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ORIGINAL ARTICLE

Volatility interdependencies of cryptocurrencies, gold, oil, and US stocks: quantile connectedness analysis with intraday data

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Abstract

The financial market is constantly affected by extreme events, such as the COVID-19 pandemic and the Russia-Ukraine war, which have significantly impacted commodity prices and market conditions. To better understand the behaviour of prices in different market situations, particularly at the bull and bear market states, this study investigates the interdependencies of volatility between cryptocurrencies, gold, oil, and US stocks by employing the quantile dynamic connectedness method and computing the Net total connectedness (NET) and the Total Connectedness Index (TCI) measures for bear, bull, and normal market situations. As a differential, it used intraday data from 2018 to 2022 to characterise relationships among these market situations. The NET measure indicates that Ethereum and Bitcoin are net transmitters of shocks in different quantile values. At the same time, Brent, gold, and SP500 showed to be net shock receivers in most situations, except for gold in quantiles 0.6–0.7 and 0.95 and SP500 in quantiles 0.9–0.95. Further, shocks are not transmitted between Bitcoin and Ethereum at any phase of the market. Regarding TCI, the results show that the different markets are strongly connected in extreme situations, mainly in the bull market. These findings into the distinct behaviors under extreme quantiles provide valuable implications for portfolio diversification and risk management strategies.

Keywords Spillover effects · Bitcoin · Ethereum · S&P500 · Commodities · COVID-19 pandemic shock · Russia-Ukraine war shock · Intraday price

Abbreviations

COVID-19	Coronavirus disease 2019
GFEVD	Generalized forecast error variance decomposition
NET	Net total connectedness
QVAR	Quantile VAR
QVMA	Quantile vector moving average

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S&P500	Standard & poor's 500 index
TCI	Total connectedness index
VAR	Vector autoregressive

Introduction

Over the past few decades, financial markets have undergone significant transformations, driven by globalization, technological advancements, and the introduction of new financial instruments. These changes have led to increased interconnectedness of these markets, making them more susceptible to systemic risks and contagion effects, especially during periods of economic turmoil. Traditional assets like stocks and commodities have been joined by new classes of digital assets, such as cryptocurrencies, which have introduced additional layers of complexity to the financial system. The interplay between these diverse asset classes, especially under extreme market conditions, has become a critical area of study, as it offers insights into market resilience and vulnerability.

The COVID-19 pandemic and the Russia-Ukraine conflict serve as recent examples of crises that have significantly altered financial market dynamics. International financial markets have experienced strong price upheavals with the prominent global crisis. The COVID-19 pandemic crisis has been considered one of the events that redefined financial markets, as was the global financial crisis of 2007–2009. The coronavirus caused a sharp reduction in financial asset prices at the beginning of its spread, followed by an upward trend in prices (Coskun et al. 2023). Furthermore, still not recovered from the health crisis, the financial market was destabilized again with the war between Russia and Ukraine declared at the beginning of 2022.

The global financial crisis of 2007–2009, emanating from the USA due to the credit crisis changed the existing relationship of different assets (Kayal and Maiti 2023). Like this crisis, the coronavirus disease, in addition to having affected the health and social system, has also altered the dynamics of the financial market, causing price fluctuations throughout its occurrence (Liao et al. 2021; Amamou and Bargaoui 2022; Habib and Kayani 2024; Kyriazis and Corbet 2024), being stronger in countries with a higher level of economic uncertainty (Ashraf 2021).

At the beginning of the COVID-19 health crisis, economic activities came to an abrupt halt, caused by the health restrictions imposed by governments to contain the spread of the disease. During this period, there was a Bear market, i.e., the prices of different financial assets that demonstrate economic strength suffered a sharp drop in performance (Corbet et al. 2020; Habib and Kayani 2024). With the creation of vaccines against the coronavirus, the countries' economies resumed activities. However, due to the slowdown, the supply of many products was unable to keep up with demand, causing price increases for different assets, highlighting a bull market (Arfaoui et al. 2023). The case of oil is cited because many oil industries had to interrupt production due to low demand. However, with demand recovering, supply was unable to keep up it, raising prices (Zakeri et al. 2022).

Not even the market was able to normalize from the pandemic (the World Health Organization announced the end of the disease as a global emergency in May 2023), the economy was affected by the Russia-Ukraine geopolitical conflict, which put even more pressure on the prices of different assets. Russia, one of the main oil-supplying countries, reduced oil supplies to Europe, once again leading to higher prices (Zakeri et al. 2022). Since oil is a commodity highly related to the global financial market (Adehoya et al. 2022; Rehman 2023), the energy crisis was greater during the war between Russia and Ukraine than during the COVID-19 pandemic (Mohammed et al. 2023; Habib and Kayani 2024).

There is concern among market agents about the behavior of asset prices in different economic situations and risk contagion between assets given economic uncertainties. Understanding price dynamics more deeply allows you to anticipate movements in similar contexts, helping to provide portfolio risk management guidance, especially in adverse situations, as well as providing insights to maximize the chances of profitable investment opportunities.

In financial literature, the price relationships of different financial assets are re-evaluated whenever there is a market crisis, due to the interrelationships between them varying according to time and market conditions (Kayal and Maiti 2023). Depending on the context, there are new variables to be incorporated and methodologies to be explored to make price behavior more accurate in relation to reality. For instance, a decade after the global financial crisis, the financial world presents other asset classes (e.g., the crypto assets), and a new kind of asset, such as cryptocurrencies (Kyriazis and Corbet 2024). In 2009, this new financial item had just been created, while in the 2020s, cryptocurrencies are one of the assets experiencing a boom in capitalization (Yaya et al. 2022a, b). These digital currencies have profoundly impacted the financial system both during the health crisis and the war between Russia and Ukraine (Nguyen et al. 2022; Kyriazis and Corbet 2024).

To better understand the relationship between the different assets, such as cryptocurrencies, commodities, and stocks, we seek to investigate the interdependencies of volatility within the network of Bitcoin, Ethereum, gold, oil, and US stocks using the quantile method. The Quantile Connectedness approach provides a robust framework for understanding the complex and dynamic relationships within financial systems, especially under extreme market conditions. Its ability to capture non-linearities, tail risks, and time-varying connectedness makes it a critical tool for researchers, policymakers, and risk managers.

The focus on these assets is motivated by their distinct characteristics and pivotal roles in global financial markets. Cryptocurrencies, represented by Bitcoin and Ethereum, are relatively new but volatile assets with growing significance. Gold and oil, on the other hand, have traditionally been viewed as safe-haven assets and key economic indicators, respectively. US stocks, represented by the S&P500, serve as a benchmark for the global equity market. The quantile dynamic connectedness method of Chatziantoniou et al. (2021) is set up in the Vector AutoRegressive (VAR) framework, and this allows the market dynamics to be explained in the extreme – bear, bull and normal market states – as well as at other quantile points in the financial market networks. Identifying bull and bear markets based on quantiles is a continuous parametric estimation method, unlike the nonparametric discrete identification method of bull and bear market regimes by Pagan and Sossounov (2003), which documents stages to identify dominant/discrete states for market conditions [see, for example, Yaya (2013)]. The Total Connectedness Index (TCI) and Net total connectedness (NET) of Gabauer (2021) are used to analyze the connectedness in variables, and the entire computation is based on the computational code described in Gabauer (2022).

While many previous studies have predominantly focused on average market effects, our study distinguishes itself by analyzing not only the central tendencies but also the behavior of financial assets under extreme market conditions, specifically bear and bull markets, fulfilling a gap in the existing literature, by exploring the complex interdependencies under extreme market conditions. The extreme quantiles are critical for understanding how market dynamics shift during periods of heightened stress and volatility. By employing the quantile dynamic connectedness method, we capture these tail risks and provide insights that are particularly relevant for risk management and policy-making. The distinct behaviors observed in these extreme market states offer a deeper understanding of the interdependencies among key financial assets, such as cryptocurrencies, gold, oil, and US stocks, which may not be evident when analyzing average market conditions alone. This focus on extreme quantiles thus represents a significant contribution to the existing literature, offering novel insights into the resilience and vulnerabilities of financial markets during periods of crisis.

Further, the present study distinguishes itself by using intraday data, which, unlike the more commonly analyzed daily frequency data, offers a granular perspective on market dynamics. As financial markets become increasingly characterized by rapid fluctuations and high-frequency trading, the need for detailed temporal analysis has grown. According to Caporin et al. (2019), Nguyen et al. (2022) and Yaya et al. (2022a, b), using intraday data allows for a more detailed analysis of the temporal aggregation effects, allowing to capture short-term market movements that are often overlooked in daily analyses yet are crucial for understanding the behavior of financial assets under extreme conditions. This fact is even more useful in markets as dynamic and highly fluctuating as financial assets and commodities. In these markets, a large volume of transactions occurs between the opening and closing of the exchanges, therefore, analysing intraday movements can bring great interference and implications in high-frequency trading (Su et al. 2022). Thus, analyzing intraday movements provides critical insights into high-frequency trading patterns and allows for a more accurate and timely assessment of market risks, which is indispensable in the current financial landscape.

