion that while pair-wise connectedness networks are significantly impacted by political and health events, asymmetric patterns in cross-market links are consistently evident. Their empirical findings offer crucial information regarding the possible diversification advantages of NFT and DeFi digital assets, which is helpful for designing investment strategies and making judgments about portfolio allocation for scholars, investors, and portfolio managers.

Focusing on digital asset classes including cryptocurrencies and NFTs, Díaz et al. (2023) investigate stablecoins as a means of reducing the downside risk associated with cryptocurrency portfolios. The authors' significant discovery is that bitcoin portfolios lessen the high volatility of the individual cryptocurrencies. The authors conclude that USD-pegged stablecoins are a particularly suitable hedge for cryptocurrency portfolios since investors in these funds are susceptible to the possibility of suffering enormous losses. The authors also note that the best way to evaluate tail risk in cryptocurrency portfolios is to examine higher order moments. Their findings enable them to draw the conclusion that all stablecoins considered for their research have strong diversification potential and lower tail risks.

In second strand of studies, Rehman and Vo (2020) use daily pricing data from March 2017 to August 2019 to examine the relationship between cryptocurrency and returns on precious metals. In order to examine shifting correlation patterns across various quantile distributions over short-, medium-, and long-term investment horizons, our study applies the quantile cross spectral framework. We also examine spillover phenomena for returns and variation between these two asset classes using the quantile framework's non-linear causality. The findings show that, in the short term, copper offers investors the best chance of diversification across all cryptocurrencies, even in the most volatile markets. However, the excessive positive return distribution of precious metals does not blend with the severe negative return distribution of cryptocurrencies for medium- and long-term investment periods, suggesting potential for investor diversification.

On the same lines, Yousaf et al. (2023b) find the relationship between metals and conventional cryptocurrencies and non-fungible tokens (NFTs) is discussed in this study. We show that there are new opportunities for hedging and reaping the benefits of diversification from NFT exposures because the total return and total volatility connectedness indices for the NFTs-metals framework are lower than the corresponding indices for the cryptocurrencies-metals framework. Their results show that the COVID-19 meltdown has caused a decoupling in the net volatility spillovers between precious and nonprecious metals. Precious metals now transmit volatility due to COVID-19, but industrial metals continue to be net recipients of volatility shocks. The best weight and hedging ratios for pairs of NFT-metal and crypto-metal are shown. Investors and policy officials may find these findings significant.

Rehman (2020) investigates the extreme dependence and risk spillover between Bitcoin and a range of commodities and precious metals, such as gold, silver, copper, wheat, platinum, and palladium. Their results show how the returns on precious metals are impacted by using gold as a hedge against Bitcoin. Our research also demonstrates that there is spillover from the precious metals market to the Bitcoin market; however, silver is not sensitive to any adverse risk spillover from precious metals to Bitcoin. Additionally, the authors demonstrate asymmetry in both positive and negative price movements, implying that extremely high or extremely low returns in one market may have an impact on extremely high gains in the other. Consequently, offer implications for fund managers and individual investors in creating the optimal portfolio that generates profits while hedging against severely negative price fluctuations.

Another important study is by Fasanya et al. (2022), who discovered a thorough examination of investor sentiments and their influence on the correlation between the precious metals market and the top five most traded cryptocurrencies. Their findings are essential for investors looking to make informed decisions. First, by showing how closely related and dependent the two markets are on one another, the study illustrates the reciprocal dependency between them. Second, although other cryptocurrencies are net transmitters of volatility, the researchers discovered that silver and tetherum are net receivers of the shocks. Investors who are interested in knowing which assets can withstand market swings should take note of this finding. Thirdly, there is compelling evidence of non-linearity from the BDS test, which emphasizes the significance of taking investor emotion into account when analyzing the relationships between the precious metals and cryptocurrency markets. Finally, the nonparametric causality-in-quantile test demonstrates that the relationship between the precious metal and cryptocurrency markets is based on speculation, indicating that investors should exercise caution when choosing to participate in either market. All things considered, the study offers insightful information about how the cryptocurrency and precious metals markets interact, which can be a helpful manual for investors trying to balance risk and optimize profits.

Ali et al. (2023) conducted a study using TVP-VAR approach to investigate the relationships between precious metals, industrial metals, and decentralized finance (DeFi) assets before and during the COVID-19 pandemic. The results showed that there is a weaker association between DeFi-precious metal and DeFi-industrial metal pairs as compared to traditional precious and industrial metals. However, the interconnectedness between these markets increased during the COVID-19 period. The authors found that all DeFi assets, as well as palladium, aluminum, zinc, and nickel, are net suppliers of return spillover, while gold, silver, platinum, and copper are net exporters of return spillovers. The return transmission between these markets is rolling, with rapid fluctuations during the COVID-19 period. Additionally, the optimal portfolio analysis revealed that adding DeFi assets to the metals-based portfolio is helpful in terms of diversification. Their findings provide insight for portfolio managers and policymakers regarding portfolio construction, portfolio adjustment, hedging, and market stability.

The world of crypto investments is still a hot topic that is receiving attention from various groups, including academics, investors, and market regulators. However, the existing studies fail to address what influences investors' decisions in risky circumstances. For example, investors tend to become risk-seeking when faced with losses and risk-averse when there are substantial gains from their investments. Yet, when unexpected events such as geopolitical risks and global pandemics occur, investors often succumb to overconfidence and over-optimism biases that lead them to overestimate the accuracy of the information they have. Therefore, there is a need for new research that explores how investors react to risky situations. Our research aims to fill this gap by looking at the impact of precious metals on cryptocurrencies. Our findings show that rational investors opt for the flight-to-safety approach when faced with challenges that they have not anticipated. They do this by positioning their investments on the safer side. Moreover, diversification becomes less effective during extreme market conditions when volatility is high. Our analysis also reveals that platinum offers the most significant hedge effectiveness, while gold is the least effective hedge for cryptocurrencies. We conclude that investors in cryptocurrencies must consider precious metals when assigning weights to their risk portfolios. This is because precious metals can provide greater diversification benefits, particularly during crisis periods.

3. Methodology

First, we use the GJR-GARCH methodology to calculate the conditional volatility of each asset in our sample. The GJR-GARCH approach is an appropriate way to model the conditional heteroskedasticity characteristics of financial markets, as they display volatility clustering characteristics. Using the traditional GARCH model (Engle, 1982), Bollerslev (1986) successfully created a dynamic model of time-varying volatility that captures some of the essential components of returns on financial assets. However, the typical GARCH model is still unable to describe the stylized part of the asymmetric effect (Black, 1976). Engle and Ng (1993) contend that the GJR-GARCH (Glosten et al., 1993) model is a better representation of the asymmetry impact in stock returns than other well-known nonlinear models, such as the EGARCH (Nelson, 1991) model. When contrasted with the conventional GARCH model, this model performs better.

We use the method of Ando et al. (2018) to calculate quantile connectedness because we are interested in extreme quantiles. Quantile VAR models the interaction of the endogenous variables at any quantile, in contrast to standard VAR, which only models the average interaction. The ideas of economic cycles, asymmetry, and volatility make the quantile VAR model relevant to the research in this study (Romer, 2012). Because of shifting market conditions and advancements in technology, asset prices exhibit erratic cycles that include boom and bust times in addition to low, moderate, and peak phases. Their pricing and risk-taking strategies would probably be impacted by this market behaviour. Ando et al. (2018) used a mix of the quantile VAR and a spillover technique based on the Diebold and Yilmaz (2012) models to analyze the link between the median and extreme quantiles. Next, the hedging ratios and hedge effectiveness of precious metals for cryptocurrencies are computed. Finally, we use Christoffersen et al. (2018) method to calculate the conditional diversification benefit (CDB) by combining each precious metal with cryptocurrencies.

3.1. Volatility estimation

Asymmetries in financial assets are typically related to individual volatility and conditional correlations. To account for asymmetric volatility effects in individual returns, we use the GJR-GARCH model. Consequently, assume that r_t represents an n × 1 vector of returns. Let r_t be the result of an AR (1) process that is conditional on the information set I_{t-1}, and is expressed as:

$$r_t = \mu_t + ar_{t-1} + \varepsilon_t \ . \tag{1}$$

The residuals are calculated using the following formula:

$$\varepsilon_t = H_t^{1/2} z_t, \tag{2}$$

where H_t is the conditional covariance matrix of r_t, and z_t is an n × 1 vector of randomly distributed random errors.

The GARCH parameters are determined in the first stage, and the conditional correlations are estimated in the second stage, as shown below.

$$H_t = D_t R_t D_t, \tag{3}$$

The conditional covariance and correlations matrices are H_t and R_t, respectively, and the diagonal matrix of conditional standard deviations for the return series is D_t.

$$D_t = diag\left(\sqrt{h_{1,t}}, \sqrt{h_{2,t}}, \ldots., \sqrt{h_{n,t}}\right) \tag{4}$$

$$R_t = diag\left(q_{1,t}^{-\frac{1}{2}}, \ldots q_{n,t}^{-\frac{1}{2}}\right) Q_t diag\left(q_{1,t}^{-\frac{1}{2}}, \ldots q_{n,t}^{-\frac{1}{2}}\right) \tag{5}$$

where h represents expression driven from univariate GARCH models, for which H_t is a diagonal matrix for where h represents expression driven by univariate GARCH models. The elements of H_t in the GARCH (1,1) model, can be represented as:

$$h_{i,t} = \omega_i + \omega_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \ . \tag{6}$$

Likewise, the symmetric positive definite matrix, Q_t, is illustrated as:

$$Q_t = (1 - \varphi - \Im)\overline{Q} + \varphi z_{t-1} z_{t-1}^{'} + \Im Q_{t-1}, \tag{7}$$

In above expression, the n × n unconditional correlation matrix of standardized residuals ($z_{i,t} = ; \frac{\varepsilon_{i,t}}{\sqrt{h_{i,t}}}$) is represented by $\overline{Q}$ and φ and $\Im$ are non-negative parameters and satisfying the condition $\varphi + \Im < 1$. As a result, the GJR-GARCH model proposed by Glosten et al. (1993) can be written as:

$$h_{i,t} = \omega_i + \omega_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + d_i \varepsilon_{i,t-1}^2 I(\varepsilon_{i,t-1}), \tag{8}$$

In above expression $I(\varepsilon_{i,t-1})$ is an indicator function that corresponds to l if $\varepsilon_{i,t-1} < 0$, and 0 otherwise. A positive value for d in this example suggests the presence of an asymmetric effect (also known as the leverage effect), which means that negative residuals are more likely than positive residuals to increase volatility. To put it another way, bad news has a greater impact on asset volatility than good news.

3.2. Quantile connectedness

Ando et al. (2018) estimate quantile connectedness by extending the mean based (DY2012) methodology with a quantile VAR model in their original work. In this paper, we first discuss the specification of a Quantile VAR, then proceeds with the process of measuring connectedness at different quantiles by following Ando et al. (2018).

