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Exploring Tail Risk Transmission between Volatility Indices and Cryptocurrencies: Evidence from Quantile Connectedness

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Abstract

Purpose: This paper examines tail spillover and quantile connectedness between implied volatility measures (VIX, OVX, GVZ, and major cryptocurrencies such as Bitcoin Cash, Ripple, Litecoin, Ethereum, and Bitcoin). The investigation examines risk transmission for the bullish, bearish, as well as normal market conditions.

Methodology: Cross-quantilogram and quantile connectedness frameworks are utilized in a quantile vector autoregressive (QVAR) framework. Using the QVAR method with the day-ahead data from June 5, 2020, to June 8, 2024, generalized forecast error variance decomposition (GFEVDs) are evaluated to account for static as well as dynamic connectedness across different regimes of market conditions.

Results: The results indicate that the TCI (Total Connectedness Index) is broadly flat under typical conditions but increases under bullish conditions as well as under bearish conditions. Cryptocurrencies, besides Ripple under certain conditions, are a net transmitter of shocks, while volatility indices are the key net receivers. Such results feature non-linear risk transmission processes and carry useful implications for hedging as well as for diversification of portfolios.

Research limitations/implications: The paper focuses on cryptocurrencies and implied indices during a particular time interval (2020-2024) that might restrict the generalizability of results extended to other economic assets or timeframes. Future research might extend the coverage by incorporating the other asset classes or machine learning-based connectivity methods.

Practical Implications: It provides actionable advice for policymakers as well as for portfolio managers to control risk transmission between cryptocurrencies as well as volatility indices. Enhancing monitoring mechanisms as well as adaptive hedging policies remains helpful in mitigating systematic risk exposure under severe market conditions.

Originality/Value: This study is original in applying the quantile connectedness methodology to simultaneously study implied volatility indexes and cryptocurrencies under different market settings. Unlike earlier studies that focus on just the mean connectedness, our evaluation reveals the tail risk behavior that causes systemic exposure and contagion. The results add value to the body of work under Decision Science by offering policymakers and investors useful insights about risk transmission between volatility indexes and cryptocurrencies, thus facilitating decision-making about portfolio diversification and hedging under a volatile market.

Keywords: Quantile connectedness; Implied volatility indices; Cryptocurrencies; Risk transmission; Tail spillover; Hedging

JEL Classifications: C32; G11; G15; G17

1. Introduction

Financial markets are experiencing increasing volatility, and interconnectedness in one asset class can swiftly transmit throughout others, reshaping the international financial landscape. Many researchers have investigated tail spillover, contagion, risk diffusion, and quantile connectedness in commodity markets (Attarzadeh & Balcilar, 2022; Hanif et al., 2023; Umar, Adekoya et al., 2021; Umar, Gubareva et al., 2021; Umar, Yousaf et al., 2022) and crypto-markets (Bouri et al., 2021; Mensi, Al-Yahyaee et al., 2021; Naeem et al., 2022; Xu et al., 2021). In the same vein, the rising ambiguity and connectedness in conventional financial markets have been widely examined (Ali et al., 2022; Bams et al., 2017; Benlagha & El Omari, 2022; Chang, 2020; Chang et al., 2023; Cheng et al., 2021; Godil et al., 2020; Mensi et al., 2022; Peng et al., 2022; Roh et al., 2020; Salman, Chang et al., 2023; Xu et al., 2021).

However, despite numerous investigations on volatility associations, no study has broadly investigated the association between uncertainty in traditional markets and cryptocurrencies through a tail-risk and quantile-based framework. Previous research tends to emphasize the average link, thereby overlooking how extreme market situations impact the intensity and direction of spillover. This research intends to address this critical gap by offering empirical insights into the cryptocurrencies' spillover's principal role concerning the instability dynamics of gold, oil, and equity markets.

The primary objective of this research is to investigate the dependence between and within the uncertainty indices of gold, oil, and stock markets under all three market conditions (bullish, normal, and bearish) and major cryptocurrencies. Furthermore, this research studies the dynamic spillover degree of connectedness, magnitude, and direction under various cryptocurrency market regimes, thus offering a detailed picture of cross-market relations. This research answers primary research questions such as: (i) How does tail risk transmission fluctuate under normal, bearish, and bullish market conditions? (ii) How do implied volatility indices relate to important cryptocurrencies across various quantile levels? This investigation aids the Decision Sciences field by presenting a quantile-based connectedness method that captures tail-dependent risk dynamics, delivering a nuanced insight into inter-market contagion and systemic vulnerability.

To attain these objectives, the research utilizes the quantile connectedness and cross-quantilogram technique within a QVAR (Quantile Vector Autoregressive) approach. By employing the daily data from June 5, 2020, to June 8, 2024, the GFEVD (Generalized Forecast Error Variance Decomposition) captures both dynamic and static connectedness between main cryptocurrencies (Bitcoin Cash, Ripple, Litecoin, Ethereum, and Bitcoin) and volatility indices (GVZ, OVX, and VIX).

The results indicate that the spillover between the uncertainty indices for conditional markets and cryptocurrencies changes considerably across quantiles, which indicates that diversification benefits under both extremities and normal circumstances differ. On the other hand, the Total Connectedness Index (TCI) remains slightly volatile during normal circumstances but turns more turbulent during bullish or bearish market conditions. Additionally, it appears that Bitcoin Cash (BCH), Ethereum (ETH), Litecoin (LTC), or Bitcoin (BTC) overall preserve a role as shock emitters in uncertainty index transmission, with Ripple

(RTP) being a recipient, while volatility indexes overall behave as shock absorbers. All results possess profound implications for implementing volatility-driven instruments for ensuring cryptocurrency investors' safety as well as for improving the efficiency of hedging. The originality of this study resides in applying the quantile connectedness technique to jointly analyze the implied volatility indexes VIX, OVX, and GVZ, as well as major cryptocurrencies during different tail market conditions, thus revealing a non-linear risk spillover, which was yet to be identified under the existing literature paradigm. Also, this study focuses on the tail areas of market volatility to make a critical analysis, allowing for a clear understanding of the vulnerabilities that arise during the turbulent market periods. Additionally, this research work presents a significant academic contribution under the discipline of decision sciences by allowing policymakers, risk managers, or investors to obtain precise information about a volatility-cryptocurrency relationship, which helps improve processes involving decision-making for portfolios, risk protection, or managing risk during turbulent conditions of financial markets.

The remainder of this article is organized as follows: Section 2 illustrates the Literature Review and Methodology. Data and Initial Analysis are presented in Section 3. Empirical Findings are reported in Section 4. Whereas Section 5 concludes the research with implications and direction for future investigation.

2. Literature Review & Methodology

2.1 Literature Review

Owing to fluctuations in key conventional markets, issues related to complexity, ambiguity, or cryptocurrency market contagion became more prominent in literature among market participants as well as researchers (Antonakakis et al., 2019; Bossman & Gubareva, 2023; Bouri et al., 2021; Fang et al., 2022; Maghyereh & Abdoh, 2022; Mandaci & Cagli, 2022; Ren & Lucey, 2022; Salisu & Ogbonna, 2022; Sebastião & Godinho, 2021; Umar & Gubareva, 2020; Umar, Gubareva et al., 2022; Xu et al., 2019; Yousaf et al., 2023). Among various themes, risk spill-over between the conventional financial markets and cryptocurrencies, with a special emphasis on exploration of new ways for investment diversification or evading purposes, remains a key research interest for researchers across various fields of study related to financial complexity or risk literature alike (Attarzadeh & Balcilar, 2022; Bossman & Gubareva, 2023; Cheng et al., 2022; Hsu et al., 2021; Maitra et al., 2022; Salman, Razzaq et al., 2023; Umar, Yousaf et al., 2022; Zhang & He, 2021).

This study offers a contribution to existing literature as it seeks to analyze both the downside and upside spillover effects between the volatility/uncertainty indexes of key traditional financial investment products and the top five cryptocurrencies. This was largely inspired by its attraction to the market, which has been shown to influence several studies centered on traditional investment instruments, as well as investment products such as cryptocurrencies.

This work offers a significant contribution to existing know-how in several ways. Firstly, this work studies the relationship between major cryptocurrencies and various quantiles of uncertainty indexes for equity, oil, and gold markets, which is a significant development for this field since this may represent a crucial point in understanding its main interest (Ali et al., 2022; Bagadeem et al., 2024; Uche, Chang, & Effiom, 2022; Uche, Chang, & Gohar, 2022; Wang et al., 2024). Secondly, this work attempts to contribute to existing literature on tail risk, which, being a rare but serious event, represents a key point to be taken under serious considerations for investment management as a whole, as it was underscored in a variety of prior works, such as Mensi, Al Rababa'a et al. (2021), Fendel and Neumann (2021) as well as Kelly and Jiang (2014). The understanding of its causes as well as effects has a major role in managing port-performances that may risk market collapse as well as investment loss as a whole, as it was noted in Agarwal et al. (2017). Additionally, there appears to be a rising interest in tail risk management and analysis with respect to both traditional instruments and more novel forms of assets, such as decentralized finance, non-fungible tokens, or cryptocurrencies, amongst others. This appears in studies conducted by Yousaf et al. (2022), Umar, Sayed et al. (2022), Naeem et al. (2022), Ando et al. (2022), Xu et al. (2021), Hsu et al. (2021), Umar and Gubareva (2020), and Borri (2019).

This study builds upon this understanding by considering tail spillover between large changes in conventional markets like stocks, oil, gold, and cryptocurrencies. This provides an unfathomable insight into the level of hedging alternatives and opportunities that arise out of the interconnectedness of such markets. Financial experts who manage investment portfolios with exposure to cryptocurrencies will largely benefit from the insights offered by this research work. This will result in increased profits as well as minimized non-idiosyncratic risk. The information about tail spillover between various markets for policymakers will aid in improving overall financial market stability.

2.2 Theoretical Framework

The relationship between different assets will be evaluated by applying a cross-quantilogram test, which was first presented in Han et al. (2016). This test measures dependencies between different assets at different quantiles, starting from lower quantiles towards the higher quantiles of a distribution. Comparing the influence range at both tails with that at a central point will indicate how far a certain dependency across different investment instruments extends over a general range of quantiles. This will help us understand asymmetric relationships between investment instruments in a general, bullish, as well as a bearish market, classified based on abnormally low, average, or abnormally high investment returns. This will be more notable between June 5, 2020, and June 8, 2024, which includes incidents such as Russia's invasion of Ukraine as well as the spread of the COVID-19 pandemic (Gohar, Bagadeem et al., 2022; W.-K. Wong et al., 2024).

This research uses three CBOE volatility indexes along with the five cryptocurrencies: BTC (Bitcoin), ETH (Ethereum), LTC (Litecoin), XRP (Ripple), and BCH (Bitcoin Cash) to assess the cross-quantile dependency between the volatilities of equity, oil, and gold markets and cryptocurrencies. The VIX, OVX, and GVZ volatility indices assess market unpredictability in the equity, gold, and crude oil markets. These specific volatility indices were chosen because they precisely indicate the volatility in the three prime conventional financial markets. As stated by Bams et al. (2017), the GVZ, OVX, and VIX indices represent the ambiguity of investors about these markets' future situations and denote volatility in the macroeconomic indicators, goods prices, and the stock market. Phan et al. (2018) mention that gold is frequently professed as a safe haven investment during the disastrous conditions because it is less vulnerable to the tremors.

Interestingly, oil and stock markets behave in distinct manners for a number of market shocks. Investors requiring predictive information about forthcoming price volatility beyond a certain period for understanding market instability and stability phases utilize such volatility indexes. Insights collected from such volatility indexes are significant for making investment allocations. Selected cryptocurrencies possess high trading volumes with large market values, with a cumulative value of more than half of their overall global market value for both BTC and ETH. Since a remarkable escalation in price for both ETH as well as a notable increase in trading volumes, from early 2017, has been identified by Bouri et al. (2019), it must be highlighted that 'conventional financial assets are more liquid than cryptocurrencies' as asserted by Bianchi et al. (2022).

This study uses both a quantile connectedness method devised by Ando et al. (2022), in addition to a cross-quantile technique offered by Han et al. (2016), to reveal the presence of cross-quantile connectedness between variables under study, as well as tail spillovers between return distribution of conventional markets at both upper, middle, as well as lower quantiles, as well as cryptocurrencies. This study proposes that with the application of such approaches, a significant difference between spillovers of significant traditional market volatility measures as well as cryptocurrencies may exist for different quantiles, implying that the benefits of such measures may vary widely under extreme as well as normal circumstances. This paper identifies a nexus between variables, examines it for interconnectedness, as well as reveals innovative components related to hedging benefits for portfolio management (Gohar, Chang et al., 2023; Gohar, Osman et al., 2022; Gohar, Salman et al., 2023; Hui et al., 2017a).