Thus, this study makes several key contributions to the existing literature. First, it provides a detailed analysis of the interconnectedness and volatility spillovers among cryptocurrencies, gold, oil, and US stocks, with a specific focus on extreme market conditions such as bear and bull markets. Second, by utilizing intraday data, this study captures high-frequency market dynamics that are often overlooked in analyses based on daily data, offering a more granular understanding of asset behavior. Third, the application of the Quantile Connectedness approach allows us to explore non-linear relationships and tail risks, providing novel insights into the interaction of these assets during periods of heightened economic uncertainty. Finally, the findings contribute to the broader discourse on risk management and portfolio optimization, offering practical implications for managing financial risks in volatile environments.

The remainder of the paper is organized as follows: Sect. "Literature review" is dedicated to the literature review, Sect. "Econometric methods" presents the econometric method, and Sect. "Data and preliminary analysis" presents the data and preliminary analyses. Sect. "Results and discussion" discusses the results, and, finally, Sect. "Concluding remarks" highlights the main conclusions.

Literature review

Many studies have analyzed the relationship between different financial assets at different moments of the Coronavirus health crisis and in the context of the war between Russia and Ukraine. The purpose of the studies is to bring more clarity to this market in the face of uncertain shocks to reduce the risks of economic losses. Cryptocurrencies represent a rapidly evolving and highly volatile asset class, while gold and oil are traditional commodities with established roles as safe-haven assets and economic indicators, respectively. US stocks, on the other hand, are a cornerstone of global equity markets and reflect broader economic conditions (Kilian and Park 2009; Bauer and Lucey 2010; Baruník et al. 2016; Corbet et al. 2019). These assets play a significant role as major financial assets in global markets. The focused literature review on these specific assets aims to provide a comprehensive understanding of the interconnectedness and volatility dynamics within and across these markets. This focus ensures that the review is relevant and directly supports the research objectives, which are to analyze the volatility spillovers among these key financial assets using a quantile connectedness approach with intraday data. Additionally, this targeted approach helps to identify existing gaps in the literature and highlights the unique contributions of this study in addressing those gaps.

Thus, the literature review below focuses on identifying gaps in the existing recent and relevant studies that involve cryptocurrencies, gold, oil, and stock markets. Previous studies have primarily explored these relationships during periods of economic stability or using daily data, which may not capture high-frequency market dynamics. Furthermore, the unique market conditions introduced by recent global events, such as the COVID-19 pandemic and the Russia-Ukraine conflict, have not been comprehensively analyzed in this context. By utilizing intraday data and a Quantile VAR approach, this study addresses these gaps, providing a novel perspective on the interconnectedness of these markets under different economic conditions. In this literature review, we delineate the periods of study into pre-pandemic, pandemic (COVID-19), and geopolitical conflict (Russia-Ukraine war) phases. Each phase is characterized by distinct economic and market dynamics. For instance, the COVID-19 pandemic led to initial sharp declines in asset prices, followed by a recovery driven by fiscal and monetary interventions. In contrast, the Russia-Ukraine conflict primarily influenced commodities, particularly oil, due to supply disruptions.

In the pre-COVID-19 pandemic period, Liu et al. (2022) found that volatility correlations between US stocks and other commodities, such as gold and oil, were weak. But after the start of the pandemic, the correlation intensified and volatility transmissions became more complex. This evidence was similar to that found by

Liao et al. (2021), when analysing the same assets, the spillovers of returns proved to be more stable than the spillovers of volatility and very sensitive to the economic effects of the pandemic.

Considering the studies devoted to the analysis of the relationship between cryptocurrencies and other markets, Bouri et al. (2022) analyzed the asymmetry and kurtosis of returns and found that until 2018, the Bitcoin and S&P 500 markets showed very weak co-movements. However, with COVID-19 pandemic driving economic and political uncertainty, co-movements between cryptocurrencies and stocks have intensified. This evidence was also found by Goodell and Gouttle (2021) and Mensi et al. (2023). Goodell and Gouttle (2021) identified that co-movement between stocks and cryptocurrencies gradually increased as the disease spread. Mensi et al. (2023) analyzed the interdependence between gold and cryptocurrencies using quantile cross-spectral and quantile vector autoregression approaches, and identified a strong connection between gold and cryptocurrencies, with the level of interconnection being stronger in moments of high uncertainty caused by crises.

Another point of analysis in financial asset price volatility studies is to determine which assets are transmitters and which are receivers. During the peak of the COVID-19 pandemic, gold proved to be the largest net receiver of shocks and risks in studies by Liao et al. (2021), Adekoya and Oliyide (2022), Fang et al. (2023) and Mensi et al. (2023). Conversely, oil was the largest net transmitter of shocks and risks (Adekoya and Oliyide 2022; Farid et al. 2022; Fang et al. 2023; Liao et al. 2021). However, Antonakakis et al. (2023), when comparing with the stock and bond market, found that oil is a net receiver of spillover shocks.

Kyriazis and Corbet (2024) also observe that oil is a transmitter of shocks, in this case considering for banking shares using Quantile-VAR dynamic pairwise and extended joint during the period of the COVID-19 pandemic and the Russia-Ukraine war. Other evidence found by these authors is that cryptocurrencies such as Ethereum and Bitcoin transmit shocks to stocks and that gold and natural gas are the main recipients of stock indexes shocks. Using the same methodology, Le (2023) analyzed the volatility of the cryptocurrencies and energy indexes. They found that the cryptocurrency indexes were recipients of shocks during almost the entire period from 2019 to 2022, except only at the beginning of 2022, where cryptocurrencies have been liquid shock transmitters, evidence justified by the conflict in Eastern Europe.

Huang et al. (2023) evaluated the transmission of volatility between energy commodities and other financial assets such as gold, stocks, bonds, and cryptocurrencies during the onset and deepening of COVID-19 pandemic cases and showed that oil is transmitting and being exposed to market volatility. Kayal and Maiti (2023) analyzed the direction of information flow between gold and oil but did not find transmission between these two commodities; however, during the 2008–2009 crisis, transmission from gold to oil was detected. This last relationship was also detected by Arfaoui et al. (2023), whose study revealed the presence of volatility transmission for oil and other energy commodities during three periods, namely: pre-COVID-19, pre-COVID-19 vaccine, and post-COVID-19 vaccine.

Given information on price movements and the direction of shocks, it is possible to identify assets that present a safe haven status. Azimli (2022) analyzed the dependence of different commodities in relation to international stock markets in the pre- and post-COVID-19 periods. Using a quantile regression approach, the author found conventional energy stocks cannot be a safe haven for post-Covid stocks. Moreover, even gold did not act as a safe asset against international stock markets in the post-Covid19 period, unlike the pre-pandemic period.

Considering Bitcoin and other cryptocurrencies, Goodell & Gouttle (2021) and Bouri et al. (2022) found that cryptocurrencies are not a safe haven for conventional financial assets in extreme market conditions. Similar results were found by Wen et al. (2022). These last authors analyzed the spillover effect of gold and Bitcoin on the oil and stock markets and found that Bitcoin is not a safe haven for either oil or stocks during COVID-19 pandemic. On the other hand, gold was a safer asset, especially for stocks. Furthermore, gold also proved to be a safer investment haven than the stock market in times of crisis in studies by Sharma (2022) and Liu et al. (2022).

Unlike previous results, Mariana et al. (2021), when examining whether cryptocurrencies are safe havens for stocks in the short term, demonstrated that Bitcoin and Ethereum have characteristics of safe havens, with Ethereum being slightly safer than Bitcoin. However, both are more volatile than gold and the S&P500.

Syuhada et al. (2022) compare Bitcoin and gold to investigate which act as a safe haven for oil, finding that gold reduces portfolio downside risk, while Bitcoin does not. Mensi et al. (2023), when analyzing the price volatility relationship between cryptocurrencies and others, found that gold is susceptible to shocks arising from the price uncertainties of cryptocurrencies, therefore, gold is not a safe haven for cryptocurrencies.

Studies generally analyze different relationships of financial assets using mainly daily data, which may result in the loss of important relevant information. To fill this gap, the present study analyzed the market for different financial assets using intraday data. Furthermore, it used three different quantiles to verify different market conditions, namely: bear, normal and bull market.