3.2.1. Quantile VAR

The dependence of y_t on x_t can be assessed in each quantile τ ($\tau \in (0,1)$) of the conditional distribution of y_t / x_t using the quantile regression of Koenker and Bassett (1978). Equation. (9) expresses the n-variable quantile VAR process of p^{th} order as follows:

$$y_t = c(\tau) + \sum_{i=1}^{p} B_i(\tau) y_{t-i} + e_t(\tau), t = 1, \ldots, T, \tag{9}$$

where y_t represents the n-vector of dependent variables at time t, $c(\tau)$ and $e_t(\tau)$ represent the n-vector of intercepts and residuals at quantile τ respectively, B_i (τ) represents the matrix of delayed coefficients at quantile with $i = 1, \ldots, p$. If the residuals fulfil the population quantile restrictions, $Q\tau(e_t(\tau)|y_{t-1}, \ldots, y_{t-p}) = 0$, $c(\tau)$ and B_i (τ) can be estimated. Indeed, with the population τ^{th} conditional quantile of response y Eq. (9) can be written as:

$$Q_\tau\left(e_t(\tau)\middle|y_{t-1}, \ldots, y_{t-p}\right) = c(\tau) + \sum_{i=1}^{p} \widehat{B}_i(\tau) y_{t-i}. \tag{10}$$

Cecchetti and Li (2008) argue that as the estimation process is deemed to have an unrelated regression structure, the model described above could be estimated on an equation-by-equation quantile regression basis if each and every possible combination in Eq. (9) has the same variables on the right-hand side.

3.2.2. DY spillover indices

Based on a quantile variance decomposition in each quantile τ, the spillover indices can be computed using the (DY2012) methodology. As a result, Eq. (9) can take the following form:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau) e_{t-s}(\tau), t = 1, \ldots, T \tag{11}$$

through,

$$\mu(\tau) = (I_n - B_1(\tau) - \cdots - Bp(\tau))^{-1} c(\tau),$$

$$A_s(\tau) = \begin{cases} 0, s < 0 \\ I_n, \quad s = 0 \\ B_1(\tau)A_{s-1}(\tau) + \cdots + B_p(\tau)A_{s-p}(\tau), s > 0 \end{cases}$$

The total of residuals e_t at each quantile τ is represented by y_t.

Furthermore, given the Cholesky-factorization ordering issue, the Pesaran and Shin (1998) and Koop et al. (1996) approaches are used, which are invariant to variable ordering. Each variable's shocks are not orthogonalized. As a result, the total forecast error variance contributions do not have to equal one. In order to compute the generalised forecast error variance decomposition (GFEVD) of a variable attributable to shocks of multiple variables, the following formulation can be employed for a forecast horizon H:

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i^{'} A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i^{'} A_h \sum A_h^{'} e_i\right)}, \tag{12}$$

where $\theta_{ij}^{g}(\mathrm{H})$ denotes the j^{th} variable's contribution to the variance of the forecast error of the variable i at horizon H, and in above equation e_{i} denotes a vector with a value of 1 for the i^{th} element only, whereas σ_{jj} represents j^{th} diagonal element of the Σ matrix, and $\sum$ represents a vector of error variances,

Furthermore, each entry's variance decomposition matrix is normalised as follows:

$$\widetilde{\theta}_{ij}^{g}(\mathrm{H}) = \frac{\theta_{ij}^{g}(\mathrm{H})}{\sum_{j=1}^{N} \theta_{ij}^{g}(\mathrm{H})}. \tag{13}$$

Using the GFEVD, we may define various connectedness measures at the τ^{th} conditional quantile within the context of Diebold and Yilmaz (2012, 2014). Accordingly, the total connectedness index (TCI) for each quantile τ can then be determined. The total forecast error variance is calculated using the (TCI), which analyses the impact of risk shock spillovers across the various assets used in the paper. At each quantile τ, the TCI is written as follows:

$$TCI(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(\tau)} \times 100. \tag{14}$$

In below equation "FROM" denotes the directional connectivity to index i from all other indexes at quantile τ and can be written as:

$$C_{i\leftarrow}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ji}^{g}(\tau)}{\sum_{j=1}^{N} \widetilde{\theta}_{ji}^{g}(\tau)} \times 100. \tag{15}$$

In below equation "TO" denotes the directional connectivity from index i to all other indexes at quantile τ and can be written as:

$$C_{i\rightarrow}(\tau) = \frac{\sum_{j=1, i \neq j}^{N} \widetilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \widetilde{\theta}_{ij}^{g}(\tau)} \times 100. \tag{16}$$

The two types of directional spillovers (TO and FROM) are measurements that breakdown overall connectedness into those that come from or go to a specific source.

The NET connectedness (NC) can be obtained by using equations (15) and (16):

$$NC(\tau) = C_{\rightarrow i}(\tau) - C_{i\leftarrow}(\tau). \tag{17}$$

The net risk connectedness is the difference between the gross risk shocks transmitted to and those received from all other assets in the sample.

Finally, at quantile τ, the net pairwise connectedness is:

$$PC(\tau) = \widetilde{\theta}_{ij}^{g}(\tau) - \widetilde{\theta}_{ij}^{g}(\tau). \tag{18}$$

The difference between the gross risk shocks conveyed from asset i to asset j and those transmitted from asset j to i is the net pairwise risk connectedness between assets i and j.

The VAR lag of order 1 is chosen based on the Bayesian information criterion (BIC). For connectedness estimation, a 10-step ahead forecast error variance decomposition was employed. Furthermore, to account for time volatility in spillover measures, a rolling-window technique is used following the studies of Diebold and Yılmaz (2014), Balli et al. (2019), Naeem et al. (2020), and Umar et al. (2022).

3.3. Hedge effectiveness

The next step in our methodology is to calculate the hedge effectiveness of precious metals for various cryptocurrencies. We do so by assessing the hedge ratio and hedge effectiveness between precious metals and cryptocurrencies in an out-of-sample setting. The hedge effectiveness, which is commonly used as a risk evaluation tool for investment portfolios, measures how much risk may be minimised by combining a portfolio of cryptocurrencies with precious metals.

In the below equation, assume the return on the hedged portfolio that includes precious metals and cryptocurrencies is represented as:

$$r_{HP,t} = r_{Crypto,t} - \varphi_t r_{PM,t}, \tag{19}$$

Where $r_{Crypto,t}$ and $r_{PM,t}$ denote the returns of a single cryptocurrency and precious metals respectively, and φ_t is the hedge ratio. As a result, the conditional variance of the hedged portfolio at time I_{t-1} can be represented as follows:

$$var\left(r_{HP,t} I_{t-1}\right) = var\left(r_{Crypto,t} I_{t-1}\right) + 2\varphi_t \, cov\left(r_{PM,t}, r_{Crypto,t} I_{t-1}\right) \tag{20}$$

We employ the ADCC-GARCH model to estimate conditional volatility and covariance, which are then utilized to compute hedge ratios, as described by Kroner and Sultan (1993). This model aids us in determining the ability of precious metals to hedge the cryptocurrencies. As a result, a long position in one asset is hedged with a short position in another, such as precious metal, as follows:

$$\varphi_t^{*} \middle| I_t = h_{Crypto(PM),t} \big/ h_{PM,t}, \tag{21}$$

where $h_{Crypto(PM),t}$ denotes the conditional covariance between the returns of cryptocurrencies and precious metals and $h_{PM,t}$ denotes the conditional variance of the returns of precious metal. Finally, in order to analyze the performance of various hedge ratios derived from different GARCH models, we develop the hedging effectiveness (HE) index. The following is how the HE index is expressed:

$$HE = \frac{var_{unhedged} - var_{hedged}}{var_{unhedged}} \tag{22}$$

A higher HE index indicates greater hedge efficiency in absolute terms. Consequently, the value of HE equals to 1 shows a perfect hedge whereas HE equals to 0 indicates no hedge. The hedge ratios are forecasted using a fixed width rolling analysis. This analysis generates 100 one-step forecasts, with model refitting after every tenth observations. These forecasted hedge ratios are then used to build the hedged portfolios.

3.4. Diversification benefit

We use the conditional diversification benefit (CDB) approach established by Christoffersen et al. (2018) to assess the diversification benefits of pairing cryptocurrencies with each of the precious metal. The potential shortfall for a probability q is quantified by CDB, which can be expressed as:

$$CDB_t(\omega_t, q) = \frac{\omega_t ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q) - ES_{p,t}(\omega_t, q)}{\omega_t ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q) - VaR_t(q)}, \tag{23}$$

In above equation ω_t denotes the weight *i* of an asset portfolio at time *t* and the potential shortfall in the probability (ES) can be calculated as:

$$ES_{z,t}(q) = -E\left[r_{z,t}\middle| r_{z,t} \le F_{z,t}^{-1}(q)\right] \tag{24}$$

The inverse distribution function of asset *z* at time *t can be denoted by* $z = i, g,$ and $F_{z,t}^{-1}(q)$. $ES_{p,t}(\omega_t, q)$ is the upper bound of potential shortfall and can be attained by $\omega_t ES_{i,t}(q) + (1-\omega_t)ES_{g,t}(q)$. The value-at-risk VaR t (q) = -F (p,t)(−1) (q) of the combined portfolio associated with the qth quantile indicating the potential shortfall at the lower bound. As a result, the CDB value ranges from 0 to 1, with a higher value indicating the benefits of diversification.

We compute CDBs for different portfolio weights based on probability values of 5 % since the degree of diversification benefit is determined on the composition of combined portfolios and probability q. As a result, we rewrite equation (24) as follows:

$$ES_{z,t}(q) = -\mu_{z,t} + \frac{\sigma_{z,t}}{q} d\left(D^{-1}(q)\right)\left[\frac{\upsilon + D^{-1}(q)^2}{\upsilon - 1}\right] \tag{25}$$

In the above equation, *D* stands for cumulative distribution function and *d* for student's *t* density function with υ degrees of freedom. Thus, *VaR* can be written as:

$$VaR_t(q) = -\mu_{p,t} + \sigma_{z,t} D^{-1}(q). \tag{26}$$

4. Empirical findings

4.1. Data and descriptive statistics

The current study examines whether precious metals sparkle for cryptocurrencies using quantile connectedness, hedging effectiveness, and conditional diversification benefits. Precious metals included in the study are S&P GSCI Gold (GLD), S&P GSCI Silver (SLV), S&P GSCI Platinum (PLT), S&P GSCI Palladium (PLD), while cryptocurrencies consist of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Cardano (ADA), and Ripple (XRP) for the period encompassing October 3, 2017, to October 27, 2021. The data of precious metals have been tracked from Datastream. We selected the top 5 cryptocurrencies from coinmarkertcap.com based on their market capitalization, which is determined by their circulating supply. Market capitalization[3] is the most used criterion to measure the market value and size of a cryptocurrency. It helps to accurately compare cryptocurrencies since the price of a cryptocurrencies may not always reflect their actual worth. The market capitalization of a cryptocurrency is calculated by multiplying its current price with the total number of coins in circulation. The circulating supply, which refers to the number of coins accessible to the general public, is the most frequently used statistic to determine the total number of coins in circulation.