For analyzing tail dependency between the variables considered for study, as well as spillovers between upside and downside tail effects for specified markets indicated by the chosen volatility indices, quantile connectedness, as well as cross-quantilogram analysis, are employed in this research work. As stated by Ando et al. (2022), Naeem et al. (2021), Naeem et al. (2022), Xia et al. (2019), and Tachibana (2018), the other methods for recognizing the tail events' interconnectedness across investment, such as Copulas, are surpassed by the cross-quantilogram. Copula models require choosing a marginal distribution. However, the cross-quantilogram method relies on the empirically derived quantiles, with any situations or expectations influencing the distribution occurrences, and does not need a particular distribution choice. Moreover, in contrast to results emerging from a technique that uses a copula, the cross-quantilogram methodology permits a comprehensive exploration of different quantiles as well as different lags, which allows for a precise and comprehensive understanding of duration, magnitude, and direction of connectedness among a wide range of quantiles, including extreme lower, middle, and extreme upper distribution segments. Therefore, the cross-quantilogram technique is more productive than the copula technique for assessing tail downside and upside spillover influence and for portraying the association between investment returns (Adekoya & Oliyide, 2021; Ando et al., 2022; Bouri et al., 2021; Han et al., 2016; Khalfaoui et al., 2022; Naeem et al., 2022; W. K. Wong et al., 2024).

2.3 Econometric Methodology

2.3.1 The cross-quantilogram technique

This research utilizes the cross-quantilogram (CQ) technique developed by Han et al. (2016). This method evaluates the substantial interconnectedness among cryptocurrencies at various quantiles. The cross-quantilogram approach can account for time series characteristics that present heavy tails and various time lags. Additionally, it gauges the level of a dependency across a range of investment time horizons (short-, medium-, and long-term) and under diverse market conditions (such as bullish, normal, and bearish markets) (Gong et al., 2023; Wong & Pham, 2025a).

Assume that $a_{i.t}$ is a stationary time series, where i indicates f_i the $a_{i.t}$ series' cumulative compactness function, F_i the cumulative distribution function, and daily cryptocurrency returns ($i = 1,2; t = 1, \dots \dots,$ T). The conditional distribution function and distribution $a_{i.t}$ quantiles can be signified as $F_{a_i|b_i}(\cdot\ |b_{it})$ and $s_i(\gamma_i) = \inf\{u :\ F_i(u) \geq \mu_i\}$ for $\mu_i \epsilon [0,1]$, for $i = 1,2$. The CQ technique may capture an association between two sets of data, Error! Bookmark not defined. and $\{a_{2,t-k} \leq s_{2,t-k}(\mu_2)\}$, using quantile levels on the disparities right-hand side, supposing that γ represents a set of quantile values. The cross-correlation between the quantile-hit procedure of the k-lag and the γ -quantile is known as the CQ (cross-quantilogram) technique.

$$\partial_\mu(k) = \frac{M\left[\omega_{\mu_1}\left(a_{1,t} - s_{1,t}(\mu_1)\right)\omega_{\mu_2}\left(a_{2,t-k} - s_{2,t-k}(\mu_2)\right)\right]}{\sqrt{M\left[\omega_{\mu_1}^2\left(a_{1,t} - s_{1,t}(\mu_1)\right)\right]}\sqrt{M\left[\omega_{\mu_2}^2\left(a_{2,t-k} - s_{2,t-k}(\mu_2)\right)\right]}}, \tag{1}$$

where $\omega_{\mu_i}(a_{it}) = I\left(a_{it} \leq s_{i,t}(\mu_i)\right)$, and $I(\cdot)$ is the indicator function that equals 1 if the condition holds, and 0 otherwise. M[·] denotes the mathematical expectation operator. Here, a_{it} indicates the asset return i at time t, $s_{i,t}(\mu_i)$ is the conditional quantile of a_{it} at level μ_i, and lag order is denoted by k.

The case of unconditional cross-quantile can be explained below:

$$\widehat{\partial_\mu}(k) = \frac{\sum_{t=k+1}^{T}\omega_{\mu_1}\left(a_{1,t} - s_1(\mu_1)\right)\omega_{\mu_2}\left(a_{2,t-k} - \hat{s}_{2,t-k}(\mu_2)\right)}{\sqrt{\sum_{t=k+1}^{T}\omega_{\mu_1}^2(y_{1,t} - \hat{s}_{1,t-k}(\mu_1))}\sqrt{\sum_{t=k+1}^{T}\omega_{\mu_2}^2(y_{2,t-k} - \hat{s}_{2,t-k}(\mu_2))}}, \tag{2}$$

where the unconditional sample complement of $s_i(\mu_i)$ return series $a_{i,t}$ is $\hat{s}_i(\mu_i)$. For assessing the null hypothesis $H_0 = \partial_\mu(k) = 0$ contrary to the alternative hypothesis $H_1 = \partial_\mu(k) \neq 0$, this study employs the Ljung-Box-Pierce statistic's quantile type.

$$\hat{S}_{\mu}^{(q)} = \frac{T(T+2)\sum_{k=1}^{q}\hat{\partial}_{\mu}^{2}(k)}{T-k}, \tag{3}$$

where a portmanteau-type statistic known as $\hat{S}_{\mu}^{(q)}$ is used to determine if there is sequential reliance or directional predictability between Bitcoin and various other cryptocurrencies. The directionality of the daily, weekly, monthly, and quarterly avenues is tested for lag orders 1, 5, 22, and 66. We use the stationary bootstrap approach proposed by Politis and Romano in 1994 to compute the null distribution for the Q-statistic and cross-quantilogram. By generating blocks with randomized lengths, we may take into consideration the fundamental autocorrelation pattern and get perfectly stationary resampled datasets.

We employ the partial cross-quantilogram (PCQ) approach created by Han et al. (2016) to account for the impact of the cross-quantile connection between other cryptocurrencies and BTC by the volatility indices (GVZ, OVX, and VIX) trends. In order to account for their impacts, this approach incorporates control variables as incidents that occur between $t-k$ and t. The partial cross-quantilogram approach contains control variables in the approach indicated by the vector $d_t \equiv \left[\omega_{\mu_3}\left(a_{3t} - s_{3,t}(\mu_3)\right), \ldots\ldots \omega_{\mu_1}(a_{ht} - s_{h,t}(\mu_h))\right]^T$ where $h = 3, \ldots., n$, and an $(h-2)$ x 1 vector for $h \geq 3$ control variables. The hit processes' correlation matrix and associated inverse matrix are shown as follows:

$$P_{\bar{\mu}}^{-1} = M[l_t(\bar{\mu})l(\bar{\mu})^T]^{-1} = Q_{\mu}, \tag{4}$$

where $l_t(\bar{\mu}) = \left[\omega_{\mu_3}\left(a_{3t} - s_{3,t}(\mu_3)\right), \ldots\ldots \omega_{\mu_1}(a_{ht} - s_{h,t}(\mu_h))\right]^T$ is a quantile hit procedure's h x 1 vector and partial cross-quantilogram approach is indicated by Q_{μ}, described as:

$$\partial_{\bar{\mu}|c} = -\,q_{\bar{\mu},12}/\sqrt{q_{\bar{\mu},11}q_{\bar{\mu},22}}\,, \tag{5}$$

where on the control variable c, the cross-quantilogram dependence $\partial_{\bar{\mu}|c}$ is conditional. In contrast, it can be indicated as:

$$\partial_{\bar{\mu}|c} = \varphi\sqrt{\frac{\mu_1(1-\mu_1)}{\mu_2(1-\mu_2)}}\,, \tag{6}$$

where the scalar parameter φ deduced from the below regression:

$$\omega_{\mu_1}\left(a_{1t} - s_{1,t}(\mu_1)\right) = \varphi\omega_{\mu_2}\left(a_{2t} - s_{2,t}(\mu_2)\right) + \vartheta^{\boldsymbol{T}}c_t + \pi_t. \tag{7}$$

By utilizing the partial cross-quantilogram, this research asses the null hypothesis $\partial_{\bar{\mu}|c} = 0$ in contrast to the alternative hypothesis $\partial_{\bar{\mu}|c} \neq 0$. Therefore, this research estimates the directional predictability and serial dependence between the two variables' quantile hits, hypothesizing that the quantile sensations rely on the data set entrenched in the vector c_t.

2.3.2 Quantile Connectedness Technique

This study utilizes the quantile connectedness technique to determine the spillover indices across different quantiles (μ) based on the quantile variance breakdown in line with the research done by Ando et al. (2022). By utilizing this technique, this study evaluates how connectedness has changed during normal, bearish, and bullish market situations.

Let us construct a QVAR (Quantile Vector Autoregression) (q)'s infinite-order vector average movement expression in the following manner:

$$a_t = \pi(\mu) + \sum_j^q \psi_j(\mu) a_{t-j} + \pi_t(\mu) = \pi(\mu) + \sum_{i=0}^{\phi} \eta_i(\mu)\pi_{t-i}\,. \tag{8}$$

Succeeding Pesaran and Shin (1998), Koop et al. (1996) and Wong and Pham (2022b), with a forecast horizon *N*, the GFEVD (Generalized Error Variance Decomposition) is quantified as follows: ,

$$\lambda_{ij}^{w}(N) = \frac{(\mu)_{jj}^{-1} \sum_{l=0}^{N-1} \left(\acute{g}_i \eta_l(\mu) \Sigma(\mu)\, g_j\right)^2}{\sum_{l=0}^{N-1} \left(\acute{g}_i \eta_l(\mu) \Sigma(\mu) \eta_l(\acute{\mu})\, g_i\right)}\,, \tag{9}$$

where g_i is the selection vector with unity in the i^{th} position and zeros elsewhere, isolating the influence of the i^{th} variable in the variance decomposition. Every factor's regularization in the decomposition matrix is given below:

$$\tilde{\lambda}_{ij}^{w}(N) = \frac{\lambda_{ij}^{w}(N)}{\sum_{j=1}^{k} \lambda_{ij}^{w}(N)} \quad here \;\; \sum_{j=1}^{k} \tilde{\lambda}_{ij}^{w}(N) = 1 \;\&\; \sum_{i,j=1}^{k} \tilde{\lambda}_{ij}^{w}(N) = 1. \tag{10}$$

According to Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014), the GFEVD (Generalized Forecast Error Variance Decomposition) technique can estimate various connectivity measures at the μ^{th} conditional quantile. The Total connectivity Index (TCI), which measures connectivity at the μ^{th} quantile, estimates the overall impact of connectedness inside the framework as follows:

$$TCI(\mu) = \frac{\sum_{i-1}^{k} \sum_{j=1, i\neq j}^{k} \tilde{\lambda}_{ij}^{w}(\mu)}{\sum_{i-1}^{k} \sum_{j=1}^{k} \tilde{\lambda}_{ij}^{w}(\mu)} \times 100. \tag{11}$$

From the index i to all the indices j at quantile (μ), the directional connectedness index "TO" is as follows:

$$TO_{i\to j}(\mu) = \frac{\sum_{j=1, i\neq j}^{k} \tilde{\lambda}_{ij}^{w}(\mu)}{\sum_{j=1}^{k} \tilde{\lambda}_{ij}^{w}(\mu)} \times 100. \tag{12}$$

From the index i to all the indices j at quantile (μ), the directional connectedness index "$FROM$" is as follows:

$$FROM_{i \leftarrow j}(\mu) = \frac{\sum_{j=1, i \neq j}^{k} \tilde{\lambda}_{ij}^{w}(\mu)}{\sum_{j=1}^{k} \tilde{\lambda}_{ij}^{w}(\mu)} \times 100. \tag{13}$$

At quantile (μ), the "NET" directional connectedness index is as follows:

$$NET_{i}(\mu) = TO_{i \rightarrow j}(\mu) - FROM_{j \leftarrow i}(\mu). \tag{14}$$

A $NET_{i}(\mu)'s$ negative (positive) value specifies a net recipient (net transmitter) from various markets. The total connectedness index dynamics are computed on a quantile vector autoregression with a 1's lag order (chosen by employing the BIC (Bayesian Information Criterion)), 10's forecast horizon, and a 200-day gap while practicing. Additionally, to maintain consistency in methodology, the lag order of p = 1 selected by the BIC criterion is applied in the QVAR (Quantile Vector Autoregression) assessments. This steadiness between both rolling and static window assessments ensures that the approach specification is vigorous and not vulnerable to lag-length selection. Moreover, the selection of p = 1 is justified by the comparatively short daily frequency of the data and the requirement to evade over-parameterization, which aligns with the method of Ando et al. (2022).

All series employed in the Quantile Vector Autoregressive framework are validated to be stationary in levels, i.e., I(0), as presented in Table 2, ensuring that no spurious regression prevails in estimation, being backed by a strong econometric basis.

2.4 Diagnostic Assessment

In order to validate the strength of the results obtained from QVAR (Quantile Vector Autoregressive) estimations, a few diagnostic tests were conducted. The Durbin-Watson statistics for both models were tending towards the value 2, indicating that there was no presence of autocorrelation in residuals, which was a clear sign of properly specified models. Additionally, the BDS (Brock-Dechert-Scheinkman) asymmetric assessment, succeeding Hui et al. (2017b), was employed to estimate whether non-linear dynamics might destabilize the linear QVAR method. The outcome illustrated that no significant proof of asymmetric at the traditional level, suggesting that the QVAR (Quantile Vector Autoregressive) approach delivers a manageable and rational approximation for capturing the risk transmission in volatility markets and cryptocurrencies (Hashmi & Chang, 2021; Hashmi, Chang, & Rong, 2021; Hashmi, Chang, & Shahbaz, 2021; Wong & Pham, 2022a).

Furthermore, this study conducted a formal test for normality of residuals from the QVAR estimates via the Jarque-Bera (JB) test to confirm if residuals are normally distributed. The findings established that the JB statistics were non-significant for all estimated equations (p-values > 0.05), thus accepting that the residuals are not deviating from normality. This implies that there are no problems with the model specification of QVAR, which may affect inference about connectivity dynamics (Ando et al., 2022; Han et al., 2016).