Considering the referred, this study contributes to the current literature by offering a multifaceted analysis of the interconnectedness and volatility spillovers across key financial assets, including cryptocurrencies, gold, oil, and US stocks, particularly under extreme market conditions such as bear and bull markets. By using intraday data, this study allows to capture high-frequency dynamics that are often overlooked in studies based on daily data, providing a more granular understanding of the market behavior. Furthermore, the application of the Quantile Connectedness approach allows us to explore non-linear relationships and tail risks, offering new insights into how these assets interact during periods of heightened economic uncertainty, such as the COVID-19 pandemic and the Russia-Ukraine war. This study not only fills gaps in the existing literature by focusing on intraday data and extreme market conditions but also contributes to the ongoing discussion on risk management and portfolio optimization in volatile financial environments.

Econometric methods

Quantile dynamic connectedness indicates the strength and transmission of connectedness from one variable to the others, taking care of the market's ups and downs in terms of bullish and bearish market states. traditional methods often assume linear relationships between financial variables. The Quantile Connectedness approach allows for the capturing of non-linear dynamics by assessing connectedness at different quantiles of the distribution. This is particularly important in financial markets, where relationships between assets or entities can vary significantly across different market conditions, such as during periods of high stress versus normal times. Chatziantoniou et al. (2021) define quantiles $\tau \in (0,1)$ for different values, specifically at the lower quantile, middle quantile, and upper quantile, corresponding to bearish, bullish, and normal financial market situations. The selection of these specific quantiles for analysis is based on the distribution of returns, which allows us to capture the market's tail conditions. This approach enables a nuanced analysis of market dynamics, which are often nonlinear across different market phases. The econometric framework relies on a quantile-defined VAR(p) model,

$$Y_t = \mu(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) Y_{t-j} + \varepsilon_t(\tau) \tag{1}$$

where Y_t and Y_{t-j} are the $K \times 1$ dimensional endogenous variable vectors from the multiple variables $(y_{1t}, y_{2t}, \ldots, y_{Kt})$, The median quantile (i.e. $\tau = 0.50$) describes the normal market condition, while the bearish and bullish market conditions are found towards the extremes $(\tau = 0.05 - 0.10)$ and $(\tau = 0.90 - 0.95)$, respectively; $\mu(\tau)$ is the conditional mean vector of $K \times K$ dimensions, $\Phi_j(\tau)$ is the $K \times K$ dimensional model coefficient matrix, $\varepsilon_t(\tau)$ are the $K \times 1$ dimensional error vector with a $K \times K$ dimensional variance–covariance matrix, $\sum(\tau)$. Assumptions underlying the model include stationarity of the data and normal distribution of errors, verified through unit root and normality tests. For ease of computation, the QVAR(p) is re-specify into a Quantile Vector Moving Average [$QVMA(\infty)$} utilizing the Wold's representation,

$$Y_t = \mu(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau) \varepsilon_{t-i} \tag{2}$$

Now, Koop et al. (1996) and Pesaran and Shin (1998) are used to obtain the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) required for the connectedness of between two markets. The derived GFEVD formula from (4) is then given as,

$$\Psi_{ij}^{\tau}(H) = \frac{\sum(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (e_i{\prime}\Psi_h(\tau) \sum(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i{\prime}\Psi_h(\tau) \sum(\tau) \Psi_h(\tau){\prime} e_i}, \tag{3}$$

which becomes,

$$\widetilde{\Psi}_{ij}^{\tau}(H) = \frac{\Psi_{ij}^{\tau}(H)}{\sum_{j=1}^{k}\Psi_{ij}^{\tau}(H)}, \tag{4}$$

where e_i is a zero vector which equates to unity on the i^{th} position. This condition leads to two equalities here: one is that, $\sum_{j=1}^{k}\widetilde{\Psi}_{ij}^{\tau}(H) = 1$, and the second one is that $\sum_{i,j=1}^{k}\widetilde{\Psi}_{ij}^{\tau}(H) = k$. Thus, $\widetilde{\Psi}_{ij}^{\tau}(H)$ gives the influence of variable j on all other variables i in terms of its share of forecast error variance/shocks. This is otherwise defined as the total directional connectedness TO others, i.e. $C_{i\leftarrow j}^{g}(H)$. Conversely, the directional volatility spillovers received by variable j from all other variables i is the total directional connectedness FROM others, computed as $C_{i\rightarrow j}^{g}(H)$. The net directional connectedness is the difference between TO and FROM, i.e.,

$$NET_i^{\tau} = C_{i\rightarrow j}^{\tau}(H) - C_{i\leftarrow j}^{\tau}(H) \tag{5}$$

where $C_{i\rightarrow j}^{\tau}(H) = \sum_{j=1,i\neq j}^{k}\widetilde{\Psi}_{ij}^{\tau}(H)$, and $C_{i\leftarrow j}^{\tau}(H) = \sum_{i=1,i\neq j}^{k}\widetilde{\Psi}_{ji}^{\tau}(H)$. Thus, NET_i^{τ} gives the net connectedness for variable i in the network of variables (i, j), and if $NET_i^{\tau} > 0$ in any variable, it implies that such a financial variable i transmits more shocks than it receives shocks from external variables j. Thus, variable i influences the other variables in the network more than being influenced by them. If on the other way, $NET_i^{\tau} < 0$, it means that the variable is a net receiver of shocks, as it is being influenced by shocks from other variables j more than the shocks it transmits in the network. The Total Connectedness Index (TCI) is given in (6) as.

$$TCI^{\tau} = \frac{\sum_{i,j=1,i\neq j}^{k}\widetilde{\Psi}_{ij}^{\tau}(H)}{k-1}, \tag{6}$$

where TCI is the connectedness index between variables i and j, which measures the strength of the connectedness in the network, and a large TCI implies high market risk while a low TCI implies low market risk.

Hence, quantile connectedness allows for the comparison of dynamic connectedness at the lower quantile (bear), upper quantile (bull), and middle quantile (normal) markets, as TCI is computed for each quantile. Chatziantoniou et al. (2021) and Gabauer (2021) have shown that TCI values are higher at the extreme quantile values compared to the normal market since the crisis that triggers market upturns and downturns reset markets to be further integrated.

Data and preliminary analysis

As a cryptocurrency proxy, Bitcoin and Ethereum were considered, both in US\$, which are the main cryptocurrencies traded and with the highest trading volume and liquidity level as of November 30, 2022, 12.00GMT, which makes buying and selling cryptocurrencies easier without significantly affecting the market prices. Another reason to select these cryptocurrencies is that they are the largest ones in terms of market capitalization, representing more than 70% of the market value of all cryptocurrencies (https://coinmarketcap.com/), frequently serving as bellwethers in broader cryptocurrency markets. Among commodities, gold prices (US$/ounce) and Brent oil prices (US$/bushel) were used. About the stock market, we considered the prices of the S&P500 index, which is the main global stock index benchmark. The complete database of intraday prices, collected every 1 h, covers the period between January 2, 2018, and November 30, 2022, making a total of 25,875 observations. This period was selected as it covers significant market developments (January 2018 follows the peak of the 2017 cryptocurrency boom, which marked the first major mainstream attention towards cryptocurrencies like Bitcoin and Ethereum), major economic events (e.g., the COVID-19 pandemic and the Russia-Ukraine war), technological innovations (the selected period captures the rise of Decentralized Finance (DeFi) and the growing significance of smart contracts, particularly on the Ethereum network), and regulatory changes (encompasses significant regulatory changes and discussions around cryptocurrencies and traditional financial markets. Regulatory developments have profound impacts on market dynamics and investor behavior). This timeframe provides a comprehensive view of the market under various stress conditions, ensuring that the analysis is robust and reflective of diverse economic scenarios. Furthermore, this timeframe ensures a thorough and relevant analysis of the interconnectedness and volatility dynamics among cryptocurrencies, gold, oil, and US stock markets. All the used intraday prices are freely accessible on the ForexTime MT4 terminals. This is a reliable data source, used for example by Yaya and Gil-Alana (2020), Chaleenutthawut et al. (2021), Yaya et al. (2022a, b), among others.

Figure 1 shows the time evolution of such prices. Cryptocurrency prices showed high volatility in the post-COVID-19 period, with significant positive and negative oscillations, particularly between 2021 and 2022. Oil prices, after a sharp drop at the outbreak of the pandemic, showed an upward trend, with sharper upward and downward movements, especially after the first months of 2022, when the conflict between Russia and Ukraine began. The S&P500 index, in turn, also suffered a significant drop at the beginning of the pandemic but recovered relatively quickly and continued to show an upward trend until early 2022, where it reversed the downward trend, with more sudden upward and downward movements at the end of the period. Gold prices, in turn, during the studied period, showed an oscillation around a growing trend until mid-2020, approximately, when they reached levels around US$ 2000, and, after that, a trend of relative stability close to this level until the beginning of 2022. After this period, it also reversed the upward trend to a downward trend, as well as oil and the American stock index, although with smoother upward and downward movements than the first ones. For the five series, a common period is the time of the COVID-19 price crash in the first quarter of 2020. As noted in Yaya et al. (2021) and Adekoya et al. (2022), stock, commodity, and energy prices were feared more during this period than during the 2007/2008 global financial crisis period.