Market capitalization is often used as a starting point for selecting cryptocurrencies for investment portfolios. However, it should also be considered as a separate criterion for portfolio optimization, as it is important for practitioners. Liquidity is a significant obstacle in portfolio construction, and cryptocurrencies require special attention in this regard due to their lower daily trading volumes compared to traditional financial assets. Trading assets on reallocation dates and buying or selling between these dates are crucial for portfolio management. A recent study by Brauneis et al. (2021) analyzed four cryptocurrencies to determine their liquidity drivers. They found that the number of transactions is one of the most important liquidity drivers, while commonly used financial market variables did not prove to be explanatory. Trimborn et al. (2020) stated that obtaining data on the spread of cryptocurrencies is challenging. As a result, they used the turnover value as a substitute for liquidity. This value is calculated for a specific period, such as 24 h, by adding up the products of the number of assets and their price. This information is recorded as the volume on coinmarketcap.com. The trading volume was chosen as the second criterion, as it is widely recognized and practiced as a measure of liquidity. It indicates how easily a cryptocurrency can be bought and sold. A low trading volume indicates infrequent trading with a cryptocurrency and, consequently, the difficulty of purchasing or selling shares. On the other hand, a high trading volume means that a cryptocurrency is highly liquid and may be bought or sold easily. Moreover, practitioners consider the volume as one of the most valuable pieces of data, which can show the direction and movement of the cryptocurrency and predict its future price and demand.

Table 1 displays descriptive statistics for the volatility series of precious metals and cryptocurrencies used in the study, including mean, maximum, minimum, standard deviation. Palladium has the highest average volatility, but gold has the lowest. Cardano has the greatest average value among cryptocurrencies, and Bitcoin has the lowest. According to standard deviations, palladium is the riskiest metal, whereas Ripple is the riskiest cryptocurrency. According to Jarque-Bera statistics, the volatilities of all precious metals and cryptocurrencies are not normally distributed.

This quick descriptive examination could lead to some conclusions. First off, the series' non-normality indicates a relative presence of an excess kurtosis and a strong right or left tail. This could also imply that there are structural shifts and/or nonlinearity along the time pathways of the series, which would make it impossible to employ linear or constant parameter models without producing erroneous findings. This provides a specific explanation for our decision to use quantile-based analysis (Iqbal et al., 2022, 2024). Second, it is necessary to investigate the relationship in both the conditional mean and conditional variance due to the evidence of heavy tails and high volatility passes (Fasanya et al., 2021).

Fig. 1 plots the dynamic conditional volatilities of the precious metals and cryptocurrencies. Notably, the different metals and cryptocurrencies do not exhibit similar volatility dynamics over time. All metals exhibit a low level of volatility till the 1st quarter of 2020. In the second and third quarters of 2020, all metals exhibit peaks, and troughs,

Table 1
Descriptive statistics of volatilities.

Markets	Symbol	Mean	Max	Min	Std. Dev.	JB
S&P GSCI Gold	GLD	0.887	2.118	0.597	0.257	1901.863***
S&P GSCI Silver	SLV	1.728	4.369	0.989	0.723	536.846***
S&P GSCI Platinum	PLT	1.718	4.437	0.993	0.621	849.303***
S&P GSCI Palladium	PLD	2.055	12.371	1.433	0.888	104762.700***
Bitcoin	BTC	4.786	14.779	2.394	1.630	1935.800***
Ethereum	ETH	6.134	19.132	4.539	1.482	14711.330***
Binance Coin	BNB	6.739	24.077	3.708	3.017	3942.521***
Cardano	ADA	7.840	36.222	4.685	3.619	19325.910***
Ripple	XRP	7.128	30.099	3.335	3.972	2474.854***

Note: Std. Dev. indicates standard deviation. JB indicates Jarque-Bera test of normality.
*** indicates rejection of null hypothesis at 1 %.

[3] https://coinmarketcap.com/.O'Connor, M. What Is "Market Cap" in Crypto, and Why Is It Important? 2019. Availableonline: https://dailyhodl.com/2019/03/06/what-is-market-cap-in-crypto-and-why-is-it-important/.

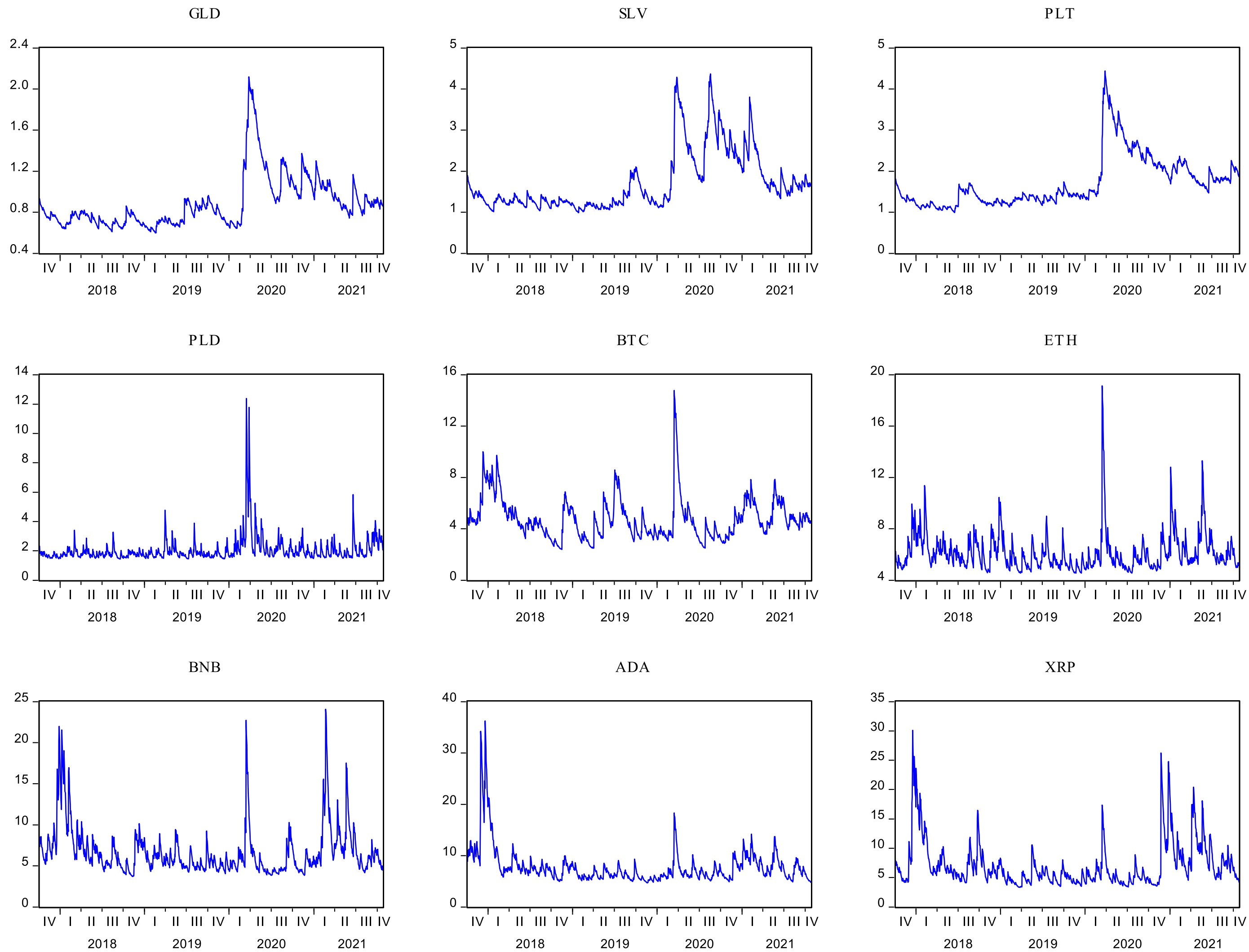

Fig. 1. Evolution of volatility series
Note: The figure presents the time evolution of the volatility series from October 3, 2017 to October 27, 2021.

with gold being less volatile in magnitude, and palladium displays the highest volatility during the COVID-19 pandemic. Thereafter, as the pandemic severity goes down in the first and second quarter of 2021 due to the availability of cures or vaccines or herd immunity, all metals maintain a low level of volatility.

In contrast, the cryptocurrencies, particularly ADA, XRP, and BNB, display higher volatility from the start of the sample period till the 1st quarter of 2018. These high fluctuations can be attributed mainly to two reasons: the cryptocurrencies bubble burst and the Federal Open Market Committee (FOMC) during 2017. According to Dreger and Zhang (2013), there are extreme fluctuations in the prices of assets, known as bubbles and bursts, to indicate a sudden price acceleration that cannot be explained by underlying basic economic variables, with the end of this phase, known as a bubble burst, resulting in abrupt price declines and significant losses to investors. Several recent studies have found empirical evidence of cryptocurrencies price bubbles (Cheung et al., 2015; Corbet et al., 2018b; Fry and Cheah, 2016; Shahzad et al., 2021). Following a year of significant gains, Bitcoin's price plummeted towards the end of 2017, losing around 65 percent of its value from its peak on February 5, 2018. Secondly, the Federal Open Market Committee (FOMC) took the monetary policy decision regarding increasing the US interest rate during 2017 has a considerable influence on Bitcoin and other cryptocurrencies (Corbet et al., 2017).

During the COVID-19 pandemic, the highest peaks can be seen in BTC, ETH, and BNB. During 2021, BNB exhibits the highest magnitude of volatility along with ETH and XRP displaying successive peaks and troughs. Overall, we observe that precious metals are less volatile than cryptocurrencies, as shown in Table 1. The finding of low volatility in precious metals is in line with Reboredo and Rivera-Castro (2014), Baur and McDermott (2010), and Baur and Lucey (2010).

Quantile–Quantile (QQ) plots are a simple and effective way to highlight asymmetry in distributions, heavy tails, outliers, multi-modality, and other data anomalies (Luo et al., 2019). In essence, a QQ plot organizes the empirical distribution (in this example, volatilities) in ascending order before plotting them against quantiles derived from the theoretical distribution (in our case, the normal). If the points on a QQ plot are nearly on the 45-degree line, it indicates that the empirical and theoretical distributions are similar. Deviations from this line, which end in an "S" shape, indicate strong tails compared to the theoretical distribution and show that our data goes beyond the simple mean-variance analysis. Fig. 2 visually shows the volatilities of precious metals and cryptocurrencies through QQ plots. When the two compared distributions are quite similar, the points of the QQ plot form a straight line (red line in Fig. 2), whereas any divergence (blue line in Fig. 2) from it indicates that the two compared distributions are fundamentally different.