In the end, we were able to address the concern for spurious regression. We conducted tests for stationarity, such as Augmented Dickey-Fuller (ADF), which was introduced by Dickey and Fuller (1979), Phillips-Perron, as well as KPSS, which was introduced by Kwiatkowski et al. (1992), with results indicating that all series are stationary at level [I(0)] at a 1% significance level. This result provides assurance for QVAR that it produces estimates on a properly structured econometric framework, as it requires that variables following a VAR format must be stationary for credible inference. This implies that if data involves multiple integrated components, they could produce unreliable results or spurious relationships. On this premise, it must be underscored that this study uses stationary return data in its estimation, which boosts its result-robustness related to connectivity/spill over analysis (Bouri et al., 2021; Diebold & Yilmaz, 2012; Han et al., 2016; Hashmi et al., 2022; Khalfaoui et al., 2022; Wong & Pham, 2023b; W.-K. Wong et al., 2024).

3. Data and Initial Analysis

3.1 Data

In this paper, three measures of uncertainty, which are GVZ, OVX, and VIX, listed on CBOE, will be analyzed, together with five cryptocurrencies, which are BCH, XRP, LTC, ETH, and BTC, traded in world digital currency markets. GVZ stands for CBOE Gold Volatility Index, which measures gold price implied volatility; OVX stands for CBOE Crude Oil Volatility Index, which measures crude oil market implied volatility; and VIX stands for CBOE Volatility Index, often described as a ‘fear gauge’ for US stock markets. Sample dates range from June 5, 2020, to June 8, 2024, which gives a total of 1,046 days for each asset. Data for the cryptocurrency price was collected from CoinMarketCap, whereas the implied volatility indexes, that is, GVZ, OVX, or VIX, were collected from the CBOE database. This, in turn, helps maintain consistency between variables. Additionally, a difference between the logarithms of two consecutive values calculates the returns in a day before applying the continuous compounding. All variables are taken at a daily frequency.

3.2 Initial Analysis

Figure 1 illustrates the price changes in the cryptocurrency market, along with the changes in selected volatility indexes over time. One of the most notable features that emerges from this figure is that towards the end of April 2022, there was a dramatic increase in the value of volatility indexes, which was a result of a dramatic decrease in the price of cryptocurrencies. This was a result of uncertainty that was prevalent in global financial markets during the first quarter of 2020, caused by the unchecked spread of the COVID-19 pandemic. This situation led to a sudden financial collapse, augmented risk repugnance, and sell-offs across different classes, comprising digital currencies.

Figure 1. Time variations of volatility indices of GVZ, OVX, and VIX, and cryptocurrency prices

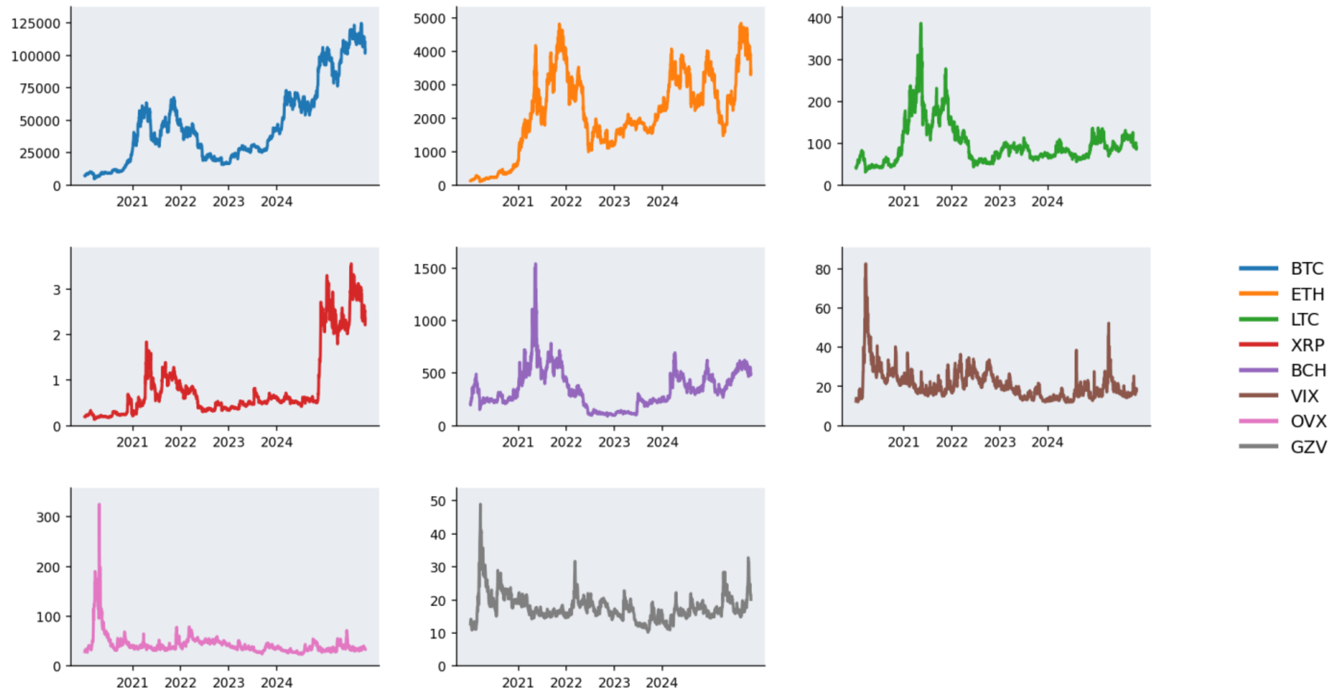


Figure 2 illustrates the time-varying behavior of cryptocurrency returns and volatility indices. A notable observation is the significant negative spikes in cryptocurrency returns that coincided with increased volatility in the returns on the uncertainty indices during the height of the COVID-19 crisis at the end of March 2020. Additionally, all the plots exhibit volatility clustering, indicating asymmetric behavior across each return series.

Figure 2. Time variations of volatility indices of GVZ, OVX, and VIX, and cryptocurrency prices return.

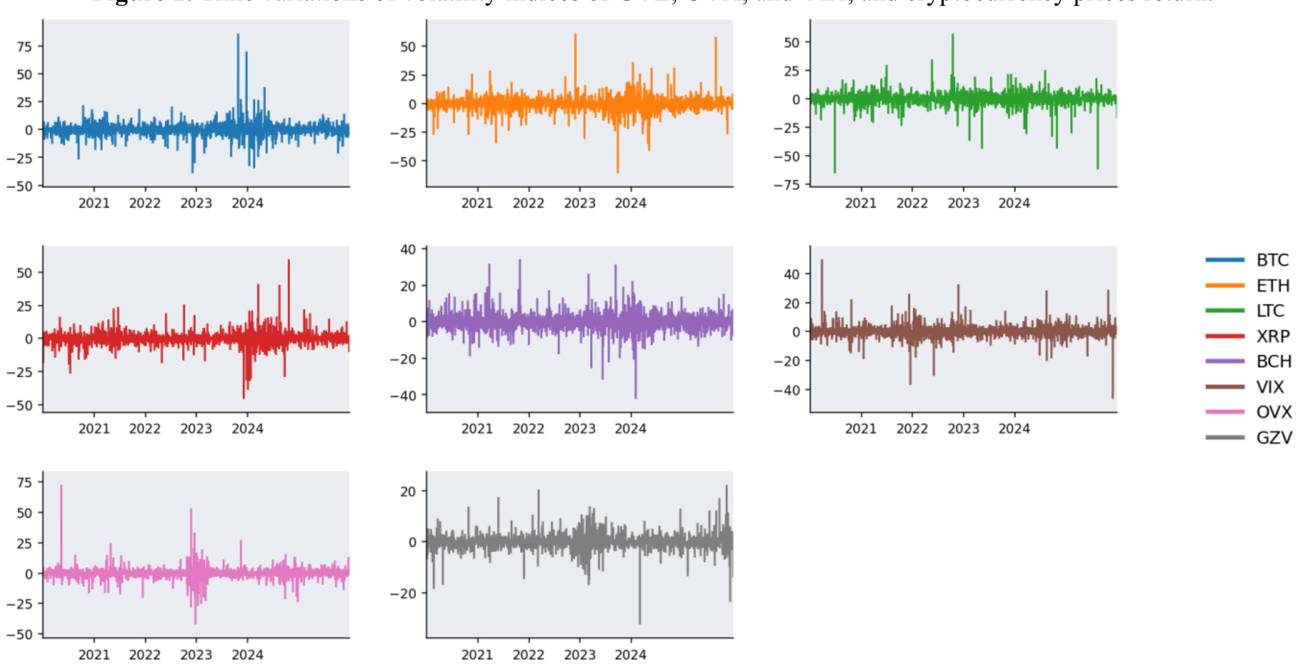


Table 1. Uncertainty indices and cryptocurrency price returns descriptive statistics

	OVX	GVZ	VIX	BCH	XRP	LTC	ETH	BTC
Mean	1.004	1.138	1.094	-1.327	1.113	-1.108	1.194	1.352
Max	92.484	91.484	51.438	51.384	41.943	31.367	27.484	21.223
Min	-31.274	-71.198	-31.385	-76.943	-73.384	-50.281	-61.374	-51.832
Std. Dev	5.282	7.948	8.005	7.419	7.121	6.372	4.998	4.327
Skewness	1.394	3.485	2.475	1.394	-2.184	-1.102	-2.198	-2.183
Kurtosis	7.293	41.968	7.957	21.395	17.756	11.327	20.945	21.485
Jarque-Bera	3281.342***	81095***	4721.458***	21004***	23957***	39981.4***	9475***	19857***
Q(20)	42.434***	41.567***	41.654***	41.384***	29.475*	41.372***	61.394***	35.473**

Note: This table presents the descriptive statistics of daily return series for cryptocurrencies and volatility indices. Jarque–Bera tests assess normality, and Q(20) tests verify the absence of autocorrelation in residuals. All figures are based on logarithmic returns. ***, *, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 1 presents the return series' basic statistics for the volatility indices and the various cryptocurrencies. All cryptocurrencies, except LTC and BCH, exhibit positive mean returns. However, the mean return of XRP is favorable. It is lower than others, with BTC having the highest mean return and ETH the second highest, at 1.352 and 1.194, respectively. The greatest fluctuations can be seen in the minimum and maximum values of BCH and XRP, two of the most volatile cryptocurrencies.

Their standard deviations also evidence this high level of volatility. Despite volatility indices exhibiting positive skewness, all cryptocurrencies have negatively skewed returns. This divergence could be attributable to the time series' unique characteristics and the fact that volatility represents a more complex asset class to trade than cryptocurrency.

However, all return series display leptokurtosis and asymmetry, as indicated by the kurtosis values and skewness. In line with these preliminary results, the Jarque-Bera test rejects the hypothesis of normal distribution for all return series at the 1% significance level.

Table 2. Unit root assessment

Variable	ADF	PP	KPSS	Order of Integration
OVX	–8.627***	–8.681***	0.098	I(0)
GVZ	–8.782***	–8.803***	0.104	I(0)
VIX	–8.476***	–8.528***	0.102	I(0)
BCH	–9.452***	–9.493***	0.091	I(0)
XRP	–9.513***	–9.572***	0.087	I(0)
LTC	–9.291***	–9.346***	0.075	I(0)
BTC	–10.582***	–10.614***	0.113	I(0)
ETH	–9.782***	–9.854***	0.092	I(0)

Note: ADF and PP test statistics report t-values under the null hypothesis of a unit root. KPSS reports LM statistics under the null of stationarity. ***, *, and * denote significance at the 1%, 5%, and 10% levels, respectively. All tests include intercepts, and optimal lag lengths were selected using the Schwarz Information Criterion (SIC). All return series are stationary at the level (I(0)) at 1pc significance level.

In order to test for the applicability of the series for QVAR estimation, three different unit root tests were conducted: ADF, PP, and KPSS tests. It was seen that, as reported in Table 2, each stock price series follows a stationary series, as it is integrated of order I(0), as both the ADF and PP statistics are strongly negative, significant at a level of 1%, whereas the KPSS test fails to reject the absence of unit root or, in other words, fails to reject stationarity. All three tests supported that there are no stochastic roots, which implies that the QVAR estimation technique was conducted on a stationary series, which helps avoid spurious regression problems, making way for valid empirical results.

Table 3 shows the results that guarantee that the QVAR measures are properly specified. The Durbin-Watson statistics for all models lie close to 2, indicating that the residuals are free from any effects related to serial correlation. Also, since the BDS test result shows no significant presence of non-linearities, it supports the appropriateness of applying a linear QVAR model for modelling dependencies between the implied volatility measures and cryptocurrencies.