Price co-movement in the five variables is not easily noticed in all except in the post-COVID-19 periods. Meanwhile, the main focus is to analyse the volatility, which is based on price changes. i.e. from log-returns. To analyse the volatility, here we use a proxy for absolute return, where the return is given by:

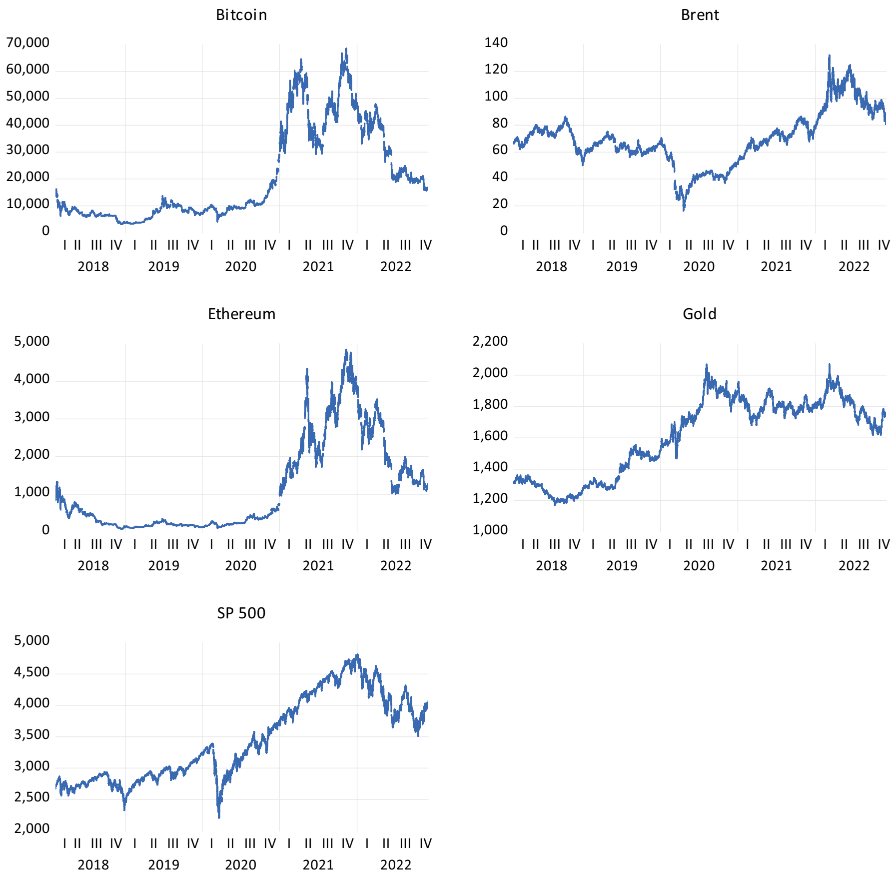


Fig. 1 Time plots showing historical intraday prices

$$y_{it} = 100 * \left(\frac{p_{it} - p_{it-1}}{p_{it-1}} \right), \tag{7}$$

considering p_{it} as the current price (time "*t*") of asset i and p_{it-1}, the price of asset *i* in the previous period, which in the present case of intraday prices collected every 1 h, represents the price of this asset lagged by 1 h. Asset return statistics, y_{it}, are presented in the upper panel of Table 1. Two characteristics of interest in the analysis of volatilities are asymmetry and non-normality in the return of variables. All variables showed positive means (suggesting that, on average, these assets have generated positive returns over the analyzed period, which is a favourable indicator for investors, implying overall growth), as well as variances, higher than their respective means (indicating high volatility or risk associated with these assets. The returns of these assets are spread out over a wider range of values, indicating that while the average return is positive, the actual returns can deviate significantly from the mean), with emphasis on cryptocurrency variances, followed by oil, the S&P500

Table 1 Main descriptives statistics and correlations

	Ethereum	Bitcoin	Brent	Gold	SP500
Mean	0.0016	0.0009	0.0010	0.0012	0.0016
Variance	1.8389	1.0802	0.3896	0.0386	0.0883
Skewness	0.121***	0.674***	1.438***	0.435***	1.467***
Ex.Kurtosis	54.723***	43.912***	136.097***	18.973***	75.686***
ERS	34.126***	59.956***	42.860***	56.654***	61.966***
Q(20)	94.408***	139.321***	77.718***	34.936***	93.726***
$Q^2(20)$	637.9***	2412.4***	562.3***	2255.8***	4202.4***
Pearson correlations					
Ethereum	1.000***	0.820***	0.088***	0.073***	0.207***
Bitcoin	0.820***	1.000***	0.084***	0.085***	0.210***
Brent	0.088***	0.084***	1.000***	0.114***	0.322***
Gold	0.073***	0.085***	0.114***	1.000***	0.096***
SP500	0.207***	0.210***	0.322***	0.096***	1.000***

Note: (i) *** represents the significance level of 1%; (ii) "Ex. Kurtosis" represents the excess of kurtosis; (iii) Q(20) and $Q^2(20)$ are the serial correlations of residuals and squared residuals for testing heteroscedasticity

index, and gold. All assets also showed positive asymmetry, which indicates that positive returns were more frequent than negative ones. Excess kurtosis estimates also indicated that all assets have a leptokurtic distribution (a stylized fact in financial markets), which indicates heavy tails, and more frequent abnormal returns compared to the normal distribution.

The Elliott, Rothenberg, and Stock (ERS) unit root test by Elliott et al. (1996) indicates the rejection of the null hypothesis of non-stationarity in all assets, which implies not rejecting the stationarity of the returns of the series. The serial autocorrelation Q tests and ARCH/GARCH errors Q2 tests were also significant, which supports further investigation of the interrelationship between returns or volatilities between assets considered via QVAR returns, according to Fisher and Gallagher (2012). Table 1 presents the main descriptive statistics and the results of Pearson's correlations, where significant positive correlations were found between the assets considered. Thus, the descriptive statistics indicated in Table 1, as well as the estimated correlation coefficients, support the empirical strategy of estimating the volatility interrelation between cryptos, stock indexes, and commodities, through a QVAR model by Chatziantoniou et al. (2021).

Results and discussion

We present here the main results based on QVAR connectedness described earlier in Sect. "Econometric methods" for middle quantile (Sect. "Results and discussion for middle quantile"), lower quantile (Sect. "Results and discussion for lower quantile"), and upper quantile (Sect. "Results and discussion for upper quantile"). Further, we obtained quantile variation analysis for net and total dynamic connectedness, as reported in Sect. "Dynamic connectedness by quantiles".

Results and discussion for middle quantile

The middle quantile, as denoted by quantile value $\tau = 0.5$ connotes the normal financial market situation implying that 50% of the data actually falls below the median value and obviously, the remaining data are above the median value. Thus, this is the case where market is calm as obvious changes are not experienced in market pricing. Table 2 therefore summarizes the average results for this situation, where the averaged dynamic connectedness measures for the volatility of five variables in the network, are presented. For instance, as revealed in the results table, at the normal market situation, the highest own-variance share volatility spillovers occur in the case of gold with 79.10% variance, which means that all other variables in the network account for 20.90% variations in gold forecast error. In detail, the Ethereum, Bitcoin, Brent, and SP500 indexes influence the gold market by 57.15%, 34.32%, 2.31%, and 3.92% forecast error variances, respectively at the normal market situation. In total, we see that the gold market pressurized the market network by 19.85%, and gold itself is influenced by 20.90% indicating that gold is a net receiver of volatility shocks with NET = − 1.05% when market is calm. Among the five assets, Brent received the most volatility shock transmitted from the network with a NET measure of − 3.81%. SP500 index is also a net receiver of shock (NET = − 1.56%) during the normal market situation. The fact that both gold and oil are net receivers of shocks implies the historic co-movement of the two assets as revealed in recent literature such as Yaya et al. (2016) and Gil-Alana et al. (2017). During this normal market situation, as indicated by the median quartile value, cryptocurrencies (Ethereum and Bitcoin) are the only net shock transmitters, as against Brent, gold, and SP500, which are net receivers of volatility shocks during this market condition. Bitcoin has own-variance share spillovers of 57.07%, while Ethereum has 57.15%. While Bitcoin is transmitting 48.28% spillovers to the network, Ethereum, Brent, gold, and SP500 index are transmitting 34.32%, 3.35%, 3.56%, and 5.05% spillovers,