Given that the theoretical distribution used in our case is normal, any deviation from the red line indicates that the volatilities of precious

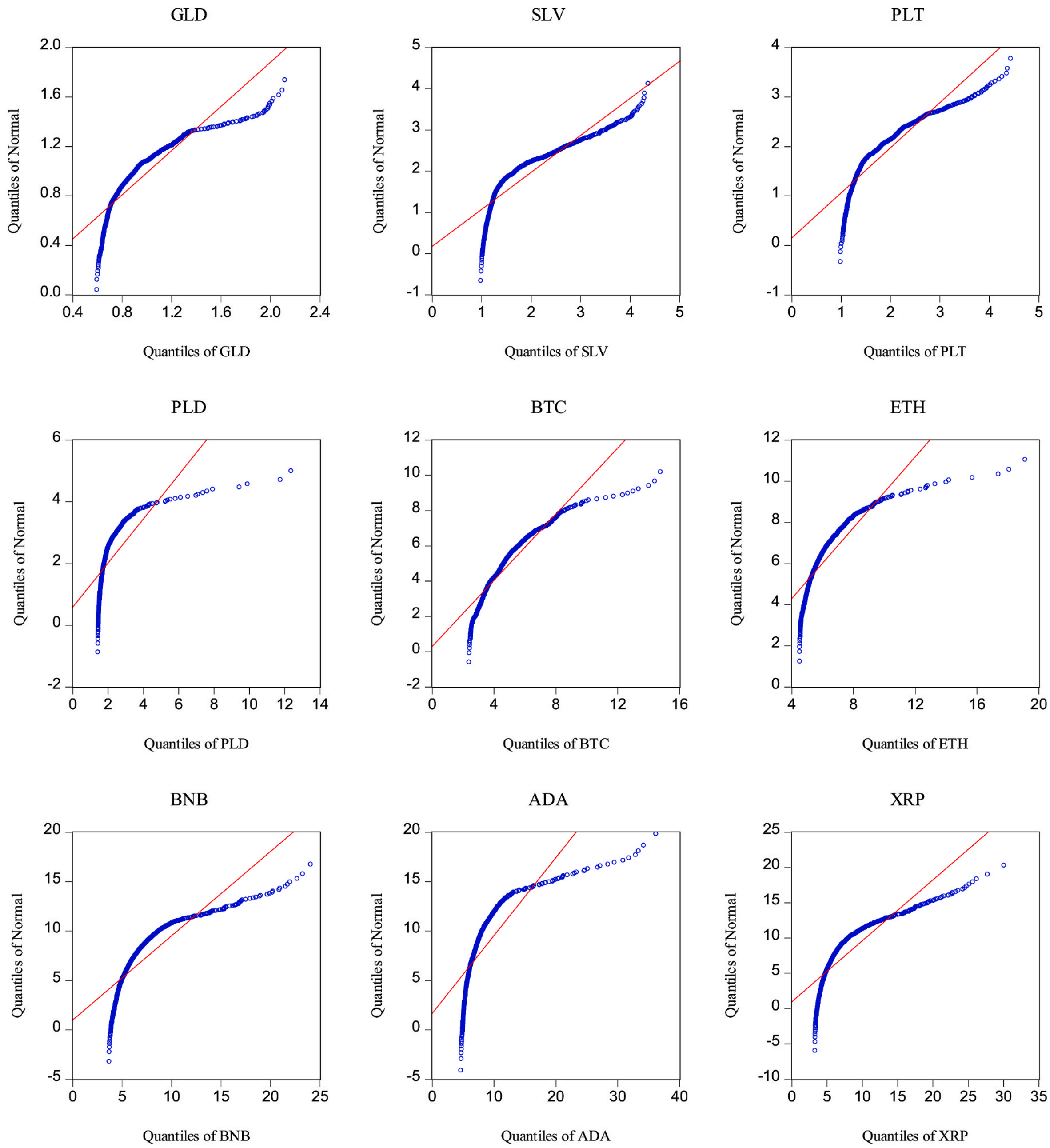

Fig. 2. Q-Q plots.

metals and cryptocurrencies are not normally distributed, as shown by blue dots. As a result, we reject normality for the volatilities of all precious metals and cryptocurrencies. After a thorough examination of the plots, it is clear that the normal distribution anticipates more mass concentrated in the tails than that. This conclusion is reinforced by the Jarque-Bera test (see Table 1), which rejects the null hypothesis of normality for the data under consideration.

The pairwise correlation among the variables under consideration and their overall distribution are depicted graphically in Fig. 3. We observe the high correlation among different precious metals in comparison to cryptocurrencies. In the same way, cryptocurrencies have high correlations with other cryptocurrencies compared to different precious metals. Among precious metals, GLD has a high correlation (0.90) with PLT and a very low correlation (0.013) with XRP. Similarly, BTC has a high correlation with ETH and a low correlation with XRP (0.48). The high correlation between various precious metals (cryptocurrencies) indicates that they belong to the same asset class. Low correlations between precious metals and cryptocurrencies indicate that precious metals can diversify the portfolios of cryptocurrencies. This finding is consistent with the findings of Rehman and Vo (2020), who suggest that there is a low/negative co-movement between precious metals and cryptocurrencies, implying greater diversification advantages. Similarly, Al-Yahyaee et al. (2020) and Reboredo and Rivera-Castro (2014) state that due to their natural hedging capabilities, precious metals are regarded as a store of economic value and are considered resilient in times of crisis.

4.2. Dynamic volatility connectedness in the quantile VAR

In order to overcome the problems of hidden patterns due to possible structural breaks, instability, non-stationery, the effect of outliers in the variables, and changing trends over time, we use dynamic estimation using a rolling window approach. Various authors have adopted this procedure studying the dynamic connectedness among variables of

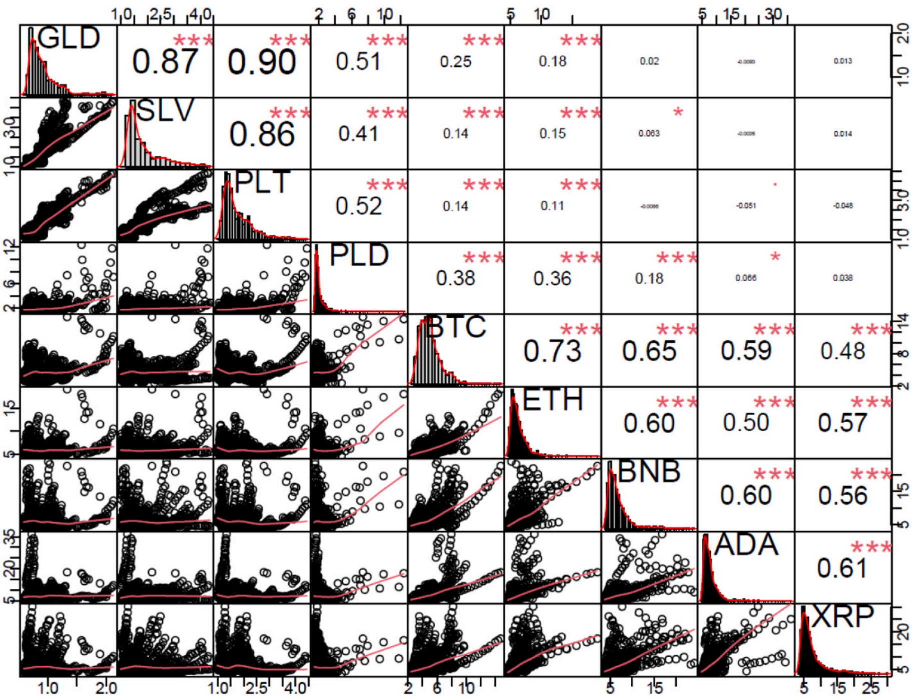

Fig. 3. Correlation plot.

interest (Diebold and Yilmaz, 2012; Bouri et al., 2021; Aharon et al., 2021). Fig. 4 shows the rolling-window estimates of total volatility connectedness, indicating the average volatility (blue line), extreme low volatility (green line), and extreme high volatility (red line) at the 50th, 5th, and 95th quantiles, respectively, among precious metals and cryptocurrencies.

At the median volatility, we broadly see three distinct levels of TCI, ranging three periods over time; 1) From the end of 2018 to the start of 2020; 2) From the start of 2020 to the beginning of 2021 and 3) during the year 2021. During the first period, the TCI varies considerably between 40 % and 60 %, then a sharp increase of 75 % at the start of 2020. The TCI remains relatively at the same high level until the end of 2020, associated with increased infected cases by the coronavirus globally and severe panic in the global economy. This result is in line with the findings of Aharon et al. (2021) and Fasanya et al. (2021). The total connectedness gradually started decreasing and eventually reached around 40 % in the first quarter of 2021. Consequently, till mid-2021, the TCI remained at the same level and gradually increased to 49 % by the end of 2021. The TCI at low volatility level almost follows the same pattern as average volatility, particularly in the middle period representing peak COVID-19 pandemic. However, at the beginning and end of the sample period, the TCI levels are almost 10 % higher than average volatility.

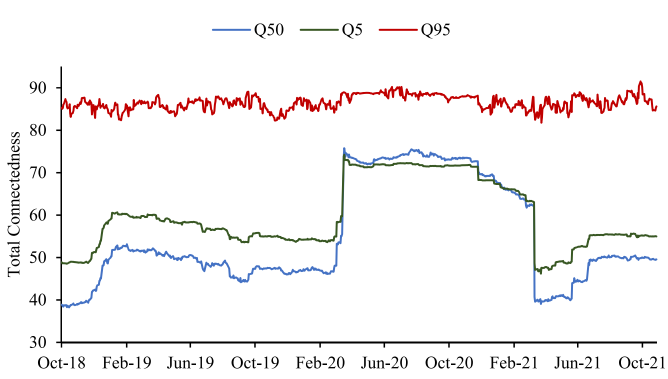

Fig. 4. Dynamic volatility connectedness in the quantile VAR
Note: This figure shows the rolling-window estimates of total volatility connectedness at the 50th, 5th, and 95th quantile, respectively, among GLD (S&P GSCI Gold), SLV (S&P GSCI Silver), PLT (S&P GSCI Platinum), PLD (S&P GSCI Palladium), BTC (Bitcoin), ETH (Ethereum), BNB (Binance Coin), ADA (Cardano), and XRP (Ripple). The rolling window size is 260 days.