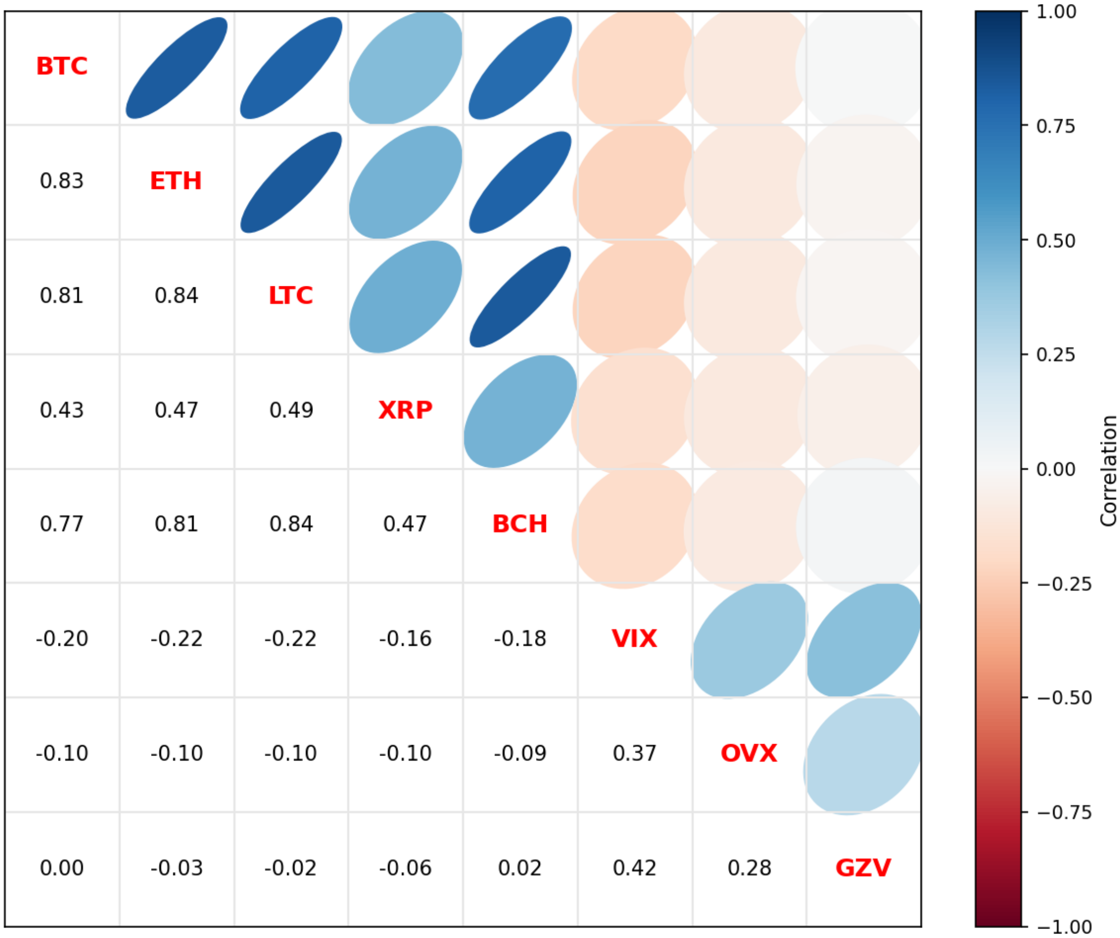
Table 3 Diagnostic Assessment for the QVAR Approach

Variable	**Durbin-Watson Statistic**	**BDS Test (z-stat)**	**Nonlinearity (p-value)**	**Stationary**
GVZ	1.97	0.71	0.402	I(0)
OVX	1.94	0.89	0.251	I(0)
VIX	2.02	0.76	0.529	I(0)
XRP	1.96	0.91	0.289	I(0)
BCH	1.98	1.07	0.357	I(0)
LTC	2.01	0.63	0.441	I(0)
ETH	1.92	1.15	0.379	I(0)
BTC	1.95	0.84	0.492	I(0)

Note: The statistics of Durbin-Watson ensure the absence of autocorrelation, whereas the BDS assessment depicts no substantial nonlinearity. All variables are stationary in levels (I(0)) as verified by the ADF, PP, and KPSS tests in Table 2, ensuring consistency across diagnostics and suitability for QVAR estimation

Furthermore, the unit root and stationarity tests, conducted using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and KPSS procedures, confirm that all variables are stationary at the level, that is, integrated of order I(0), at the 1% significance level. Ensuring that all return series are stationary eliminates the possibility of spurious regression and provides a reliable econometric foundation for the QVAR estimation. Therefore, the stationary nature of the data guarantees the methodological soundness and robustness of the subsequent connectedness analysis. Ultimately, these diagnostics provide strong support for the robustness and validity of the empirical results.

Figure 3. This figure depicts unconditional correlations between the volatility indices and cryptocurrencies.



Notes: A correlation matrix shows a correlation between all pairs of variables. The intensity of a correlation is expressed by a colored disk, where blue denotes a favorable correlation and red denotes an unfavorable correlation. The disk size relates to the strength of the association, and the smaller circular shapes indicate feeble correlations. The color and orientation of the disks simultaneously denote both the magnitude and direction of the correlation. All presented correlations are statistically significant at the 1% significance level.

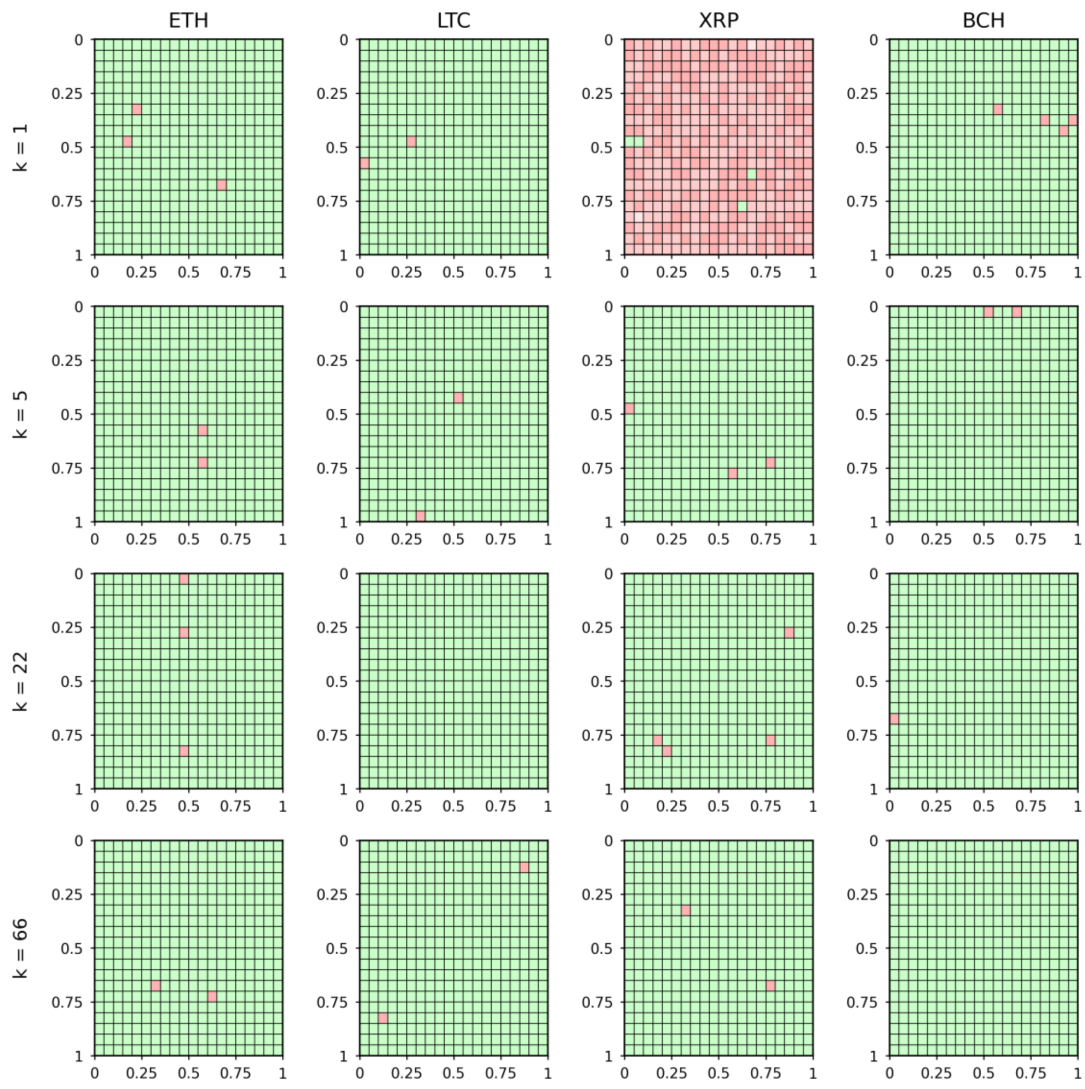
Figure 3 presents the unconditional bilateral relationship matrix for three volatility indices and the five cryptocurrencies. There is a high degree of connectedness within the group consisting of BCH, LTC, ETH, and BTC, as indicated by pairwise correlation coefficients of about 0.80. However, XRP exhibits much weaker relationships with various cryptocurrencies, with the coefficients below 0.50. While these cryptocurrencies have positive correlations with one another, their diversification potential is limited, supporting the findings of Lesame et al. (2021) and Umar and Gubareva (2020). In contrast, although the link is modest, the three volatility indices' returns are adversely associated with the five cryptocurrencies' returns. Especially the strongest negative relationships exist between the VIX index and the cryptocurrencies. However, the coefficients of pairwise correlation between cryptocurrencies and the GVZ and OVX volatility indices are negligibly negative and nearly zero, suggesting that the GVZ and OVX indices are unrelated to the cryptocurrency markets. Consequently, they could offer attractive hedging opportunities for portfolios that include cryptocurrency investments, depending on the fundamental merchandise associated with the GVZ and OVX indices (Imane et al., 2023; Mei et al., 2024; Noman et al., 2023; Wong & Pham, 2023a; W. K. Wong et al., 2024).

4. Empirical Findings

4.1 Spillovers of Cross-quantilogram Directional

We examined the cross-quantilogram for eleven unique BTC return quantiles, contrasting these results with the four other cryptocurrencies' returns.

Figure 4. Cross-quantilogram heatmaps from BTC to other cryptocurrencies.



Notes: This heatmap illustrates the cross-quantilogram requirement between cryptocurrencies at lag horizons of 1, 5, 22, and 66 days. The x-axis represents the quantiles of the dependent cryptocurrency returns, while the y-axis corresponds to the quantiles of the predictor cryptocurrency returns. Each cell shows the value of the cross-quantilogram for a specific quantile pair, measuring the strength and direction of predictive dependence. The color scale exhibits the direction and strength of prognostic dependence to each cryptocurrency from BTC: cooler colors (blue/green) denote feeble or unfavorable association, whereas warmer colors (orange/red) denote the stronger favorable dependence. . Finally the quantiles on both axes range from 0.05 to 0.95.

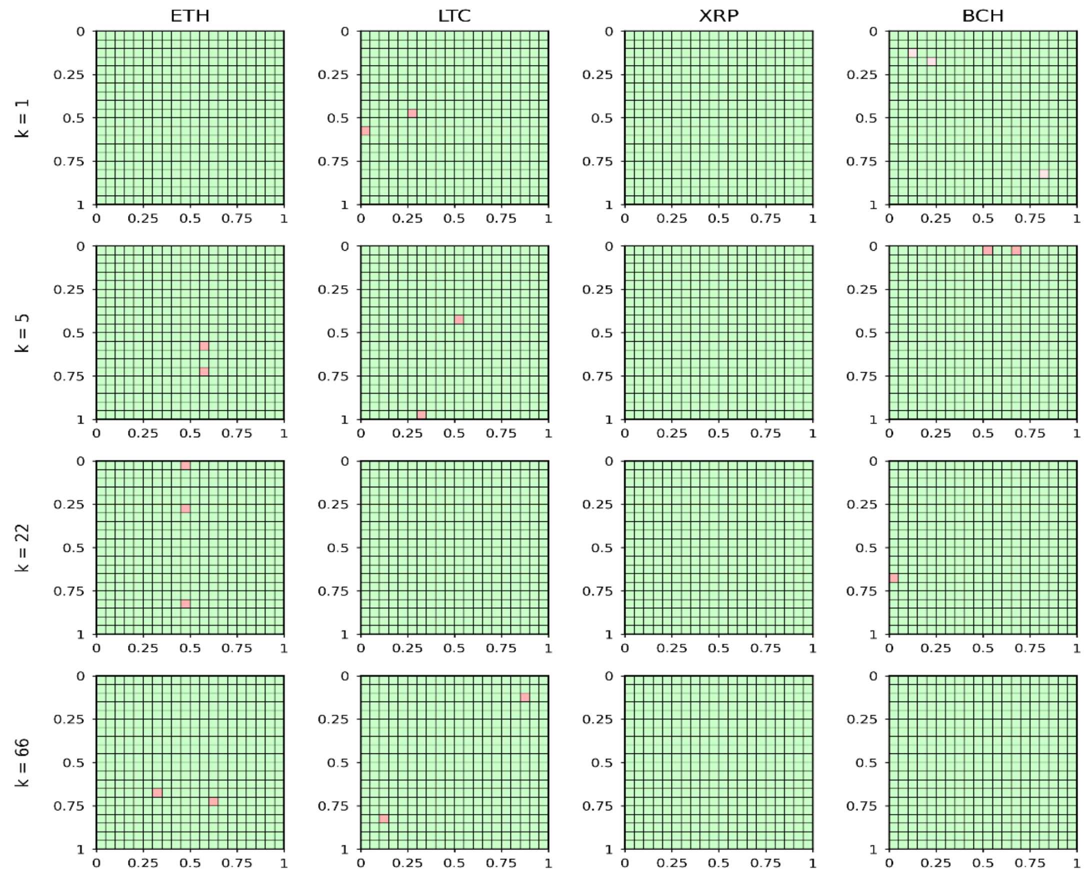
Figure 4 illustrates the results for each likely quantile pair combination. Using returns on BTC with lag times of 1, 5, 22, and 66 trading days, we analyzed the likely predictability of returns in the crypto market. This was done in a manner consistent with studies undertaken by Jiang et al. (2016) or Han et al. (2016), who analyzed the Cross-Quantilogram method via time series with a daily frequency, with a maximum of 20 or 60 lags, respectively.