Table 2 Average dynamic connectedness for middle quantile, $\tau = 0.5$

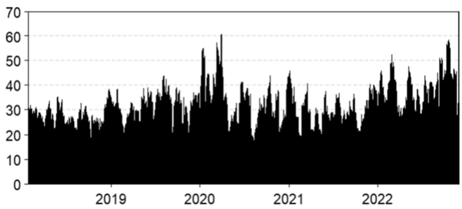
	Ethereum	Bitcoin	Brent	Gold	SP500	FROM
Ethereum	57.15	34.32	2.31	2.30	3.92	42.85
Bitcoin	34.28	57.07	2.20	2.46	3.99	42.93
Brent	3.40	3.35	77.91	6.71	8.63	22.09
Gold	3.24	3.56	5.63	79.10	8.47	20.90
SP500	4.99	5.05	8.14	8.39	73.43	26.57
TO	45.92	46.28	18.28	19.85	25.01	155.34
Inc.Own	103.07	103.35	96.19	98.95	98.44	TCI
NET	3.07	3.35	− 3.81	− 1.05	− 1.56	31.07

Notes: (i) NET, TO, and FROM are explained in the methodology; (ii) positive NET value implies shock transmitter, and negative NET value implies shocks receiver respectively, to the network. Also, Bitcoin receives up to 34.28%, 2.20%, 2.46%, and 3.99% spillovers, respectively, from Ethereum, Brent, gold, and the SP500 index. Altogether, Bitcoin receives up to 42.93% spillovers from other variables in the network, and it transmits up to 46.28%. Thus, Bitcoin becomes a net transmitter of volatility shocks with NET = 3.35% during the normal market situation. Bitcoin's price volatility has a negative relationship with gold, as observed in Yaya et al. (2022a, b). Ethereum, like Bitcoin also emerges as a predominant net transmitter of volatility shocks during normal market conditions. This suggests that fluctuations in Bitcoin and Ethereum prices can exert a substantial influence on other assets in the network. Conversely, Brent, Gold, and the SP500 index are identified as net receivers of volatility shocks, indicating their vulnerability to external market movements. These findings underscore the asymmetrical impact of market movements on different asset classes. On the other hand, Brent, gold, and SP500 are net receptors of volatility shocks, suggesting that these assets are more influenced by the movements of the other assets than in the reverse case.

The average *TCI* value at the median quartile is 31.07. This is very low, but note that this is an average value. There is a need to investigate the historical pattern of connectedness over the sampled period of 2018 to 2022 having in mind events that have influenced the connectedness, particularly for the normal market condition.

To further probe the average *TCI* value, we have in Fig. 2 the plot of the dynamic connectedness measured by the *TCI*. This gives us the evolution of the connectedness of those five financial assets over the historic period, in hours, from 2018 to 2022. In early 2020, *TCI* had its highest mark, around the 50–60 mark in the first quarter of 2020. The highest value from 2018 to 2022 is recorded during the first quarter of 2020. This is a post-COVID-19 pandemic period where market prices of assets reset and became more integrated (Coskun et al., (2023). Also, in early 2022, *TCI* gained momentum and increased in value. Early 2022 was the period of the Russia-Ukraine war, as the crisis triggered price changes in the energy and commodity markets (Adekoya et al. 2022). These periods saw increased integration among asset prices, reflecting broader economic uncertainties and market adjustments observed in previous studies. Extreme events, such as the COVID-19 pandemic or the war between Russia-Ukraine are identified as moments of higher connectivity between assets, signaling that geopolitical events and economic crises have a significant impact on the dynamics of global financial markets. Assets like Bitcoin and Ethereum, which act as net shock transmitters, may offer diversification benefits in volatile market conditions. During mid-2020 and some periods in early 2021, the connectedness of these five market prices reached a lower value, about 15.

Fig. 2 Dynamic total connectedness for middle quantile. Note: the vertical axis presents the TCI



Further probe into the net connectedness of the assets revealed in Table 2 is given based on the dynamic net total directional connectedness plotted for the five assets in Fig. 3. For Ethereum and Bitcoin, connectedness is found on the positive side of the vertical axis in most cases from 2018 to 2022, even though fewer cases are observed where connectedness is in the negative vertical axis scale. A closer look also shows that the connectedness becomes stronger from 2020 to 2022 compared to the early 2018 case. This further supports the assertion by Coskun et al., (2023) that markets become more integrated and co-integrated after the global health crisis. Gold, Brent, and SP500 index have most instances of connectedness in the negative part of the vertical axis, justifying the results of average net connectedness reported in Table 2, though Brent is a stronger net shock receiver during the normal market situation compared to gold and SP500 stock. In the post-COVID-19 period (2020—2022), Brent and SP500 indexes were more hit by shocks during this period than during the earlier period such as 2018 to early 2020. Brent market has been a consistent net receiver of shocks during the normal market compared to gold and SP500 stock, thus, with the average net value of − 3.81 as reported in Table 2.

Figure 4 presents the net pairwise directional connectedness (NPDC) in the normal market situation. The results allow us to highlight that: (i) The net connectedness between a net transmitter (Bitcoin or Ethereum) and a net receiver (Brent, gold, or SP500) in the NPDC pairs plotted in Fig. 4 (Ethereum – Brent, Ethereum – Gold, Ethereum – SP500, Bitcoin – Brent, Bitcoin – Gold, and Bitcoin – SP500 pairs), is mostly found on the positive side of the vertical axis in most cases during the sampled period.; (ii) Between Ethereum and Bitcoin (Ethereum-Bitcoin), the dominance of the NPDC is not obvious as connectedness is mixed between positive and

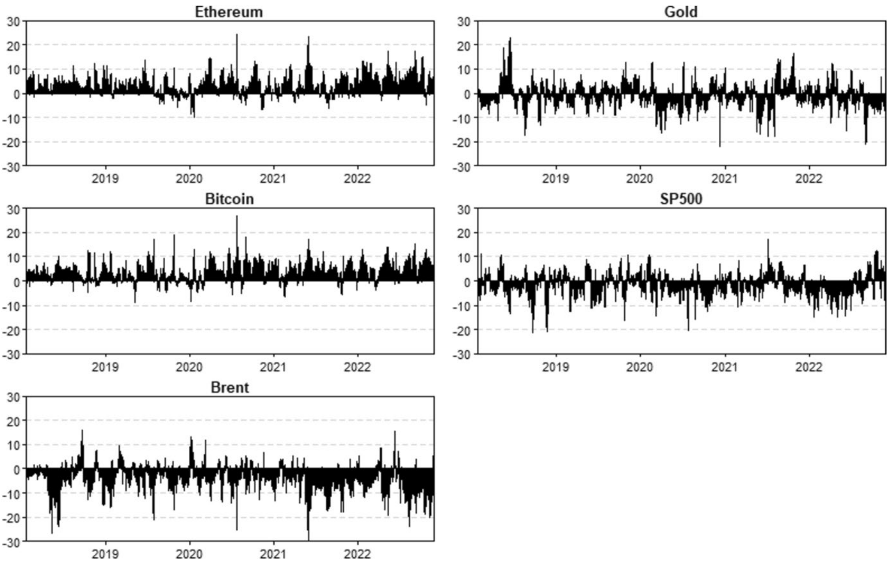


Fig. 3 Net total directional connectedness for middle quantile. Note: the vertical axis on each graph represents the value of the net total directional connectedness

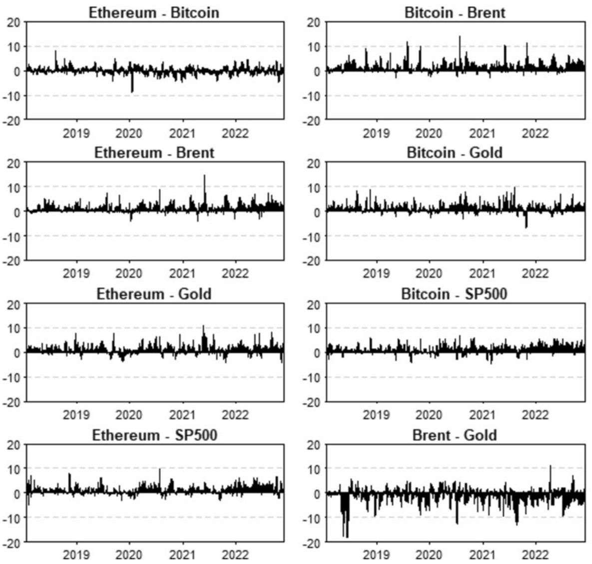
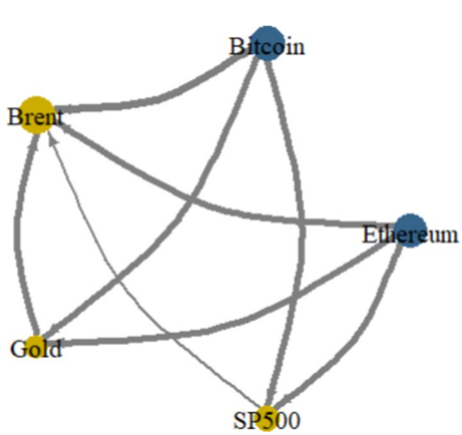


Fig. 4 Net pairwise directional connectedness for middle quantile. Note: the vertical axis on each graph represents the value of the net pairwise directional connectedness (NPDC) in the normal market situation

negative vertical axes; (iii) In the case of the three net receivers (Brent, Gold, and SP500), with the pairs: Brent – Gold, Brent – SP500, and Gold – SP500, we observe the dominance of Brent on gold as a net receiver of shocks. Thus, net connectedness is found mostly on the negative side of the axis. In the case of Brent – SP500 and Gold – SP500, this dominance is not obvious. To make the dominance and transmission of shocks between two assets clearer, we use the network plot obtained from NPDC.