A noticeably different pattern of risk spillovers is seen during extreme high volatility conditions. We find a very high TCI level in each quantile that reaches and sustains 85 % with very few fluctuations during the onset of COVID-19. The high value of TCI implies the increased sensitivity within the risk interconnectivity of precious metals and cryptocurrencies at extreme high volatility conditions. According to Antonakakis et al. (2019) and Ji et al. (2019), the COVID-19 pandemic intensified the magnitude of spillover in the high volatility condition and implied that the dynamics of the total spillovers are rapid to adapt to external shocks (Mirza et al., 2023; Rehman et al., 2023; Naeem et al., 2023a,b). This finding can also be corroborated by contagion effects highlighting large and abrupt changes in market links (Farid et al., 2021; Naeem and Arfaoui, 2023; Baele and Inghelbrecht, 2010). Therefore, the systemic risk associated with the emergence and progression of the COVID-19 pandemic heightens the potential of risk spillover across cryptocurrencies (Goodell and Goutte, 2021) as well as precious metals (Uddin et al., 2019).

Moreover, our results correspond to the literature supporting asymmetric spillovers among different markets, particularly during the crisis, and can be connected to numerous behavioural finance theories. According to Baker and Wurgler (2007) and Ortmann et al. (2020), investors may experience a variety of biases during the turbulence period, including the "home bias" which occurs when investors believe that investing in stocks, they are familiar with will keep their money safe, and "overtrading bias" which occurs when investors overthink about their investment buying and selling. Therefore, we argue that it is consistent with investor behaviour literature that the TCI level is substantially higher during high volatility conditions. It implies that the high-risk spillovers are caused by investors switching between assets in an attempt to find safety due to the significant unpredictability of asset values. This adds credence to the body of evidence that suggests investors may turn to precious metals as flight-to-safety opportunities when facing volatility in financial markets (Foley et al., 2021; Lucey and Li, 2015; Semeyutin and Downing, 2022). This finding is useful for institutional and individual investors exploring diversification opportunities among various asset classes (Waring and Mamou, 2020). Our findings exhibit higher volatility conditions as the volatility spillovers between precious metals and cryptocurrencies differ strongly between extreme left and right tails and support the growing literature on asymmetric volatility spillovers among various financial assets (Iqbal et al., 2022, 2024; Caporin et al., 2021; Baruník et al., 2017).

Fig. 5 presents the total connectedness variation across various quantiles. The evidence of strong connectedness between precious metals and cryptocurrencies can be found in the upper tail, indicating that the intensity of volatility connectedness rises with shock size for extreme high volatility shocks. This is in line with previous studies showing the spillover of extreme events (Londono, 2019). Fig. 5 demonstrates that the TCI between the 0.05 and 0.85 quantiles fluctuates close to the mean value, ranging from 55 % to 52 %. When severe shocks hit the network of connectedness, however, mutual connectivity across precious metals and cryptocurrencies enhances risk spillover, and the TCI reaches 85.78 % at the 95th percentiles. Our findings are consistent with earlier research showing that massive shocks have a greater impact than tiny shocks (Dendramis et al., 2015; Antonakakis et al., 2019; Ji et al., 2019).

4.3. Net directional volatility spillovers

This section analyses the time-varying net directional risk spillovers for each precious metal and cryptocurrencies, identifying the net transmitters and receivers of volatility shocks over the period of interest. The net risk spillovers estimated are shown by Fig. 6(a) median, 6(b) extreme low, and 6(c) extreme high volatility levels.

The pattern revealed by Fig. 6(a), corresponding to the median volatility, distinguishes three periods: from the end of 2018 to the beginning of 2020, a fluctuating net directional position with a low magnitude that does not exceed 2 % for cryptocurrencies and −2 % for precious metals. The heightened fluctuation is seen in precious metals and cryptocurrencies during peaks of COVID-19, running from 2020 through the first quarter of 2021. The net spillovers increase to roughly 4.3 % for the highest net shock transmitters: ETH, and 2 % for the lowest net shock transmitters: XRP. The positive risk spillovers of all cryptocurrencies depict their volatile nature during crises and are in line with Yarovaya et al. (2021) and Le et al. (2021). All precious metals are viewed as net shock receivers simultaneously, with GLD being the highest (−4.9 %) and PLT being the lowest (−1.92 %). Following the severity of COVID-19, both precious metals and cryptocurrencies go towards the neutral position and maintain low magnitude values ranging from −2 % to 2 %, respectively, after the 1st quarter of 2021.

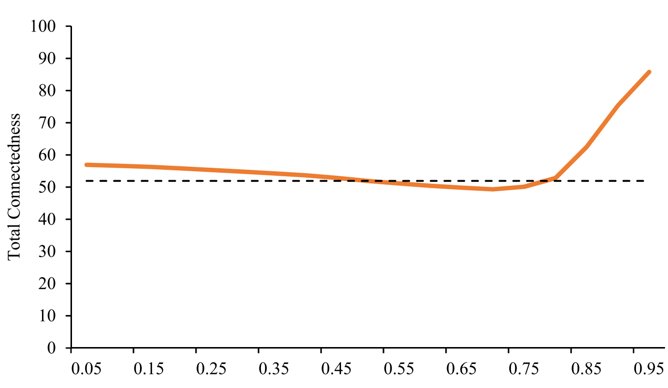

Fig. 5. Variation in Total Connectedness across various quantiles
Note: Total Connectedness is estimated at various quantiles (Tau). The horizontal (black-dashed) line is estimated at the conditional mean.

Both ADA and ETH are considered as net shock transmitters at the extreme low volatility level (Fig. 6(b)), while XRP and PLD are seen as net shock receivers in cryptocurrencies and precious metals, respectively. We visualize a shift in XRP's role from shock receiver to shock transmitter from the beginning of 2020 to the end of 2020, with continuous fluctuations. All cryptocurrencies appear to be net shock transmitters in response to the COVID-19 pandemic shock, while all precious metals appear to be net shock receivers. During turbulent times, the negative net volatility spillovers of precious metals indicate their diversification potential and safe-haven proprieties (Baur and Lucey, 2010; Baur and McDermott, 2010).

The pattern found is quite different for the extreme high volatility (Fig. 6(c)), showing fluctuating net directional risk spillovers with a high magnitude that is exceeded by 37 % for ADA and −7 % for BNB among cryptocurrencies. In contrast, precious metals remain close to zero, with tiny fluctuations in the last quarter of 2018. During the extreme pandemic situation from 2020 to the beginning of 2021, the net directional risk spillover of both precious metals and cryptocurrencies appears to transmit risk at the same magnitude as they receive risk from the entire network, resulting in a neutral position except for GLD, PLD which act as net shock transmitters and XRP as net shock receivers. After that, until the end of our sample period, the net directional risk spillovers fluctuated mildly around their neutral position, implying an equivalent shock spillover in both directions, except for PLD acting as net shock transmitter displaying the highest peaks and XRP as net shock receiver showing lowest troughs during the period.

4.4. Network of volatility spillovers

After reviewing the dynamic analyses, we look at the network topologies of the pairwise directional risk spillovers corresponding to the median, extreme low, and extreme high volatility conditions. The network diagram and net directional risk spillover for each of the precious metals and cryptocurrencies across the sample period are shown in Fig. 7(a) and (b), and 7(c). There is a strong risk spillover with a magnitude greater than 20 % between GLD-SLV and BTC-ETH among precious metals and cryptocurrencies at the median volatility level (Fig. 7(a)). In precious metals, we show moderate bidirectional risk spillovers ranging from 10 to 15 % between SLV-PLT, PLT-PLD, GLD-PLD, and GLD-PLT, whereas, in cryptocurrencies, we see moderate bidirectional risk spillovers with a magnitude between 10 and 15 % between ETH-BNB, XRP-ADA, XRP-ETH, BNB-ADA, and BTC-XRP. However, the occurrence of weak risk spillovers and disconnection between PLD-ADA, PLD-ETH, SLV-ETH, GLD-ETH, and PLD-BNB suggests the potential of precious metals as a risk diversifier for cryptocurrencies. These results are consistent with the findings of Rehman and Vo (2020), who found that precious metals are insensitive to cryptocurrencies, hence indicating diversification potential. Likewise, the pattern at extreme low volatility (7b) seems remarkably similar to the median volatility.

The risk spillover network patterns at the lower and median volatility levels are considerably different from those at the extreme higher volatility level, when prices oscillate strongly during acute crisis periods, with noticeable peaks and troughs attributable to catastrophic occurrences. As a result, investors' fear manifests itself in their behaviour during high volatility periods, as they jump from one asset to the next in search of higher returns with more consistent price fluctuations (Ortmann et al., 2020). At extreme volatility level, we find that PLD, in particular, is a strong net risk transmitter for SLV and PLT with a magnitude of greater than 15 %, whereas ADA is a strong risk transmitter for BNB with a magnitude of greater than 20 %. In precious metals, PLD has a substantial bidirectional risk spillover with GLD. There are also moderate bidirectional risk spillovers with a magnitude of 10–15 % between SLV-GLD, ETH-GLD, SLV-ETH, SLV-BTC, BTC-PLT, BTC-ETH, and moderate risk transmission between XRP-BNB and ADA-XRP, BTC-BNB. There is a low bidirectional risk transmission at