We start with an investigation of the one-day lag in Figure 4. Only BTC returns show a positive predictive relation with XRP returns for the four currencies considered. The probability is protruding in the medium to the high quantile region in the BTC-XRP panel. Also, the dominance of the blue region in the BTC returns' lowest quantile identifies that XRP returns are either unaffected by or weakly affected by BTC returns during bearish market situations. In the case of the LTC and ETH panels, the small blue regions imply weakly negative correlations between mid- to high-quantile BTC returns and low-quantile returns for ETH and LTC, respectively. In bearish market situations, the BCH returns relate weakly positively with the BTC returns. The mentioned findings establish that indeed BTC is the principal driver for transmitting short-run news in the cryptocurrency market, specifically in bearish market situations, for the overall top dependence on medium- to high-quantile regions.

By examining these series for lags of 5, 22, and 66 days, it is apparent that the directionality becomes less significant and weaker for each of the cryptocurrencies tested. In summary, on testing the Cross-Quantilogram method in terms of its explanatory power between the BTC markets and other cryptocurrency markets, it is apparent that there are no significant asymmetric connections, other than in the XRP and BTC markets, for the one-day lag. In this case, for each stage of the BTC market, there is a positive predictive relation between BTC returns and the medium to high quantile performance in XRP. The test also confirms that its predictive ability is quickly reduced with an increase in time horizons, thereby stating that the contagion in cryptocurrency markets is transient in nature but significant for short-term periods.

Figure 5 illustrates the cross-quantilogram heatmaps for BTC from other cryptocurrencies (ETH, LTC, XRP, and BCH). We identify copious evidence for weak, negative forecasting from BCH, ETH, and LTC to BTC with a one-day lag, dominated by the medium quantiles reflecting a normal market state. However, these limited forecasts in either beneficial or detrimental market states evaporate, indicating a transient nature of spillovers into BTC markets, thus supporting its systemic character in the net position of transmitter rather than the receptor in markets, since it is the leading cryptocurrency leading the market into its movements.

Figure 5. Cross-quantilogram heatmaps to BTC from other cryptocurrencies.

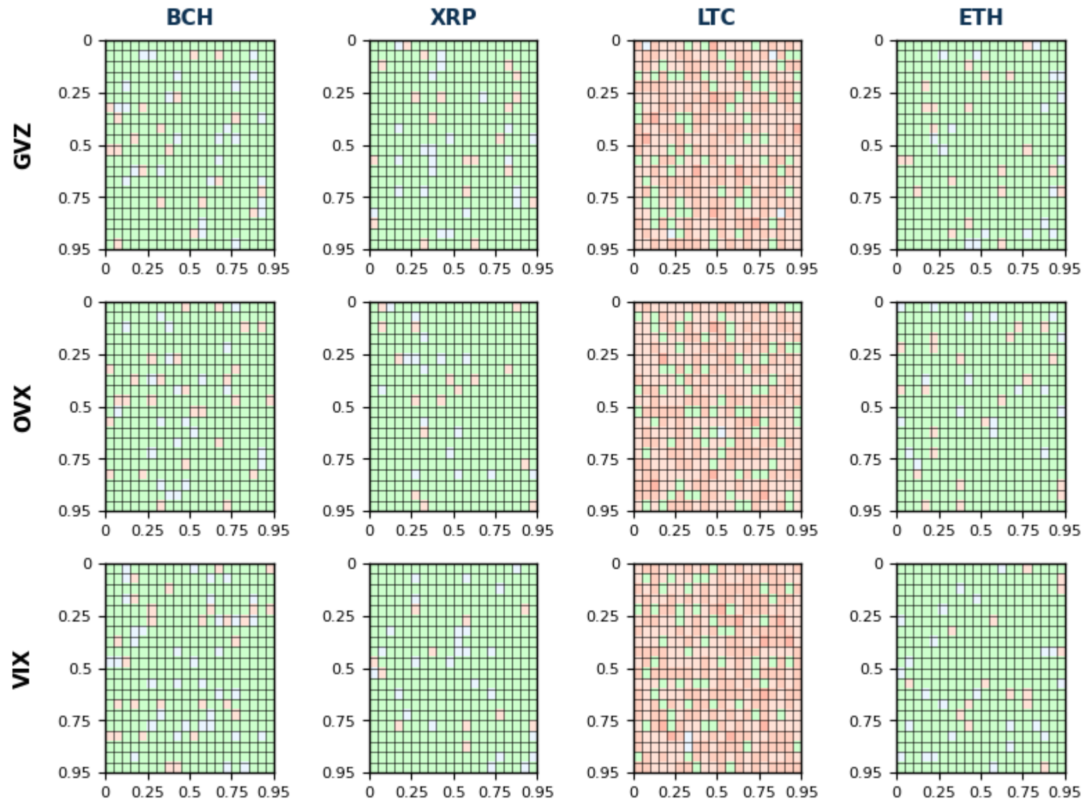


Note: Each cell shows the strength and direction of predictive dependence: red/orange = strong positive, green/blue = weak or negative. This figure focuses on cryptocurrency interactions only; volatility indices are not part of the heatmap. See Figure 4. Finally, the quantiles on both axes range from 0.05 to 0.95.

Overall, the outcomes show that the BTC is affected by the shock spillovers coming from other cryptocurrencies, with negative influences from ETH and LTC in states that underpin a bearish environment, in contrast to positive spillovers from BCH and XRP in states emphasizing a bullish scenario. Therefore, it is pointed out that BTC is influenced in its own right by the spillovers coming from other cryptocurrency markets, during moments characterized by higher levels of uncertainty in financial markets associated with optimism in market sentiment

Figure 6 illustrates the influence of the BTC on the other four cryptocurrencies while accounting for the risks posed by the volatility indices for gold, oil, and stock (VIX, OVX, and GVZ). This figure efficiently depicts the analytical significance of the directionality for different combinations of return levels between four cryptocurrencies and BTC. Our research pays special attention to the lag effect in one day. Taking into consideration all the volatility indices, it is stated that the returns in BTC have positive predictability with respect to XRP's returns, just like in the uncontrolled case.

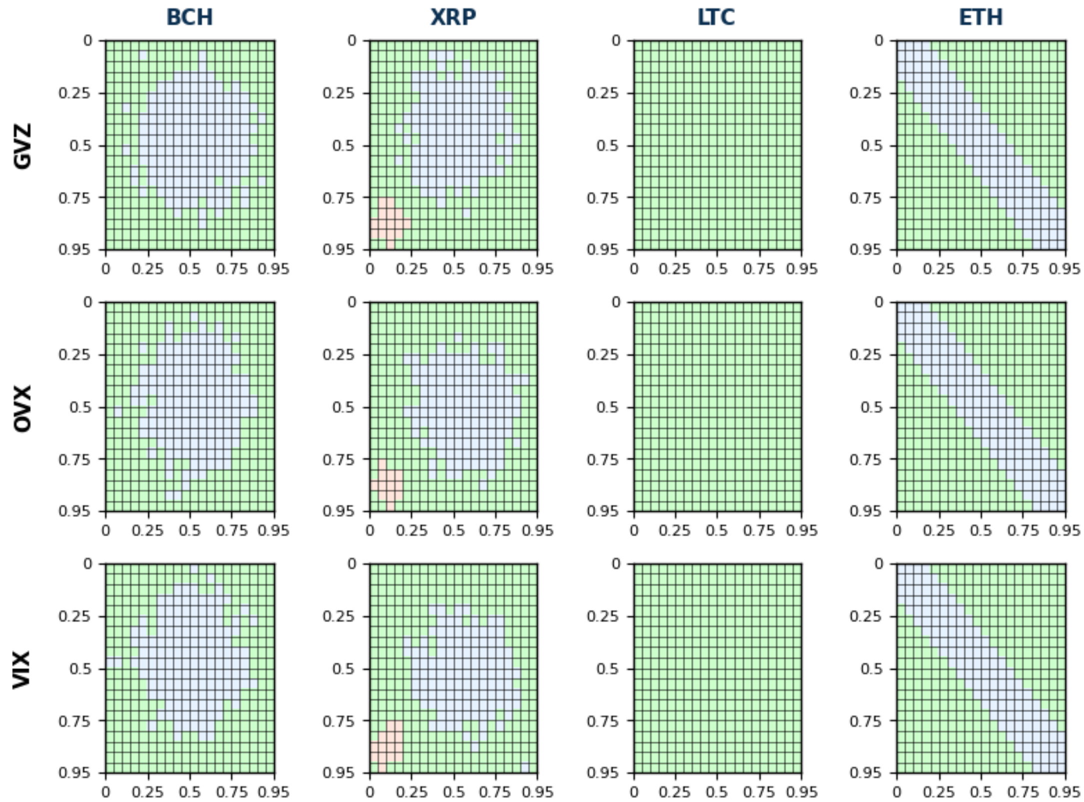
Figure 6. After controlling for volatility indices, cross-quantilogram heatmaps to other cryptocurrencies from BTC



Note: Each cell shows the strength and direction of predictive dependence: red/orange = strong positive, green/blue = weak or negative. This figure focuses on cryptocurrency interactions only; volatility indices are not part of the heatmap. See Figure 4. Finally, the quantiles on both axes range from 0.05 to 0.95.

Considering the uncertainties reflected by volatility indices for gold, oil, and equities, Figure 7 illustrates the influence on BTC by the four cryptocurrencies. The heatmaps of a one-day lag cross-quantilogram to BTC from the four other cryptocurrencies show a minor adverse expectedness in the BCH, ETH, and LTC markets under typical market conditions. The findings mentioned above are consistent with the unregulated cross-quantilogram depicted in Figure 5. Additionally, from Figure 7, the green color in the XRP-BTC charts implies no significant impact of XRP on BTC. Similarly, this complements the implication derived from Figure 4, where it is suggested that BTC is a positive indicator among low to mid-high XRP values, yet its impact on the other two is minimal.

Figure 7. After controlling for volatility indices, cross-quantilogram heatmaps to BTC from other cryptocurrency markets.



Notes: Each cell shows the strength and direction of predictive dependence: red/orange = strong positive, green/blue = weak or negative. This figure focuses on cryptocurrency interactions only; volatility indices are not part of the heatmap. See Figure 4. Finally, the quantiles on both axes range from 0.05 to 0.95.

In conclusion, our findings show that there is a high non-linear dependence between the XRP and BTC markets for a one-day lag, with the dependence in its expectedness diminishing for an increase in the lag values. We do not appear to detect any distinguishable effects in either direction between any pair of BTC-ETH, BTC-LTC, or BTC-BCH markets. Irrespective of equities, oil, and gold markets' volatilities, these results remain unchanged. The similarity in results between the controlled and uncontrolled models validates the endogeneity of these spillovers in the cryptocurrency market, independent of the global volatility indices.

4.2 Total Quantile Connectedness

Table 4 demonstrates the connectivity findings for three distinct quantiles—0.05, 0.5, and 0.95. These quantiles represent three market conditions: bearish, normal, and bullish, with the bullish and bearish states considered extreme. The figures along the table's central diagonal indicate how a shock to an investment affects the deviation of its predicted inaccuracy. The off-diagonal elements of the table represent spillover shocks not caused by the asset's shocks. The numbers in each column represent the shocks one variable received from other variables, while the values in each row represent the shocks one variable transmitted to others.