Figure 5 depicts, based on the NPDC for the middle quantile, the plotted network. The BLUE-coloured assets in the plot are the net shocks transmitting assets, while

Fig. 5 Network plots based on Net Pairwise Directional Connectedness for middle quantile. Notes: (i) The blue-coloured assets are the net shocks transmitting assets; (ii) the gold-coloured assets are the net shocks receiving assets; (iii) The spillover magnitude's strength or weakness is determined by the node's size



GOLD-coloured ones are the net shocks receiving assets. The node's size determines the spillover magnitude's strength or weakness. Recall from Table 2 that Bitcoin and Ethereum have been found as the only net shock transmitters during normal market condition, i.e., for the middle quantile analysis. We can see in the plot that Ethereum can transmit shocks of similar magnitude to Brent, gold and SP500, while it cannot transmit shock to Bitcoin (as the connection line between Ethereum and Bitcoin is not joined). Ethereum also transmits shocks of similar magnitude to Brent, gold, and SP500 as well in their respective pairs Ethereum-Brent, Ethereum-gold, and Ethereum-SP500. This suggests that changes in Ethereum prices can significantly influence these assets, contributing to their overall volatility. While SP500 transmits shocks of small magnitude to Brent, and gold transmits shocks of large magnitude to Brent (indicating a stronger influence during market fluctuations), even though gold and SP500, as well as Brent remain the three net shocks receivers during the normal market situation given as middle quantile's case.

Our findings indicate that cryptocurrencies, particularly Bitcoin and Ethereum, are net transmitters of volatility shocks, highlighting their significant influence on other asset classes. This behavior suggests that during periods of market stress, cryptocurrencies may not serve as safe-haven assets but rather contribute to market instability. This insight is critical for investors considering diversification strategies, especially in volatile market conditions.

Results and discussion for lower quantile

Lower quantile such as $\tau = 0.10$ is the case where 10% of the data are actually falls in the bearish state of the financial indexes. Thus, this is the period of intense downturns. Based on the results in Table 3, the volatility in the five markets at this stage co-move more than as it was in the normal market, as revealed by the high *TCI* of 53.00. This suggests that market shocks propagate more extensively among assets during periods of market downturns, such as observed during the COVID-19 pandemic and the Russia-Ukraine crisis in early 2022. The own-variance share spillovers have reduced in magnitude in all five, for example,

Table 3 Average dynamic connectedness for lower quantile, $\tau = 0.10$

	Ethereum	Bitcoin	Brent	Gold	SP500	FROM
Ethereum	42.81	30.41	8.55	8.36	9.87	57.19
Bitcoin	30.78	43.39	8.07	8.19	9.57	56.61
Brent	10.09	9.48	50.41	14.03	16	49.59
Gold	9.91	9.66	13.99	50.51	15.93	49.49
SP500	11.03	10.62	15.29	15.17	47.89	52.11
TO	61.81	60.17	45.9	45.74	51.37	264.99
Inc.Own	104.61	103.56	96.31	96.26	99.26	TCI
NET	4.61	3.56	– 3.69	– 3.74	– 0.74	53.00

Notes: (i) NET, TO, and FROM are explained in the methodology; (ii) positiveNET value implies shock transmitter, and negative NET value implies shocks receiver

Ethereum reported 57.15% as the own-variance share of volatility spillovers at the normal market, while this has reduced to 42.81% in the bear market case. Reductions in the own-variance share spillovers allow for stronger inter-connectedness with others and among variables. Thus, a higher connectedness index at the bear market phase. In bearish markets, the elevated TCI highlights the intense interconnection between assets as market stress increases. This finding is consistent with the notion that connectedness is not static but varies significantly across different quantile levels, reflecting the underlying market conditions. The quantile connectedness framework is thus crucial in revealing these dynamics, which are often masked when using aggregate measures that do not account for the distributional properties of returns.

Both Ethereum and Bitcoin still remain the net transmitters of volatility shocks while Brent, gold, and SP500 remain the net receiver of shocks. Bitcoin and Ethereum transmit volatility shocks to other assets, albeit with reduced own-variance share spillovers compared to normal markets. This indicates that movements in cryptocurrency prices can amplify market volatility across the financial network. The remaining assets emerge as net receivers of volatility shocks during bearish phases, highlighting their heightened sensitivity to external market fluctuations, possibly due to their roles as commodities heavily influenced by economic uncertainties and geopolitical tensions.

During bearish market conditions, the increased connectivity and stronger spillovers among assets can be attributed to panic selling and flight-to-quality phenomena. Investors typically liquidate riskier assets like cryptocurrencies and seek refuge in safer assets such as gold, though the study shows that even gold acts as a net receiver of shocks in such conditions. This behavior is consistent with the financial contagion theory, which suggests that during times of crisis, correlations between asset classes increase, leading to more significant volatility spillovers.

Figure 6 presents the dynamics of the total connectedness index for the bear market phase, as it is observed that those five markets experienced the strongest connectedness during the COVID-19 pandemic around February-April 2020. In early 2022, there is another obvious upsurge, induced by the energy/commodity issue during the Russia-Ukraine war.

Looking at the net directional connectedness plots in Fig. 7, Ethereum and Bitcoin are still the net shock transmitters during the bear market, meaning there is a strong relationship between these cryptocurrencies in transmitting shocks. The gold market further becomes a stronger net receiver of shocks during this market

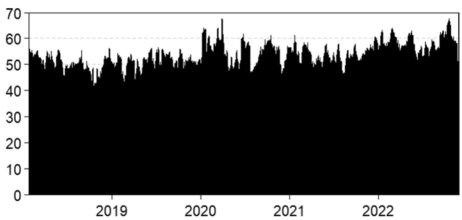


Fig. 6 Dynamic total connectedness for lower quantile. Note: the vertical axis presents the TCI

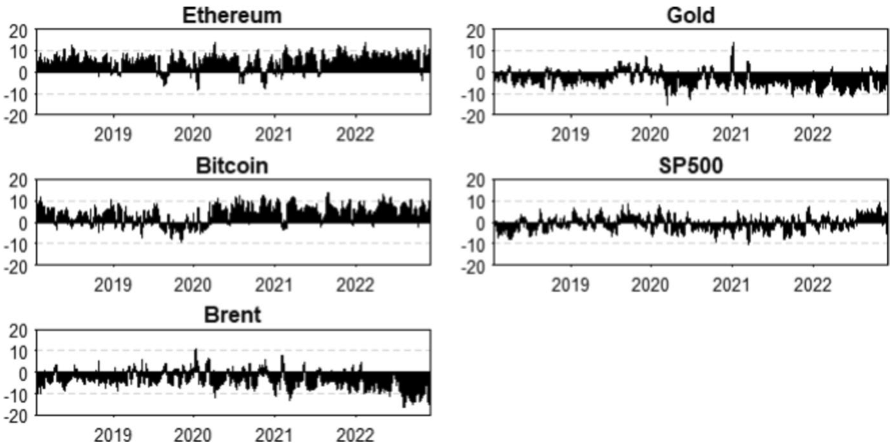


Fig. 7 Net Total Directional Connectedness for lower quantile. Note: the vertical axis on each graph represents the value of the net total directional connectedness

phase when compared with its situation during the normal market. Thus, Brent and gold are two strong net receivers of shocks with average net values of about − 3.6 to − 3.7.