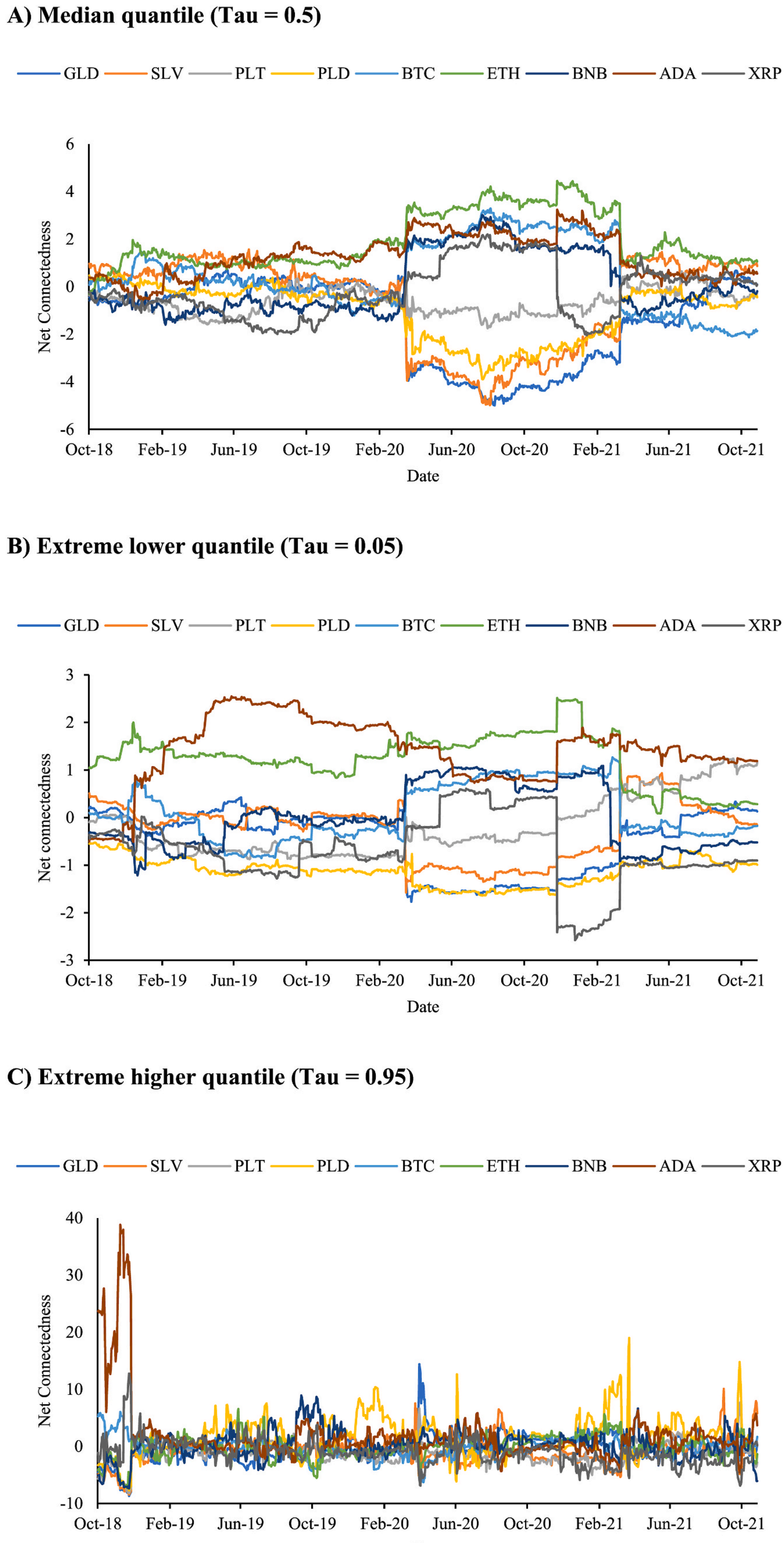

Fig. 6. Net directional volatility connectedness
Note: These figures show the rolling-window estimates of NET volatility connectedness at the 50th, 5th, and 95th quantile among GLD (S&P GSCI Gold), SLV (S&P GSCI Silver), PLT (S&P GSCI Platinum), PLD (S&P GSCI Palladium), BTC (Bitcoin), ETH (Ethereum), BNB (Binance Coin), ADA (Cardano), and XRP (Ripple). The rolling window size is 260 days.

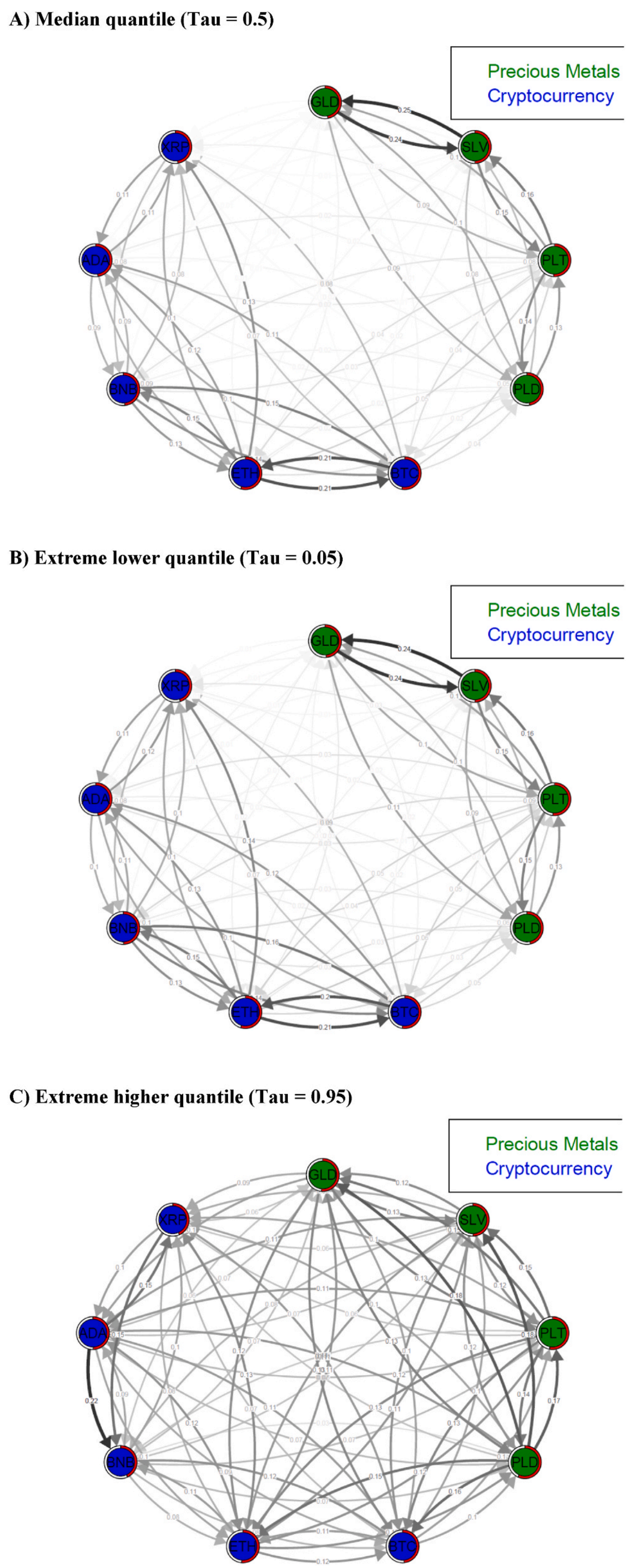

Fig. 7. Volatility spillovers based on quantile VAR
Note: These network graphs illustrate the degree of network connectedness at the 50th, 5th, and 95th quantile among GLD (S&P GSCI Gold), SLV (S&P GSCI Silver), PLT (S&P GSCI Platinum), PLD (S&P GSCI Palladium), BTC (Bitcoin), ETH (Ethereum), BNB (Binance Coin), ADA (Cardano), and XRP (Ripple). The red color in the node implies contribution from the variable under consideration to the other variables of the system.

high volatility levels between GLD-BNB, SLV-BNB, PLT-BNB, and PLD-BNB with a magnitude less than 10 %. The weak bidirectional risk spillovers between BNB with all precious metals suggest its diversification potential.

The high connectedness among other cryptocurrencies and precious metals increases during high volatility periods, thus reducing the potential diversification opportunities between asset classes. These findings suggest that the systemic risk connected with the outbreak and spread of the COVID-19 pandemic increases volatility spillovers of both markets: cryptocurrencies as well as precious metals, and in accordance with prior studies comparing cryptocurrencies and stock markets (Goodell and Goutte, 2021; Corbet et al., 2020), cryptocurrencies and commodities markets (Dutta et al., 2020) and precious metals, energy, and stocks (Farid et al., 2021).

4.5. Hedging effectiveness

To study the hedging characteristics of each of the precious metals with the set of cryptocurrencies independently, we estimate hedge ratios (HR) and hedging effectiveness (HE) in Table 2. The optimal HR can reduce the conditional variance of the hedged portfolio, whereas the HE index measures how effective an asset is at hedging, with higher values indicating higher efficiency. We combine each precious metal with cryptocurrencies in a portfolio to see how efficient each precious metal is at hedging the volatility of cryptocurrencies. The average hedging ratios between GLD and each of the five cryptocurrencies are positive, as shown in Table 2(A). The HR of ETH is the highest when the cryptocurrencies in a portfolio are combined with GLD, followed by BNB, ADA, XRP, and BTC. Mean HR suggests that a $100 long position in any of the cryptocurrencies: ETH, BNB, ADA, XRP, and BTC can be hedged by taking a short position of $61.6, $61.3, $60.2, and $44.7 and $10.3 in GLD respectively. Moreover, taking a long position in cryptocurrencies and short position in precious metals exhibit that BTC-GLD is the cheapest average hedge, while ETH-GLD is the most expensive.

The hedge effectiveness is highest for ADA and minimal for BTC in the portfolio of GLD and cryptocurrencies. Table 2(B) shows the HR and

Table 2
Summary statistics of the hedge ratios (HR) and hedge effectiveness (HE).

	Mean.HR	Min.HR	Max.HR	HE
A) Gold				
BTC	0.103	−0.948	1.002	−0.008
ETH	0.616	0.369	1.011	−0.004
BNB	0.613	0.028	1.256	0.002
ADA	0.602	−0.197	1.624	**0.015**
XRP	0.447	−0.007	1.429	0.000
B) Silver				
BTC	0.263	0.011	0.445	0.004
ETH	0.511	0.279	0.747	0.023
BNB	0.463	0.302	0.653	0.014
ADA	0.508	0.156	0.937	**0.033**
XRP	0.494	0.292	0.754	0.019
C) Platinum				
BTC	0.376	0.236	0.694	0.006
ETH	0.410	0.322	0.580	0.023
BNB	0.526	0.324	0.877	0.017
ADA	0.529	0.303	0.801	**0.067**
XRP	0.457	0.261	0.742	0.037
D) Palladium				
BTC	0.279	0.162	0.549	−0.002
ETH	0.319	0.168	0.479	**0.035**
BNB	0.272	0.147	0.506	0.004
ADA	0.372	0.212	0.676	0.017
XRP	0.404	0.193	0.730	0.007

Note: Fixed window rolling analysis was used to calculate the hedge ratios in order to estimate the one step ahead forecast. Multivariate normal distribution was used for estimating the ADCC-GARCH estimates. For all specifications, a constant and an AR(1) term was included in the mean equation. The bold value indicates highest hedge effectiveness of precious metals for cryptocurrencies.

HE among the portfolio of SLV and each of the five cryptocurrencies and indicates that the highest HR is for ETH and the lowest is for BTC. At the same time, HE is highest for ADA and lowest for BTC. Similarly, in Table 2(C), among the portfolio of PLT and all cryptocurrencies, the HR and HE is the highest for ADA and lowest for BTC. Finally, in Table 2(D), we present the HR and HE among the portfolio of PLD and each of the five cryptocurrencies. The highest HR is for XRP and the lowest is for BTC, whereas ETH and BTC show the highest and lowest HE, respectively.

These results provide considerable implications for investors who want to protect themselves against the volatility spillovers of cryptocurrencies. Compared to GLD, SLV, and PLD, the results suggest that PLT provides the highest hedging effectiveness, implying that PLT is a preferable hedge for cryptocurrencies. Investing in the SLV and PLD, respectively, provides the second and third most effective hedging. In comparison, GLD offers the least possible hedging opportunities to high-volatility cryptocurrency investors, corroborating the findings of Klein (2017), who used a dynamic correlation model to show that gold served as a hedging function for US and European stock market indexes only before 2013, after which the role faded away, and contradicting the findings of Hassan et al. (2021), who show that gold is a more consistent safe-haven and hedging asset than other assets, while Shahzad et al. (2020) find that gold is an undeniable safe haven and hedge for a number of G7 stock indices.