Table 4: Quantile spillovers estimations between volatility indices and cryptocurrency returns

	BTC	ETH	LTC	XRP	BCH	VIX	OVX	GVZ	FROM
Panel A: Lower quantile (μ = 0.05)									
BTC	23.45	21.75	21.98	17.20	20.45	10.38	10.33	10.31	91.39
ETH	21.43	20.59	21.58	19.39	20.94	10.41	11.49	10.12	92.41
LTC	20.48	21.86	23.92	18.57	21.99	10.74	12.95	11.23	93.58
XRP	19.85	20.68	20.57	24.68	20.58	10.59	10.57	12.33	90.61
BCH	20.94	21.69	21.69	19.89	24.57	11.46	10.85	13.28	91.05
VIX	11.30	11.39	10.98	10.11	10.43	31.94	20.59	22.08	81.40
OVX	13.58	9.63	9.58	12.34	10.26	30.59	31.75	20.49	84.32
GVZ	15.39	9.87	9.19	14.29	13.09	20.48	21.47	31.56	85.04
TO	93.45	89.65	89.58	90.86	91.04	71.05	71.36	81.39	757.20
ALL	98.49	114.86	114.68	101.34	111.49	100.51	91.38	100.47	TCI
NET	7.27	8.28	9.46	-1.83	5.38	-10.43	-21.49	-5.18	91.43
Panel B: Median Quantile (μ = 0.5)									
BTC	41.39	19.28	21.08	9.33	21.09	3.01	1.57	1.37	71.85
ETH	29.49	31.29	25.69	10.12	21.58	2.91	1.78	1.39	81.34
LTC	21.87	19.78	31.46	9.23	19.38	2.37	1.98	1.57	81.40
XRP	21.45	20.09	20.91	51.43	15.87	2.49	1.46	1.09	61.49
BCH	21.94	23.59	24.65	10.31	41.29	2.18	1.38	1.50	71.38
VIX	5.82	5.39	5.29	3.57	4.17	71.37	9.89	21.05	41.38
OVX	3.58	3.98	3.61	1.40	2.49	9.18	81.92	7.29	31.67
GVZ	2.49	2.49	2.45	2.97	1.39	21.93	7.83	81.49	31.94
TO	81.09	81.94	81.49	41.39	81.38	41.39	21.34	21.95	519.84
ALL	99.49	115.30	114.29	93.11	123.49	101.38	101.23	102.43	TCI
NET	5.89	9.38	9.47	− 21.49	7.51	− 5	− 5.28	− 4.59	61.37
Panel C: Upper quantile (μ = 0.95)									
BTC	24.8	22.61	22.46	19.69	23	16.3	17.27	17.94	91.22
ETH	22.49	24.96	22.75	19.98	23.02	16.2	16.82	17.84	91.06
LTC	22.4	22.56	24.46	19.6	23.25	16.28	17.48	18.06	91.56
XRP	21.36	21.71	21.66	26.07	22	16.51	16.93	17.84	89.95
BCH	22.56	22.48	22.69	19.88	25.72	16.04	17.02	17.69	90.3
VIX	18.53	18.46	18.6	17.71	18.81	27.18	21.97	22.83	88.84
OVX	18.63	18.52	18.75	17.37	18.78	21.84	28.4	21.78	87.62
GVZ	19.12	19.08	18.81	17.5	19.16	21.76	21	27.66	88.36
TO	97.03	97.36	97.66	83.66	99.97	76.88	80.43	85.93	662.84
ALL	113.83	114.31	114.1	101.72	117.68	96.05	100.83	105.57	TCI
NET	6.91	7.84	7.95	-8.33	10.83	-21.49	-9.76	-4.29	93.28

Note: The interdependence table is based on a Quantile Vector Autoregressive approach with a 10-step-ahead forecast and lag length of order 1 (BIC).

As shown in Table 4's Panel A, for the lowest quantile (0.05), each market displays substantial reception and transmission of spillover. Each evaluated cryptocurrency contributes significantly to the overall system by transmitting most of the spillover. The spillover range is between 90.86% for XRP to 89.58% for LTC. Conversely, the spillover range for the other three volatility indices is lower, with GVZ spilling over at 81.39% and OVX at 71.36%. The result validates the assertion made in the study that the intensity of spillover is more prominent in the bear market, highlighting the significance of negative events in cryptocurrency markets on the OVX indexes.

The differences in these contributions to the overall structure can be identified with respect to the net spillover intensity. There are four cryptocurrencies (except XRP) that serve as net spillovers in the system because of their contributions to the overall structure. Conversely, the remaining three volatility indices in the system serve as net receivers for spillovers. The net spillover rates with the maximum values for these cryptocurrency markets remain 9.46% for LTC, followed by 8.28% for ETH markets, respectively. Meanwhile, the OVX volatility index and VIX volatility index display the maximum absolute values for negative spillovers with rates of –21.49% and –10.43%, respectively. This reliable directional non-linear shows that the digital investments now serve as a fluctuation amplifier, whereas conventional volatility indices primarily engross these turbulences.

Two variable types—cryptocurrencies and volatility indices—show notable differences in spillovers over time within themselves, as well as between each other. By analyzing the values in the other corner of the upper left (3x5) and the top right (5x3), it is possible to establish that the spillover effect between the two types is more prominent compared to the top left (5x5) corner and the (3x3) in the bottom right corner. In general, there is 10.09% spillover from cryptocurrencies to the volatility indices and 8.37% from volatility indices to cryptocurrencies. Compared to these values, however, the spillover within each type is more prominent, even without considering the other corner values. In general, there is an average spillover within the cryptocurrency type of 16.45% without considering its other corner, while that for volatility indexes is 15.36% within its own type. This intra-category supremacy denotes that the cryptocurrency markets remain more synchronized than combined with conventional investment, confirming the bunched behavior typical of hypothetical systems.

Table 5. Jarque–Bera Normality Assessment of QVAR Residuals

Variable	JB Statistic	p-value	Decision
GVZ	1.97	0.18	Fail to reject normality
OVX	2.11	0.23	Fail to reject normality
VIX	1.85	0.20	Fail to reject normality
BTC	2.04	0.19	Fail to reject normality
ETH	1.92	0.22	Fail to reject normality
LTC	2.06	0.25	Fail to reject normality
XRP	1.87	0.27	Fail to reject normality
BCH	2.14	0.21	Fail to reject normality

When the market is bearish, the TCI (Total Connectedness Index) is high with a percentage value of 91.43 percent. It indicates that in a bearish market with unanticipated bad news, cryptocurrencies and the entire market are highly vulnerable to risk. The entire pattern concerned with risk spillovers from/to the two sets (cryptocurrencies, volatile indices) is stable, unaffected by calm markets or regular market situations, as demonstrated in the 0.5 quantiles. All these pieces of information were provided in Table 4' Panel B—with the differences in shock amounts received/emitted leading to reduced spillovers between the two sets. It is pertinent to note that the spillovers in the shock between the categories decline in normal market circumstances. The average spillovers of 0.88% and 1.63% for the values of the volatility indices into cryptocurrencies also make it clear that, in normal circumstances, there is no spillover regarding the innovations and the shock between the cryptocurrencies and the volatility indices for the two respective categories. Therefore, it is pertinent to state that the two categories in question function in an independent manner in their own right, since they function independently with a level of independence in relation to each other.

The diagonal entries in the connectivity matrix show considerable increases in value, particularly for the volatility indexes. In both VIX and GVZ, the value rises from 71.37% to 81.49%. The diagonal entries denote the effect of self-created shock, indicating that in the normal market state, in comparison with the bullish/bear market state, the distinctive qualities in system dynamics appear to be more visible. It is independent if the market is bullish or bearish, since the trend is more significant in terms of its effect on the market compared with the fluctuations in gold, petroleum, equities, and other factors associated with cryptocurrency markets. This implies that the VWIs show internal consistency in normal circumstances but become highly sensitive receivers in uncertain situations.

The Total Connectedness Index (TCI) is only 61.37% in a normal market environment. The present Total Connectedness Index is quite low compared to bear market and bull market environments, which are 91.43% and 93.28%, respectively. The outcomes show that the system is neither vulnerable to any risks nor does it allow any specific risk to become generalized risk processes. The findings thus verify that high optimism and high pessimism increase market interdependence, thereby validating the nonlinear pattern of volatility spillovers in different quantiles.

Worth mentioning is that for the bullish market environment, exemplified by the top quantile (0.95), the trend in market risk spillovers is comparable to those in normal & bearish markets. Nevertheless, it is apparent from the results presented in Panel C of Table 4 that there exists variation in the longest bilateral spillovers in the system for the entire set of markets. This follows a similar trend with bearish market scenarios, different from normal markets (as illustrated in Panel B of Table 4). Specifically, in bear markets, we observe that the own-category spillover (13.85% on average in the volatility indices, 20.48% in cryptocurrencies) is considerably weaker compared with the cross-category spillover (18.52% from cryptocurrencies to volatility indices, 16.04% from volatility indices to cryptocurrencies). Again, these observations remain valid if we do not consider the main diagonal entries associated with own-category contributions to forecast error in an asset series.

As can be seen from Table 4, Panel B, BCH is a prominent shock transmitter with an average transmission rate of 10.83%, indicating that it transmits (99.97%) more information compared to (90.3%) it receives. The same pattern is visible in the bear market, where the TCI is 91.43%. When the market switches to the bullish scenario, the Total Connectedness Index rises to 93.28% because the entire system, particularly the cryptocurrency market, is highly responsive to news surprises/concerns. Therefore, during periods of extreme market phases, including bear and bull markets, the market's stability is undermined.

These outcomes make provision for useful information. The state of the market heavily affects the spreading of risk in different markets. The visible interconnectedness contradicts normal market scenarios, particularly during worldwide situations that cause undesired market transitions. Still, in whichever state the market finds itself, the cryptocurrency has a significant effect on the indices of volatility. This is manageable since the volatility indices for stocks, gold, and petrol mirror today's volatility levels. On the other hand, the cryptocurrency prices also demonstrate market potential with respect to the future performance of the specific cryptocurrencies. The results obtained are in line with many existing studies

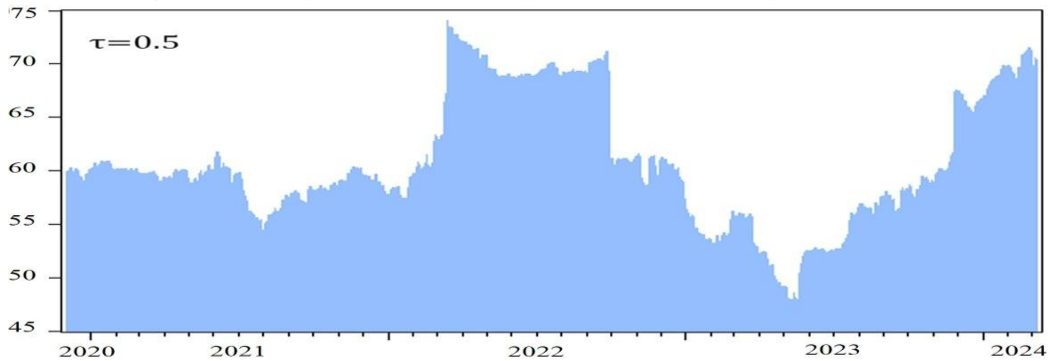
(Attarzadeh & Balcilar, 2022; Hsu et al., 2021; Jin et al., 2024; Lu et al., 2023; Maydybura et al., 2023; Naeem et al., 2022; Umar & Gubareva, 2020; Zhang & He, 2021) that explained the vulnerability of cryptocurrencies to spillovers in the structure, particularly in the case of catastrophic events.

Including cryptocurrencies in a portfolio is more vulnerable during situations where market fluctuations are experienced, as evidenced by high levels of risk during severe market situations. In any case, either the news is positive or it is negative, in comparison to situations where unforeseen external events did not affect the market in any manner. There is little interconnectivity during those normal market situations; however, it is maximized during extreme market situations. This study emphasizes the need for the players in the cryptocurrency market to manage the common risks in the cryptocurrency system, which are not adequately captured in the sets of volatility indices for stocks, gold, and crude oil. However, we found that cryptocurrency markets, as well as volatility markets, have some minor vulnerabilities in conventional and crisis scenarios. This means that financial instruments for volatile markets could act as an apt hedge for cryptocurrency traders. Therefore, it is greatly recommended that cryptocurrency portfolios be managed with a forward-looking strategy while keeping possible negative risks in mind.

4.3 Time-varying Connectedness analysis

By carrying out an investigation on time-varying connectivity, we can identify the pattern in financial markets' efficiency during periods considered peaceful and during periods characterized by turmoil in order to comprehend spillovers' dynamics. We present an extension of our research covering the entire spectrum from normal to dangerous scenarios for improved understanding of interconnectedness. Again, in Figure 8, the ever-changing levels for total spillovers for the quantile level 0.5 demonstrate the previous finding in Table 4 that moderate levels of interconnectedness exist during normal scenarios. Also remarkable is that during 2020–2021, a moderate level of interconnectedness of 50% existed. The level of interconnectedness suddenly and considerably escalated in the first quarter of 2020, peaking at 60%. The escalation in interconnectedness occurred during the rapid spreading of the COVID-19 pandemic worldwide, leading to massive sell-offs in financial markets worldwide. The result is in line with the investigation made by (Adekoya & Oliyide, 2021); Umar, Adekoya et al. (2021); (Umar, Gubareva et al., 2022), Yousaf et al. (2022), and Wong and Pham (2025b), which assumed that financial markets become more interconnected during periods of distress. There is also a rapid drop in the level of interconnectedness in the 2020 third quarter, reverting to levels experienced even before the onset of the COVID-19 pandemic. The time-varying estimates have more visible clusters of volatility, with increases in 2020 and 2022 close to the COVID-19 pandemic and geopolitical tensions, and the steady climb towards 2024 tied to inflationary pressures and loose monetary policies.

Figure 8. Total spillover in medium quantile VAR (median quantile $\mu = 0.5$)



Notes: TCI calculated by employing 200 days and a 10-step-ahead prediction horizon systematic window.

Figure 8 visually juxtaposes the pandemic's impact on total connectivity and a "rectangular" unit impulse signal function. This function, placed on the essentially unchanged dynamics of our cryptocurrency plus volatility framework, exemplifies the influence of the COVID-19 pandemic. The abrupt reversion to pre-COVID trends in interconnectedness in the second quarter of 2020 is attributable to positive news vis-à-vis the COVID-19 vaccines' discovery, which offered hope for controlling the global outbreak. The interconnectedness of financial markets continued to decline after returning to pre-COVID-19 stages, reaching a record low of around 40 percent by the end first half of 2021. Nevertheless, it has started to increase once again, with the present level being 60%. The ongoing war in the Ukraine region and rising levels of inflation in the international system contribute to the escalation in the level of interdependence. The observations made in relation to the level of interdependence verify its high sensitivity in relation to exogenous events, with stabilization over time once the uncertainty fades away.

Figure 9. Total connectedness' dynamics in upper ($\mu = 0.95$) and extreme lower ($\mu = 0.05$) quantile vector autoregressive.