In terms of net pairwise connectedness, we are very interested in the following pairs: Ethereum-Brent, Ethereum-gold, Ethreum-SP500, Bitcoin-Brent, Bitcoin-gold, and Bitcoin-SP500. It is observed that Ethereum and Bitcoin dominated their pairs as the cryptocurrencies are generally found in the positive vertical axes of the plots in Fig. 8, except on a few occasions during the COVID-19 price shocks in early 2020. Also, there is no domination of either Brent or gold in Brent-gold pairs. For Brent-SP500, it is observed in the plot in Fig. 8 that SP500 dominates Brent

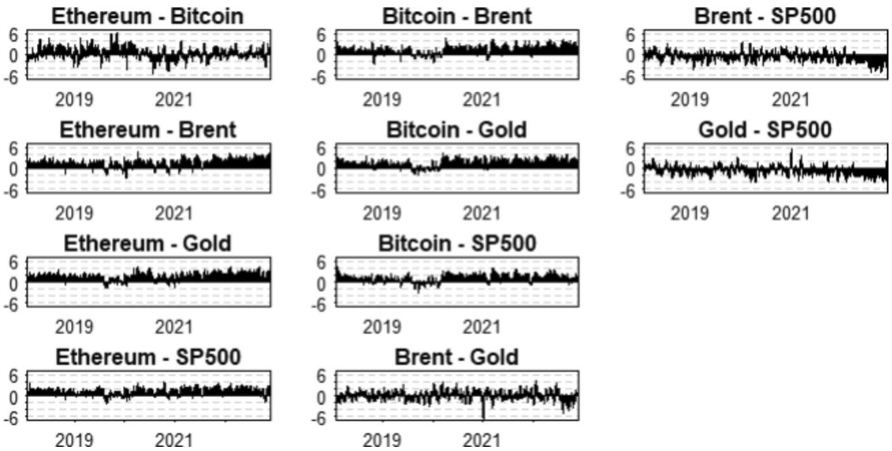


Fig. 8 Net pairwise directional connectedness for lower quantile. Note: the vertical axis on each graph represents the value of the net pairwise directional connectedness (NPDC) in bear market situation

in the connectedness as the plot moved majorly in the negative vertical axis side, implying the weaker net receiving tendency for shocks for Brent as compared to that of SP500. Similarly, in the Gold-SP500 pair in Fig. 8 again, gold has a weaker net shock receiving tendency compared to SP500. Then, what of Brent and gold? As revealed in their average net value in Table 3, as given in the dynamic net directional connectedness in Fig. 6, and as indicated in the paired net dynamic connectedness in Fig. 8, neither Brent nor gold dominates the other in the network of connectedness during the bear market phase.

Figure 9, therefore, gives the network plot. We can see in the plot that Ethereum can transmit shocks to Brent, gold, and SP500, while it cannot transmit shocks to Bitcoin (as the connection line between Ethereum and Bitcoin is not joined). Also, Brent cannot transmit shocks to gold, nor can gold transmit shocks to Brent, as the line is also not joined. Thus, Ethereum-Bitcoin and Brent-gold pairs shock dominations have been initially detected in the NPDC in Fig. 8. Further, it is clearer that Ethereum transmits shocks of similar magnitude to Brent and gold, while lesser shock is transmitted to SP500 stock. Bitcoin transmits shocks of similar magnitude to Brent, gold, and SP500.

Results and discussion for upper quantile

At the upper quantile where more than 90% of the data are at the bull state, i.e., $\tau = 0.90$, it is observed in Table 4 that the connectedness becomes the strongest for the five asset prices at this bull phase with a *TCI* value of 66.61. This suggests that volatility shocks propagate extensively among assets, indicating a period of heightened market integration and synchronized movements among asset prices. During bullish phases, the sharp increase in TCI suggests a high degree of market integration, where assets move more synchronously. The use of quantile connectedness in this context allows us to observe how connectedness intensifies in periods of market optimism, potentially leading to higher systemic risk. This method is particularly valuable for capturing the non-linear dependencies that emerge during such phases, offering deeper insights into the propagation of shocks across the financial network.

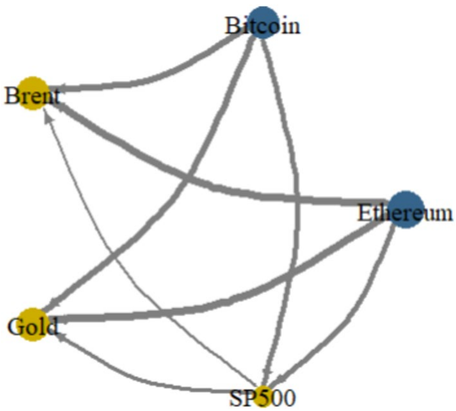


Fig. 9 Network plots based on Net Pairwise Directional Connectedness for lower quantile. Notes: (i) The blue-coloured assets are the net shocks transmitting assets; (ii) the gold-coloured assets are the net shocks receiving assets; (iii) The spillover magnitude’s strength or weakness is determined by the node’s size

Table 4 Average dynamic connectedness for upper quantile, $\tau = 0.90$

	Ethereum	Bitcoin	Brent	Gold	SP500	FROM
Ethereum	32.94	25.31	13.37	13.32	15.06	67.06
Bitcoin	25.51	33.27	12.95	13.32	14.95	66.73
Brent	14.37	13.91	33.02	18.8	19.91	66.98
Gold	14.01	13.88	17.77	34.84	19.5	65.16
SP500	14.55	14.35	18.87	19.37	32.86	67.14
TO	68.44	67.45	62.96	64.8	69.42	333.07
Inc.Own	101.37	100.73	95.98	99.64	102.28	TCI
NET	1.37	0.73	– 4.02	– 0.36	2.28	66.61

Notes: (i) NET, TO, and FROM are explained in the methodology; (ii) positive NET value implies shock transmitter, and negative NET value implies shocks receiver

The own-variance share spillovers in the table diagonal are generally low compared to their corresponding values in the case of lower quantiles in Table 3. Thus, bull market analysis results indicate the lowest own-variance share spillovers compared to that of normal and bear markets. This fact makes the bull market to be weak such that a small shock can cause a destabilization in the market. Further, Ethereum and Bitcoin are still net transmitters of shocks but with weak net value, and Ethereum transmitting more shocks in the network to other assets than Bitcoin. This evidence the higher influence of Ethereum during bullish phases. SP500 stock now becomes the main net transmitter of shocks as it is found to be stronger than the two cryptocurrencies, having a net value of 2.28. Thus, net transmitters at the bull market phase are SP500, Ethereum, and Bitcoin. Therefore, Brent and gold remain the net receivers of volatility shocks, while Brent is a stronger net receiver of shocks than gold. This suggests that Brent is more susceptible to external market movements, possibly due to its ties to global economic conditions and geopolitical events affecting energy markets.

The findings that the S&P500 becomes a main net transmitter of shocks during bullish markets reflect the broader economic optimism and increased risk appetite among investors. As stock prices surge, the positive sentiment spills over to other asset classes, including cryptocurrencies and commodities. This aligns with the wealth effect theory, where increased stock market wealth boosts investor confidence and spending, thereby affecting other markets. The relatively lower own-variance share spillovers indicate a more integrated market environment, with shocks more evenly distributed across asset classes.

Figure 10, the dynamic total connectedness for the bullish market situation shows that connectedness of volatility has been short-lived during in the hourly sampled period between 2018 and 2022.

Figure 11 shows plots of net dynamic connectedness for the bull market case. These plots show that Ethereum, Bitcoin, and SP500 only dominate the market sporadically, i.e., in short time intervals across the sampled period. The plots for net pairwise dynamic connectedness in Fig. 12 further confirm this. Meanwhile, the network plot based on NPDC will make the domination clearer.

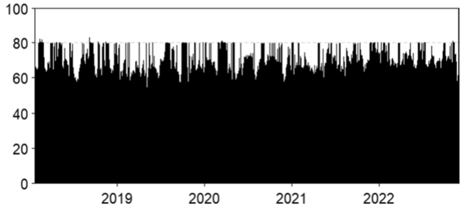


Fig. 10 Dynamic Total Connectedness for upper quantile. Note: the vertical axis presents the TCI

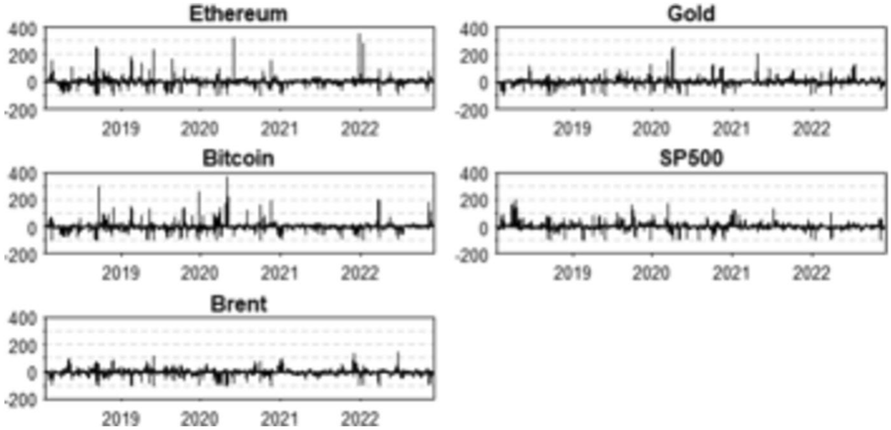


Fig. 11 Net Total Directional Connectedness for upper quantile. Note: the vertical axis on each graph represents the value of the net total directional connectedness