4.6. *Conditional diversification benefits*

We evaluate the diversification benefit of integrating each precious metal in a portfolio setting with cryptocurrencies instead of simply relying on estimates of risk spillovers to determine the best investment strategies. In this case, we use the Conditional Diversification Benefits (CDB) measure utilizing the methodology of Christoffersen et al. (2018). This measure is based on the expected shortfall with the probability threshold (p) of a portfolio of precious metals and each cryptocurrency. We choose p = 5 % because it is consistent with the original measure. Because diversification benefits may change with portfolio composition and the probability p, we compute CDB for different portfolio weights, assuming a passive trading strategy so that those weights remain constant over time, and for p values of 5 %, corresponding to the lower tail of the distribution. We first calculate the diversification benefits of an equally weighted portfolio in Fig. 8.

We note the time-varying nature of CDB for an equally weighted portfolio of precious metals and cryptocurrencies. We can show that the CDB analysis corresponds to three distinct periods. Firstly, the period from the start of the sample period till the final quarter of 2018, combining 50 % of GLD, SLV, PLT, and PLD with each of the cryptocurrencies, provided a diversification benefit ranging from 0.1 to 0.6, as can be seen in Fig. 8 (A, B, C, and D). During this time, all precious metals provide maximum risk diversification to BTC and minimum to XRP and ADA. This period is corroborated with the burst of the cryptocurrencies bubble, when the Bitcoin price faced a historical drop towards the end of 2017, losing around 65 percent of its value (Baur and Dimpfl, 2021).

The second period corresponds to April 2019 to October 2020, including the severe period of COVID-19, the range of diversification benefits is between 0.2 and 0.6. During COVID-19, we find significant CDB of GLD, SLV, and PLT for all cryptocurrencies, with the highest benefits for BTC and lowest for ADA (Fig. 8, A, B, & C). Similarly, the CDB of PLD indicates the highest diversification benefit for XRP and the lowest for ADA (Fig. 8 D). The diversification potential of precious

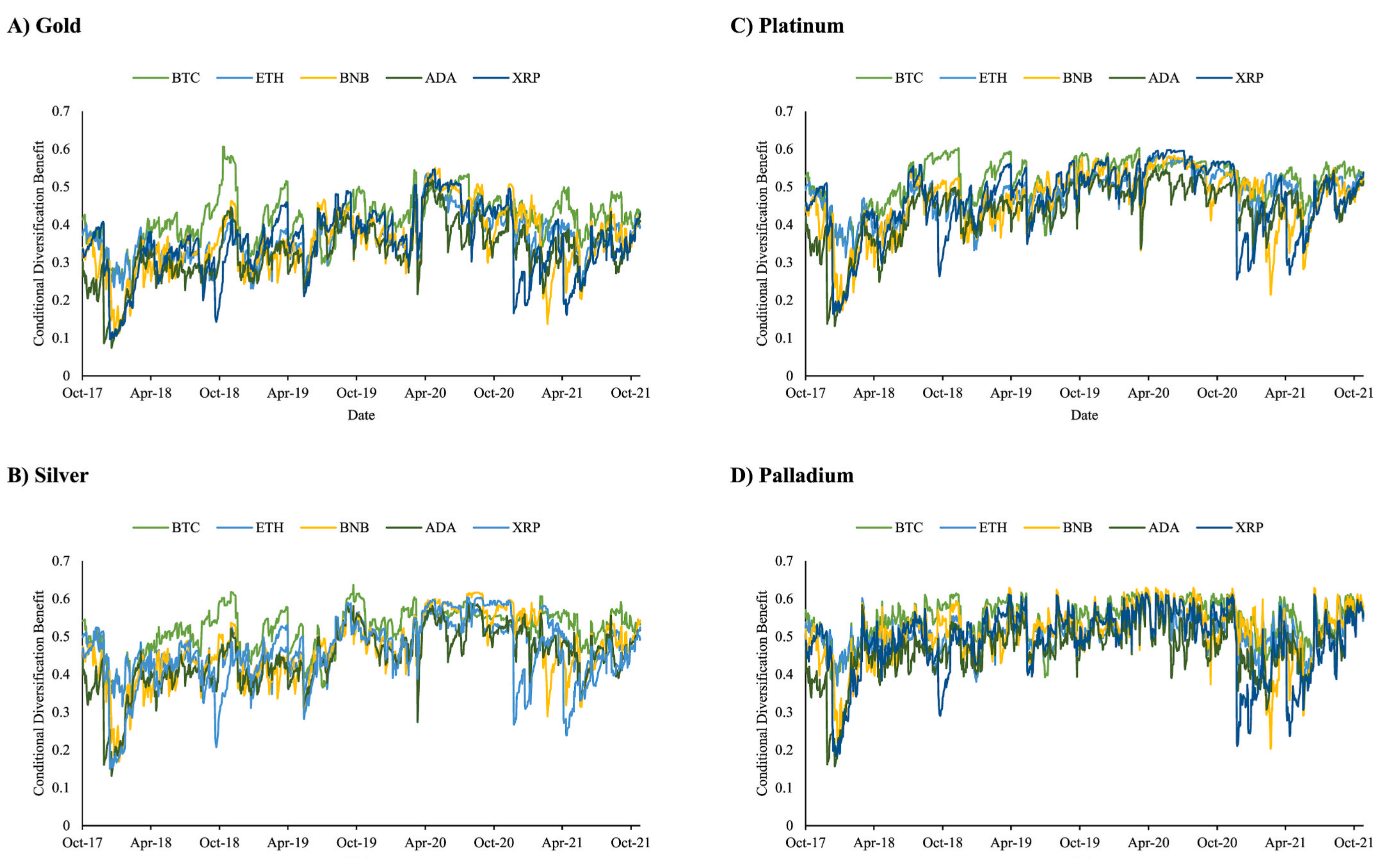

Fig. 8. Conditional diversification benefits from adding precious metals to cryptocurrencies portfolios (at 5 % level - equally-weighted portfolios).
Note: Time series plot of the conditional diversification benefits (CDB) of precious metals for cryptocurrencies. Equally weighted portfolios consisting of 50 % GB and 50 % of each other asset are examined to estimate the conditional diversification benefit at a 5 % level.

metals during turbulence time is in accordance with prior literature (Baur and Lucey, 2010; Baur and McDermott, 2010).

Finally, the third phase from October 2020 till the end of sample period indicates strong peaks and troughs in the diversification potential of precious metals with all cryptocurrencies. GLD and SLV offer BTC, BNB, and XRP additional diversification advantages, oscillating between 0.1 and 0.5, with large peaks and troughs for BNB and XRP. During the same period, PLT gives XRP and BTC a larger CDB than other cryptocurrencies, whereas PLD gives ETH and BTC a larger CDB than other cryptocurrencies, with dramatic peaks and troughs (Fig. 8, A, B, C, & D).

Overall, we observe that the diversification potential of all precious metals towards cryptocurrencies is stronger during the cryptocurrency bubble burst and COVID-19 turbulence period, confirming previous findings (Baur and Dimpfl, 2021; Rehman and Vo, 2020).

Fig. 9 show the CDB analysis at a 5 % level, representing the extreme left tail distribution for various portfolio weights. In Fig. 9(A), diversification benefits show a gradual growth with an increase in the proportion of GLD in a portfolio and reach an optimal diversification level at 60 % for all cryptocurrencies, after which the CDB declines. Similarly, including the increased portion of SLV with all cryptocurrencies in Fig. 9 (B) reach an optimal diversification level at 60 % for all cryptocurrencies, after which the CDB declines. Diversification advantages indicate a progressive increase in the proportion of PLT in a portfolio, reaching an optimal diversification level of 60 % for all cryptocurrencies before starting to decline, as shown in Fig. 9(C). Finally, Fig. 9(D) demonstrates that raising the percentage of PLD with all cryptocurrencies results in an optimal degree of diversity at 60 % for all cryptocurrencies, beyond which the CDB drops.

Overall, our portfolio management analysis shows that investors of cryptocurrencies should have more precious metals in their portfolios than cryptocurrencies during extremely volatile periods and in times of external shocks like the COVID-19, to reduce risk and maintain the expected return.

5. Conclusion

The current study brings new insights on the sparkling avenues of precious metals for cryptocurrencies for the period encompassing October 3, 2017, to October 27, 2021. We employed mutli-step analysis to unveil the underlying relationship between precious metals and cryptocurrencies. At first, we estimated volatilities using GJR-GARCH; then we utilized quantile connectedness approach to identify spillovers at median, extreme lower, and extreme higher quantiles. Third, we calculated hedge ratios and hedge effectiveness to obtain effective hedge for cryptocurrencies. Finally, we unlocked conditional diversification benefits to classify the diversification avenues by adding precious metals in a portfolio of cryptocurrencies.

We reported higher volatilities between precious metals and cryptocurrencies at extreme left and right tails signifying asymmetric volatility arrangement between two streams of financial markets. Network connectedness analysis indicate that precious metals act as a diversifier for cryptocurrencies and there is disconnection between precious metals and cryptocurrencies at extreme lower and median quantiles. In addition, at extreme higher quantile, the connectedness increases during volatility periods reducing the diversification avenues of precious metals for cryptocurrencies. Findings pertaining to hedge ratios indicate that a