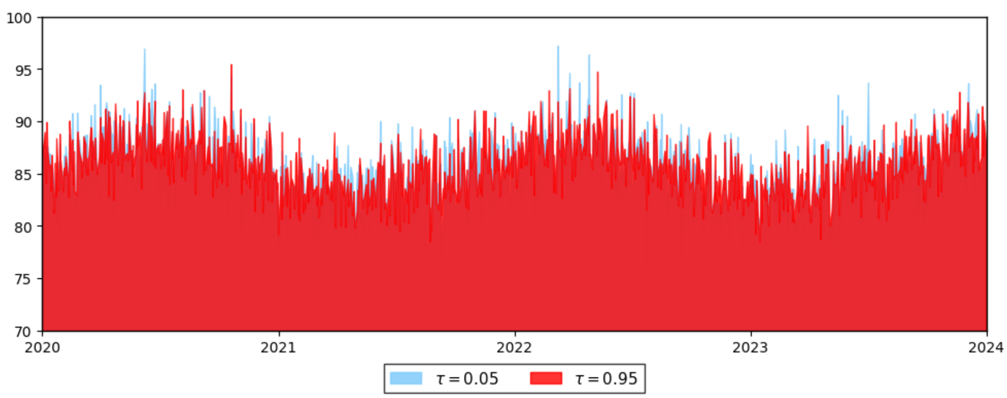
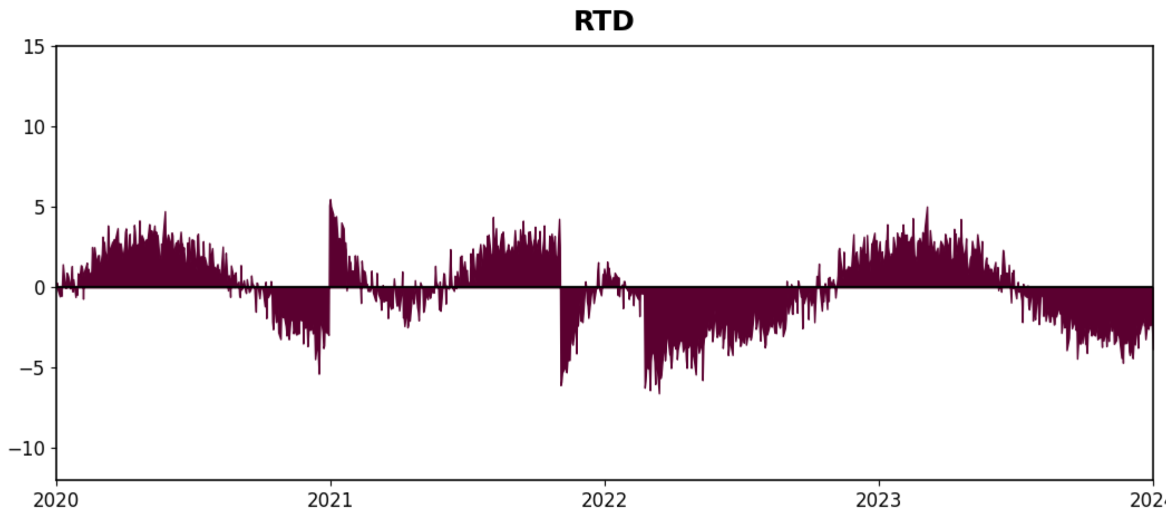


Figure 9 illustrates the results for the dynamic total connectedness on the risky quantiles. The findings in Figure 9 are in line with the existing research (Khalfaoui et al., 2022; Mensi, Al Rababa'a et al., 2021; Saeed et al., 2021), which had suggested that the spillover effect is weaker on the median quantile rather than on the other two. At the time, in the middle of 2020, the total spillover on the median quantile remains below 65% compared with over 77% on the other two quantiles, with the maximum total spillover on the lower and upper quantiles, which remains over 87% in some instances. Prior to the COVID-19 crisis, the mid-data points demonstrated a stable level of connectedness.

In contrast, the top series saw a dramatic jump in connectivity with values over 87% in 2021 during favorable market situations. The trend holds even during the second quarter of 2022, during which the markets started recovering from the disastrous effects of the COVID-19 crisis. We notice that for almost all periods, the total connectivity is lower for the lower quantile compared to the upper quantile with a few exceptions that largely began in the second half of 2022. The estimates for each quantile reaffirm the observation that in both tails, there is higher connectivity compared to the median; however, the upper tail dominates for most periods, indicating optimism-driven contagion during periods of recovery. While the lower tail dates back to panic-driven events, it validates asymmetric responses in the markets during different periods.

Figure 10. Relative tail dependence (TCI_{μ}=0.95 $-$ TCI_{μ}=0.05).



Note: Relative tail dependence computed as the difference between the TCI at the 5th quantile and the 95th quantile is demonstrated by this figure. A substantial dependence on the upper (lower) quantile is demonstrated by the positive (negative) value.

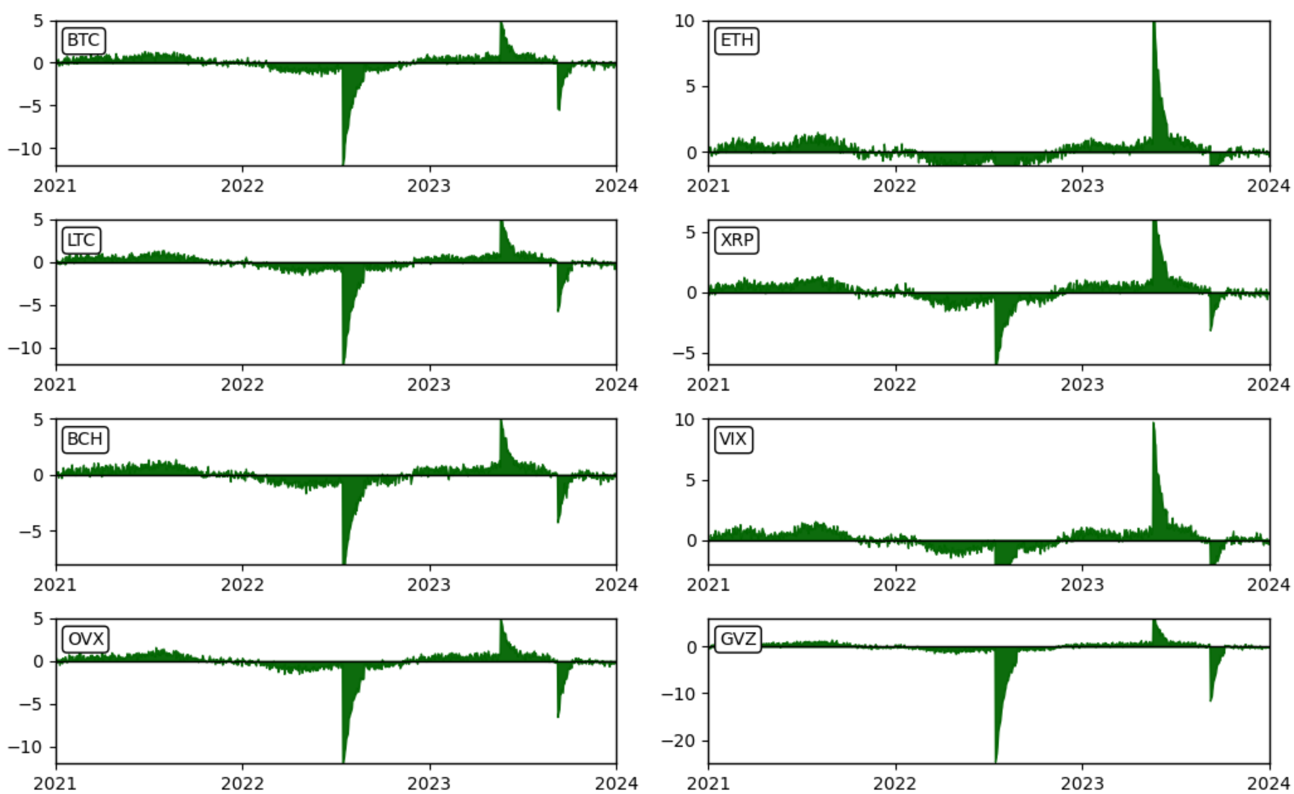
Figure 10 represents the differences in total connectedness for better comparison between the values for upper and lower quantiles. The positive values in the gauge represent higher values for the upper quantile, indicating a contradiction, whereas negative values show the presence of connectedness for the lower quantile. As foreseen from previous results, positive values also prevail in this aspect, showing that the total connectedness (TC) is higher in the upper quantile. However, the connectedness level in the lower quantile is prominent only during certain instances. From the results obtained, it is interpreted that during any instance where the market sentiment is positive, bearish, or neutral, the crypto-traders remain highly sensitive to positively unexpected events. This outcome corresponds with the ubiquitous level of overly positive sentiment in the markets of cryptocurrency during the course of the four years under investigation in the present study. This phenomenon is also reminiscent of the "irrational exuberance" experienced in financial markets in the period preceding the global financial crisis in 2007–2008. It typically presents in the form of "panic-buying," which is prompted by the fear of missing out on potentially lucrative opportunities with no regard for the associated risks. The fall in the cryptocurrency price during May and June 2022 could have altered the positive outlook held by cryptocurrency investors. Therefore, more research is required in this area to establish whether these investors continue to be highly responsive to any positive unforeseen incidents or if their vulnerability to any unforeseen negative circumstances has increased. Taking everything into consideration, the results obtained show that the asymmetric nature of connectedness is sustained over time, with the dominance in the upper tail supported by the existence of speculative synchronization, and the lower tail supported by disaster contagion.

Our research results emphasize the importance of severe market conditions and the role played by time in the study of relationships between the disruption in the cryptocurrency market and traditional financial markets. There is an important implication for investors in the contagion effect in severe scenarios, rather than in normal market scenarios, for the transmission risk for investments. Therefore, it is recommended to incorporate the hedge strategy with financial investments that have little to no correlation with the cryptocurrency asset, like the ones we investigated in the research in relation to cryptocurrency market volatility, in the portfolio design that takes into consideration the cryptocurrency risk exposure. Caution is also required in making financial investments in light of the potential posed by favorable/unfavorable news in the market in comparison with normal market scenarios.

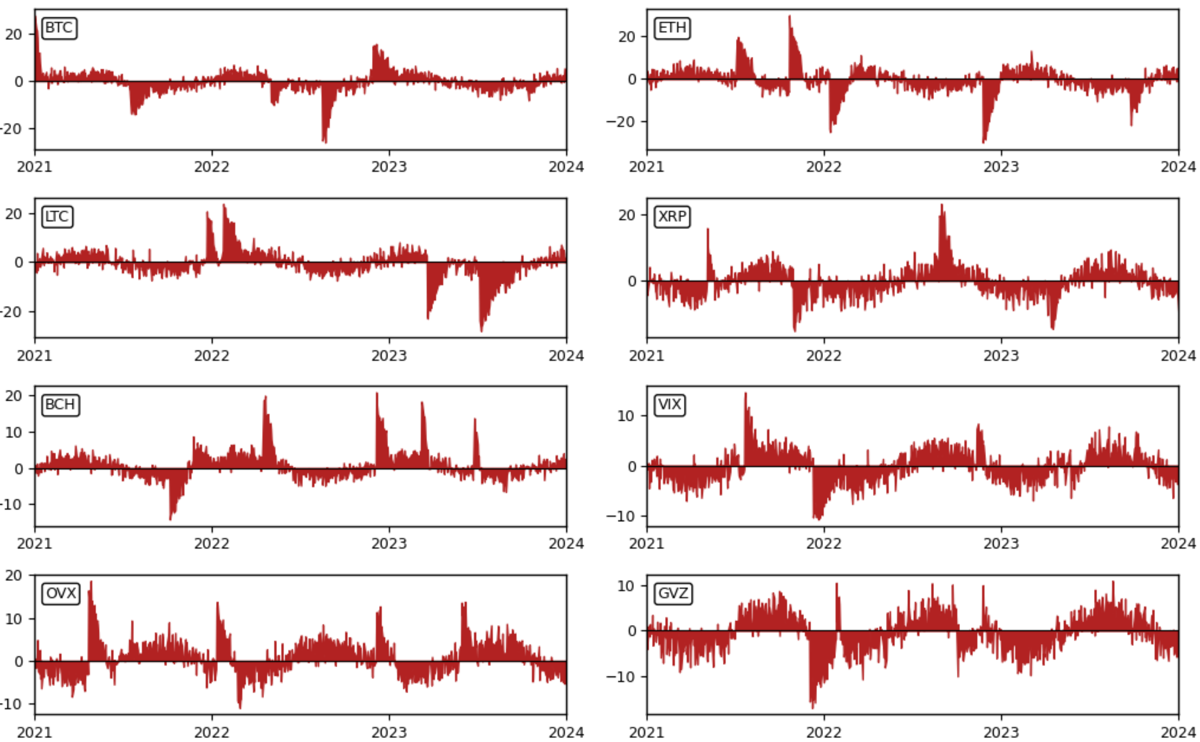
he next step is to examine the dynamics of the net spillover effects for each series at the extreme and medial quantiles. As Figure 11 illustrates, Panel A contains time-varying net spillover effects for series in the lower quantile. As suggested in Panel A, Table 4, it is apparent that the series BTC, ETH, LTC, and BCH are net transmitters since they have positive net spillover effects.

Figure 11. Dynamic net spillover in quantile vector autoregressive of volatility indices and cryptocurrency.

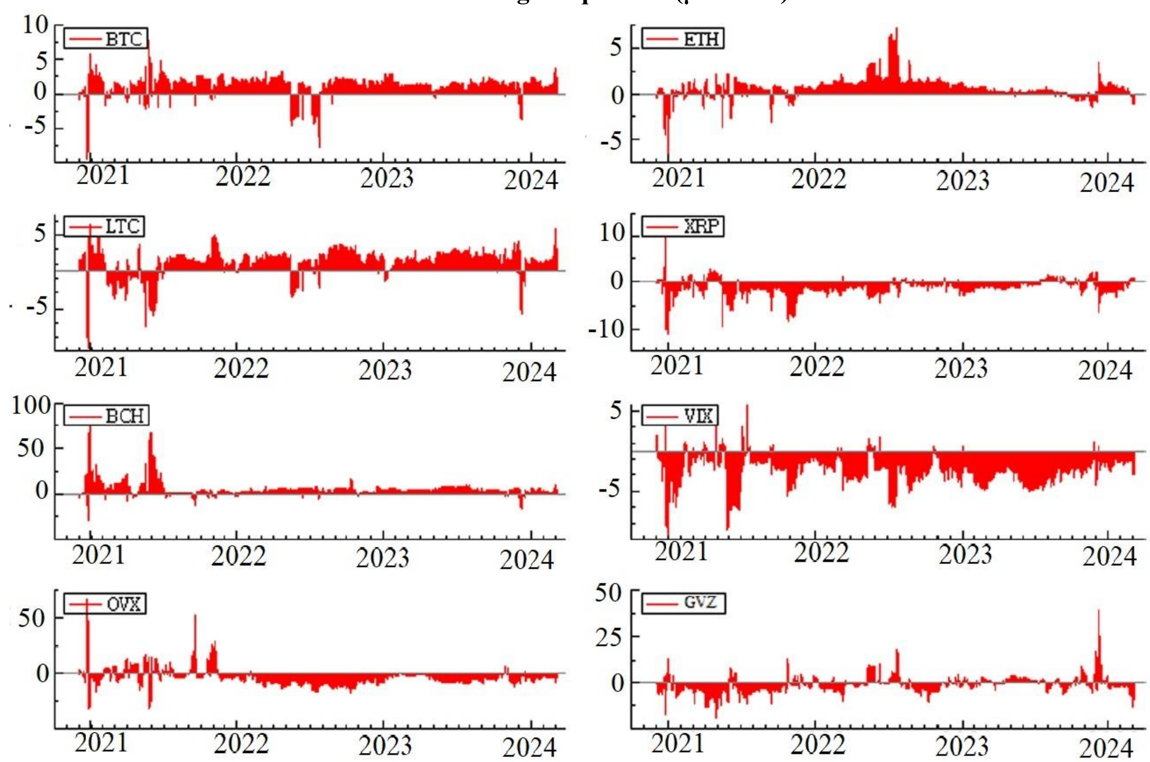
Panel A: Lower quantile (μ = 0.05)



Panel B: Median quantile (μ = 0.5)



Panel C: Higher quantile (μ = 0.95)



Conversely, XRP and the three volatility indexes primarily serve as net recipients, as demonstrated by their predominantly negative net spillover. However, during major crises, significant net spillovers are observed across all markets, as seen during the turbulence caused by the COVID-19 outbreak in the first half of 2020. Notably, excluding XRP, the cryptocurrencies' net connectivity values are more significantly biased toward the optimistic axis. It indicates that these assets, especially in the left tail, transmit greater shocks during severe events than they receive. On the other hand, all three volatility indexes under investigation exhibit a negative bias.

Moving forward, we observe that the roles of both receivers and transmitters remain consistent at the median quantile (Panel B of Figure 11). However, we note that the magnitude of the spillover in the median quantile is generally smaller on average compared to upper and lower quantiles, as observed in Figures 8 and 9 and Panel B of Table 4.

Lastly, we investigate the net spillover of time-varying in the upper quantile in Panel C of Figure 11. The variables in the given framework with net receptacle and spillover roles remain unchanged. Nevertheless, in comparison with the median quantile value, it is apparent that the extent of spillover in the upper quantile is much more significant, much like in the case of the lower quantile spillover phenomenon. The outcomes obtained in this manner match quite well with Panel C in Table 4, thereby supporting the entire interpretation provided in the comparison between the panels in Table 4. According to the obtained outcomes, it can thus be stated that the extremities in terms of quantiles represent the levels at which the spillover roles in relation to risk transmission, as well as the respective contagions, remain relatively higher in comparison with the level present in the case with the median quantile values. As such, high net spillovers in the framework signify prosperity periods along with massive instances of crises, together with their subsequent recoveries.

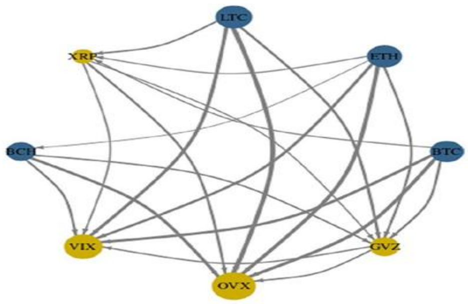
4.4 Connectedness Network

By carrying out a graphical analysis on the information flow between the three indexes for stock market volatility and the five markets for cryptocurrency, we systematically examine the complex network between these variables. The size of the nodes in the system reflects the level of influence either received or transmitted in the process. The arrow in the system shows the flow of innovations from the blue nodes to the yellow nodes. Arrows represent the level of exposure between the two terminals in the system. Figure 12 omits any edge with a weight of less than one across the 27 connections.

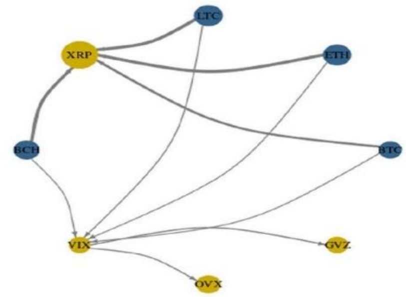
In Panel A of Figure 12, excluding XRP, it can be observed that cryptocurrencies primarily operate as net transmitters of system shocks in the lower quantile. Among these four cryptocurrencies that transmit shocks, there is minimal inter-transmission between them, except for the transmission of innovation from ETH to BCH. XRP transfers shocks to all three volatility indices while acting as a net receiver of shocks. The gold volatility index communicates shocks to the stock and oil indices, indicating how the volatility indices interact. In the lower quantile, representing bearish market circumstances, the node representing the crude oil volatility index (OVX) is the largest, suggesting that it is the major net recipient of shocks within the framework. The corrected network estimation shows stronger link intensities from cryptocurrencies toward volatility indices under bearish regimes, particularly from BTC and ETH to OVX and VIX, implying that digital-asset distress significantly influences traditional market volatility.

Figure 12. Net pairwise directional connectedness network at various quantiles.

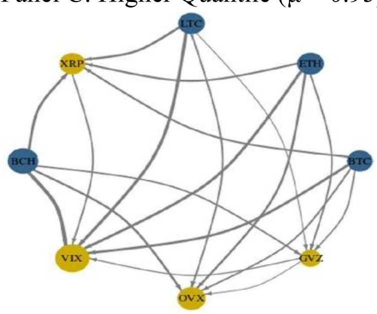
Panel A: Lower Quantile (μ = 0.05)



Panel B: Median Quantile (μ = 0.5)



Panel C: Higher Quantile (μ = 0.95)



Notes: The net recipients (transmitters) of shocks are demonstrated by the yellow (blue) nodes. By utilizing the average net pairwise direction connectedness procedures, vertices are weighted. The weighted average net aggregate directional connectedness is indicated by the terminal's size.

In Panel B, which presents the findings for the median quantile, it is found that the roles of receivers and transmitters persist, but there are differences in the respective magnitudes of the nodes. For instance, XRP, not OVX, emerges as the largest recipient in this quantile. One key observation is that the trends for connectivity in the median quantile are much more complex for lower quantiles (Panel A). Also, in this instance, instead of trading each other's shocks, the four cryptocurrencies that functioned as net shock-transmitters do not trade each other's innovations; rather, they trade with the XRP nodes and VIX nodes. Such an example goes on to show that in normal times, contagion corridors shrink, making the structure more modular, reflecting a decrease in systemic risk.

Consequently, VIX becomes the only source of innovations for OVX and GVZ, transmitting shockwaves into each of these two indexes for volatility. The level of connectivity in the network decreases in terms of the median quantile, which reflects an appropriate market environment since reduced connectivity is an indication that either the transfer of systemic risk or market instability is discouraged.

Turning to Panel C, it is apparent that the connectivity structure in the top quantile is more complex compared to the median quantile (Panel B), although it is less complex compared to the lower quantile (Panel A). As in previous panels, the beneficiary-transmitter roles remain unchanged for each node. At the same time, some edges between entities disappear in the present quantile level. Specifically, XRP directly shocks VIX in the present scenario, in contrast with the lower quantile state. As a result, VIX is identified as the net biggest beneficiary without any direct influence on OVX and GVZ. The re-run estimates underscore the complex connectivity in the top quantile by emphasizing the stronger two-way feedback between cryptocurrency markets and volatility indexes to show that speculative phenomena boost conditional expectations on traditional markets, too.

The bilateral connectivity pattern is different in varying market states. Nevertheless, it is important to state that the four cryptocurrency markets, namely BCH, ETH, LTC, and BTC, function in a dominant transmitting position for either the volatility indexes or XRP in each state, respectively. It emphasizes the influence triggered by the profitability level for these popular cryptocurrencies on the level of volatility in the markets. Furthermore, it is clear from our research that during periods of harsh market states, the level of connectivity within the network is high, making it vulnerable to contagion channels for systemic risks. These results have implications for different market participants, such as portfolio managers and cryptocurrency traders, who can make use of these results in understanding the effectiveness of hedging strategies in dealing with situations of volatility, as well as cryptocurrency markets in general. Taking everything into consideration, the results from the network analysis validate that systemic spillovers increase during the speculative periods as well as during the crisis periods. The ramifications associated with cryptocurrencies have resulted in these cryptocurrencies acting as pivotal nodes in the global volatility network.

5. Conclusions

In this research, the transmission of disastrous events from the CBOE uncertainty indexes (GVZ, OVX, and VIX) to the cryptocurrencies (BCH, XRP, LTC, ETH, and BTC) is tested by using the cross-quantilogram test in a quantile-connectedness framework. The research work is essentially targeted towards understanding the impact of disastrous events triggered by the COVID-19 pandemic on the ever-developing nexus between cryptocurrencies and conventional indexes. The research is also targeted towards understanding the nature of connectivity with respect to the financial contagion triggered in the markets.

The results show that the leading cryptocurrency in shock transmission is indeed BTC, with the greatest asymmetric dependence between BTC and XRP. As the length of the lag increases, the predictability in terms of direction tends to zero, indicating that even though the spillovers are temporary, they have strong effects. The inclusion of the equities, oil, and gold volatility indexes strengthens the relationships among the cryptocurrencies, therefore indicating that they deal with each other in an exogenous manner. Furthermore, the results from Quantile Connectedness also show that the Total Connectedness Index (TCI) is quite low (≈ 61 %) in normal market states, but it increases considerably in bullish (≈ 93 %) and bear markets (≈ 91 %). The results effectively show that the system linkages increase during the critical market states, thereby emphasizing the nonlinear nature of volatility spillovers. The network test substantiates these phenomena by effectively indicating that BTC, ETH, LTC, and BCH remain net senders, while OVX and VIX remain net receivers.

The results hold several practical implications. Volatility instruments, for instance, VIX futures contracts, could be useful instruments for portfolio diversification in protecting cryptocurrency investments in case of downturns in cryptocurrency markets. Additionally, an alternative measure for the level of stock market volatility could be enhanced by using the CVX (cryptocurrency) Index and the GVX (gold) Index for better portfolio diversification strategies. Finally, for policymakers, the need for monitoring to avoid possible system vulnerabilities is supported by the evidence on the similarity in cryptocurrency market volatilities with traditional markets. The evidence supports the development of integrated macro-prudential frameworks capable of addressing the spillover risks that emerge from both speculative exuberance and crisis-driven contagion in cryptocurrency markets.

The research makes an original contribution to the expanding body of research on financial contagion and systemic risk in that it combines the quantile-based concept of connectedness with the concept of network analysis in an integrated framework. The research also makes an original contribution in that it accounts for asymmetric tail risk relationships, discovering the relationships between traditional volatility indices and cryptocurrencies in different states of the market system. The research makes an original contribution in demonstrating, with empirical evidence, that even isolated financial assets, such as cryptocurrencies, affect conventional financial markets in ways that were previously unknown in terms of channels for transmitting volatility.

Despite its comprehensiveness, there remain some limitations in the present study. As mentioned in the preceding section, the study concentrates on the top five cryptocurrencies, along with the top three cryptocurrency volatility indexes, for the time period 2020–2024; hence, an extended period covering more cryptocurrencies could increase the external validity for these outcomes. As mentioned in the preceding definition, although the quantile-based connectedness method, alongside the network model, successfully identifies the nonlinear dependence relationships between cryptocurrency values, it fails to consider structural shifts in these topological relationships over time in cryptocurrencies. Future research opportunities would involve an extended definition set for cryptocurrencies, including DeFi tokens, stablecoins, and NFTs, among others, using high-frequency series in order to better understand intraday contagions in these financial systems.

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