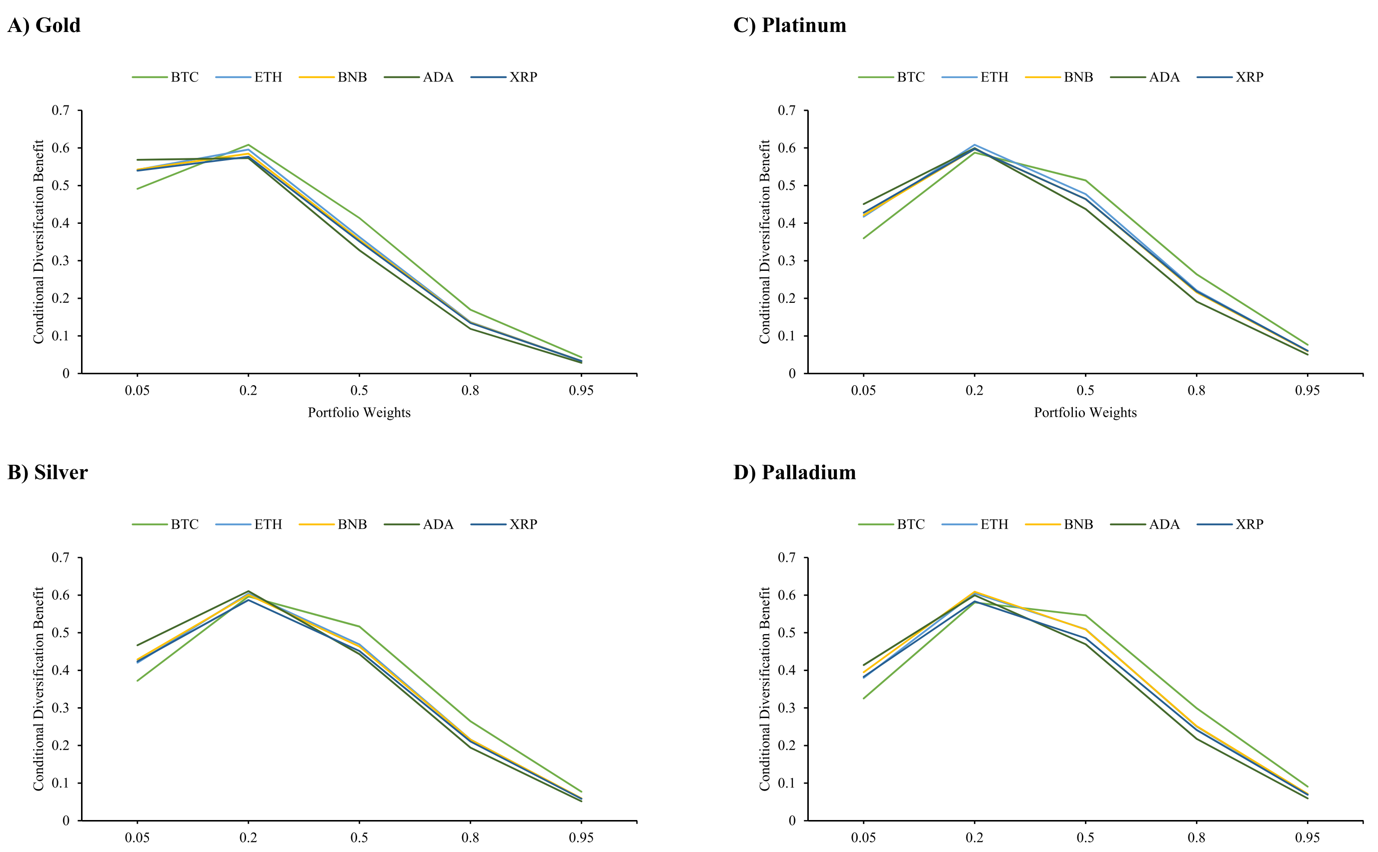

Fig. 9. Diversification benefits (at 5 % level) of precious metals for different portfolio weight compositions.
Note: These figures show the conditional diversification benefit for portfolios composed of precious metals and cryptocurrencies. Portfolio weights for the cryptocurrencies are indicated on the horizontal axis. The diversification benefit is computed by considering expected shortfall values at the 5 % probability level. For each portfolio, the figures report the time-average of the conditional diversification benefit.

long position in cryptocurrencies and short position in precious metals results in the cheapest combination of BTC-GLD whereas the most expensive hedge is ETH-GLD pair. Out of precious metals, PLT is considered as an effective hedge for cryptocurrencies following the hedge effectiveness of SLV and PLD. In contrast, GLD provides least hedge effectiveness for the investors of cryptocurrencies. Our research on conditional diversification advantages shows that precious metals offer superior diversity benefits than cryptocurrencies, especially during times of crisis. This adds credence to the collection of studies that corroborate that precious metals provide flight to safety avenues to investors amid uncertainties in the financial markets (Foley et al., 2021; Lucey and Li, 2015; Semeyutin and Downing, 2022). Similarly, the portfolio management analysis substantiate that cryptocurrency investors must include precious metals in their assets combinations while weighting their risk and evaluating the periods of economic turmoil.

Our findings are of higher importance for policymakers, regulatory bodies, financial markets, investors, and portfolio managers. For policymakers, our findings propose that risk of cryptocurrencies can be mitigated using precious metals and to avail better hedging facility when markets are undergoing distressed times. Thus, policymakers can re-assess their existing policies regarding cryptocurrencies and precious metals to encourage investing in the precious metals as they are less volatile in comparison to the cryptocurrencies. By re-formulating their mandates for each individual financial market, regulators can also direct their subordinate institutions to overcome the risk of cryptocurrency investing by adding precious metals as they sparkle against cryptocurrencies volatile nature being strongly integrated in the market and bearing low-risk potential. Given the uncertain financial and economic environment, our findings devise implications for financial markets to explicitly indicate the markets with high and low risks as the connectedness of precious metals and cryptocurrencies highlight their solitary characteristics and independent spillovers. However, at extreme upper quantiles, during heightened market sensitivities, markets are strongly connected referring the contagion phenomenon among financial markets.

Following this, investors can relish the findings of the study by carefully examining the risk-return relationship of cryptocurrencies and precious metals and assigning weightage to their probably risk. Since cryptocurrencies are net transmitters of spillovers due to their high volatility and price jumps, including precious metals in their existing portfolios can significantly minimize their exposure to the externalities as they offer diversification avenues for the investment streams. Similarly, considering hedge ratios and hedge effectiveness of the cryptocurrencies and precious metals combinations, investors can consider the cheapest and most expensive hedge along with superseding hedge effectiveness of PLT among other precious metals for cryptocurrencies. In this way, our findings reveal crucial implications for portfolio managers in terms of diversification benefits as precious metals glitter more against cryptocurrencies by providing the avenues for diversification and portfolio management. In a nutshell, our findings are unique in the current body of literature by defining the volatilities of cryptocurrencies and precious metals, identifying their connectedness at various quantile levels, network connectedness, hedge ratio and hedge effectiveness, and conditional diversification benefits of precious metals against cryptocurrencies by stipulating numerous ramifications for practitioners.

We acknowledge that our study has certain limitations which could be addressed in future research. Firstly, we only analyzed the most popular cryptocurrencies and precious metals, but we could incorporate other precious metals, commodities, or assets such as real estate or crude oil as more data becomes available. Secondly, it would be interesting to examine whether precious metals still provide a hedge during periods of market volatility caused by growing geopolitical risk, given the current state of the Russian-Ukrainian conflict. Investors should take note of this, as preliminary data suggests that growing political risk during the conflict between Russia and Ukraine leads to increased market connectivity and shock transmission from cryptocurrencies to precious metals, causing even safe-haven assets like gold to become more volatile. Finally, to ensure the reliability of our findings, it would be beneficial to use the same or different econometric methods on high-frequency intraday data, which is becoming increasingly accessible. In conclusion, there are many directions that future research could explore to expand the scope of our analysis and improve our understanding of the relationship between precious metals and cryptocurrencies, as well as their potential uses in the constantly changing cryptocurrency market.

CRediT authorship contribution statement

Afsheen Abrar: Methodology, Writing – original draft, Writing – review & editing. **Muhammad Abubakr Naeem:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Visualization, Writing – review & editing. **Sitara Karim:** Writing – original draft. **Brian M. Lucey:** Supervision, Writing – original draft, Writing – review & editing. **Samuel A. Vigne:** 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 A

Table A1
Averaged connectedness tables across median and extreme quantiles

A) Median quantile (Tau = 0.5)

	GLD	SLV	PLT	PLD	BTC	ETH	BNB	ADA	XRP
GLD	0.488	0.255	0.109	0.102	0.012	0.016	0.007	0.007	0.005
SLV	0.238	0.481	0.157	0.077	0.010	0.018	0.007	0.006	0.006
PLT	0.092	0.150	0.460	0.126	0.050	0.051	0.031	0.024	0.016
PLD	0.094	0.077	0.142	0.566	0.038	0.036	0.023	0.016	0.007
BTC	0.008	0.006	0.040	0.025	0.402	0.213	0.137	0.099	0.071
ETH	0.012	0.011	0.038	0.021	0.212	0.387	0.125	0.092	0.102
BNB	0.006	0.007	0.031	0.017	0.154	0.148	0.467	0.093	0.076
ADA	0.006	0.005	0.024	0.013	0.114	0.118	0.093	0.513	0.114

(continued on next page)

Table A1 (*continued*)

A) Median quantile (Tau = 0.5)									
	GLD	SLV	PLT	PLD	BTC	ETH	BNB	ADA	XRP
XRP	0.004	0.006	0.018	0.007	0.078	0.134	0.082	0.110	0.561
B) Extreme lower quantile (Tau = 0.05)									
	GLD	SLV	PLT	PLD	BTC	ETH	BNB	ADA	XRP
GLD	0.459	0.245	0.114	0.101	0.018	0.026	0.015	0.012	0.010
SLV	0.236	0.443	0.160	0.088	0.014	0.023	0.015	0.011	0.011
PLT	0.102	0.147	0.409	0.127	0.056	0.059	0.044	0.032	0.024
PLD	0.106	0.095	0.150	0.485	0.046	0.046	0.031	0.024	0.016
BTC	0.015	0.012	0.050	0.035	0.369	0.209	0.143	0.102	0.066
ETH	0.020	0.018	0.050	0.033	0.198	0.350	0.132	0.098	0.100
BNB	0.013	0.013	0.044	0.026	0.159	0.155	0.412	0.096	0.081
ADA	0.012	0.011	0.035	0.022	0.122	0.125	0.105	0.457	0.111
XRP	0.010	0.012	0.029	0.016	0.086	0.140	0.095	0.120	0.494
C) Extreme higher quantile (Tau = 0.95)									
	GLD	SLV	PLT	PLD	BTC	ETH	BNB	ADA	XRP
GLD	0.137	0.124	0.147	0.178	0.099	0.114	0.069	0.070	0.062
SLV	0.134	0.128	0.153	0.183	0.097	0.113	0.065	0.067	0.060
PLT	0.134	0.120	0.149	0.173	0.101	0.116	0.071	0.072	0.063
PLD	0.134	0.117	0.145	0.178	0.101	0.116	0.072	0.073	0.063
BTC	0.128	0.118	0.130	0.158	0.107	0.116	0.078	0.092	0.072
ETH	0.123	0.109	0.127	0.150	0.105	0.123	0.085	0.095	0.083
BNB	0.062	0.080	0.057	0.033	0.119	0.107	0.165	0.224	0.153
ADA	0.103	0.105	0.109	0.113	0.107	0.117	0.094	0.149	0.103
XRP	0.092	0.088	0.097	0.097	0.109	0.126	0.099	0.149	0.144

Note: These connectedness tables illustrate the degree of network connectedness at the 50th, 5th, and 95th quantile among GLD (S&P GSCI Gold), SLV (S&P GSCI Silver), PLT (S&P GSCI Platinum), PLD (S&P GSCI Palladium), BTC (Bitcoin), ETH (Ethereum), BNB (Binance Coin), ADA (Cardano), and XRP (Ripple).

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