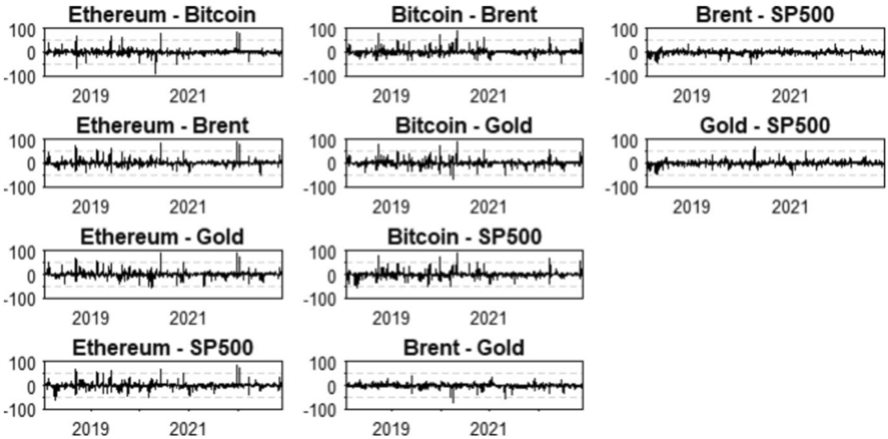


Fig. 12 Net pairwise directional connectedness for upper quantile. Note: the vertical axis on each graph represents the value of the net pairwise directional connectedness (NPDC) in the bull market situation

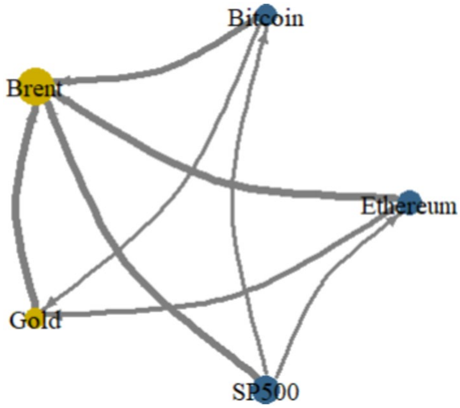


Fig. 13 Network plots based on Net Pairwise Directional Connectedness for upper quantile**.** Notes: (i) The blue-coloured assets are the net shocks transmitting assets; (ii) the gold-coloured assets are the net shocks receiving assets; (iii) The spillover magnitude's strength or weakness is determined by the node's size

As it is observed in the NPDC-based network plot in Fig. 13 for the upper quantile's case, in the Bitcoin-Brent, Bitcoin-gold, and Bitcoin-SP500, it is clear that Bitcoin actually transmits shocks to Brent, gold, and SP500 in their respective pairs, with larger shock transmitted to Brent in its pair with Bitcoin. Ethereum transmits shocks to Brent, gold and SP500 in Ethereum-Brent, Ethereum-gold, and Ethereum-SP500 pairs with larger shock transmitted to Brent. Also, SP500 transmits larger shocks to Brent, and this stock also transmits shocks to Bitcoin and Ethereum.

Dynamic connectedness by quantiles

The variation in connectedness across quantiles highlights the differential impact of market conditions on asset volatility. In particular, the high connectedness during the lower and upper quantiles suggests heightened systemic risk during market downturns and upturns. This phenomenon aligns with the theory of financial contagion, where extreme market movements lead to increased correlations among asset classes, exacerbating market-wide volatility.

Table 5 Net and TCI for various quantile (τ) values

τ	Ethereum	Bitcoin	Brent	Gold	SP500	TCI
0.1	4.61	3.56	– 3.69	– 3.74	– 0.74	53.00
0.2	4.63	4.01	– 3.96	– 3.76	– 0.92	48.35
0.3	4.47	4.18	– 4.15	– 3.37	– 1.14	42.82
0.4	3.89	3.98	– 4.08	– 2.41	– 1.37	36.65
0.5	3.07	3.35	– 3.81	– 1.05	– 1.56	31.07
0.6	2.83	2.99	– 4.13	0.13	– 1.82	28.30
0.7	3.37	3.2	– 4.92	0.76	– 2.42	30.89
0.8	4.82	4.26	– 6.66	– 0.62	– 1.79	44.39
0.9	1.37	0.73	– 4.02	– 0.36	2.28	66.61

To check for the consistency of connectedness across quantiles, we obtained various *TCI* and NET values for quantile values, $\tau = 0.1, 0.2, \ldots, 0.9$ as summarized in Table 5. It is observed that Ethereum and Bitcoin have been the consistent net transmitters of shocks across different quantile values with Ethereum controlling the market volatility dynamics at the extreme quantile values. Thus, Ethereum dominates and drives the Bitcoin market at the bear and bull market phases while Bitcoin only dominates in the normal market situation. Several papers have shown these dynamics of Bitcoin driving other cryptocurrencies including Ethereum but they assumed normal market situation only in their analysis (see Yaya, Ogbonna, and Olubusoye, 2019, among others). Brent, gold, and SP500 are net transmitters of shocks across the quantile values except at $\tau = 0.9$ for the SP500 index where it dominated the entire market volatility dynamics. Also, gold seized in being a net receiver of shocks at quantile values, $\tau = 0.6 - 0.7$. Towards the extreme quantile values, *TCI*s are larger, say from 50–70 while around the median quantile, *TCI*s are about 28–36. The distribution of *TCI* therefore, further justifies the usage of quantile connectedness to study the dynamic movement of the five assets because traditional mean-based measures of connectedness may obscure critical variations that occur under different market conditions, particularly in extreme scenarios where tail risks dominate. By employing a quantile approach, this study captures the nuanced shifts in connectedness that occur across varying market states, from calm to turbulent periods. This approach is particularly effective in highlighting how assets behave differently under stress compared to normal conditions, providing a more comprehensive understanding of market dynamics.

The consistent finding that Ethereum and Bitcoin are net transmitters across different quantiles highlights their role as significant influencers in the financial market's volatility dynamics. This can be explained by the liquidity and high trading volumes associated with these cryptocurrencies, making them pivotal in the transmission of market shocks. The higher TCI values at extreme quantiles suggest that market conditions characterized by extreme bullishness or bearishness lead to greater interconnectedness and systemic risk, a concept supported by systemic risk theory in financial economics.

Concluding remarks

In modern investment markets, some assets play a prominent role, such as cryptocurrencies, which have been gaining increasing importance since the launch of Bitcoin, as well as traditional investment assets, such as gold and oil, two fundamental commodities in finance. Stock indices, like the S&P500, reflect the financial health of publicly traded companies and are crucial for the long-term economic growth of any modern economy.

A deeper understanding of the intricate complex relationships between such fundamental assets is crucial for a myriad of agents, such as private investors, public policymakers and academics. The COVID-19 pandemic and the subsequent outbreak of war between Russia and Ukraine have significantly altered market expectations and the global geopolitical order, highlighting the need for a comprehensive analysis of financial interdependencies.

This present paper investigates the interdependencies of volatility among cryptocurrencies, gold, oil, and US stocks using the quantile method. Specifically, Ethereum and Bitcoin are analysed alongside other assets in the network of connectedness. The quantile connectedness approach of Chatziantoniou et al. (2021) is set up in the VAR framework that allows it to provide information for market volatility dynamics in the bear, bull, and normal market conditions, as denoted by the lower extreme quantile, upper extreme quantile, and median value of quantile.

Results indicate that, in a normal market situation, the connectedness is the weakest compared to bear and bull markets. Bitcoin is stronger than Ethereum as a net transmitter of volatility shocks during normal conditions, whereas Ethereum becomes stronger during bear and bull phases. Brent, gold, and SP500 stock are net receivers of shocks in the network, with Brent receiving more shocks than gold at the bull and normal market cases. The historic comovement of Brent oil and gold, as noted in recent research such as Yaya et al. (2016) and Gil-Alana et al. (2017), among others, is further justified by these findings. Network plot based on the net pairwise directional connectedness measures further indicate that shocks are not transmitted between Bitcoin and Ethereum at any phase of the market.

Our findings reveal distinct patterns of volatility interdependence across the assets studied, with variations observed under different market conditions. While in normal markets, cryptocurrencies, such as Bitcoin and Ethereum, act as net transmitters of shocks, this dynamic shifts in bear and bull markets. In bear markets, both cryptocurrencies remain net transmitters, but the overall connectedness increases significantly, reflecting heightened market stress. Similarly, in bull markets, the S&P500 emerges as a more prominent transmitter of shocks, particularly influencing traditional commodities like gold and oil, which continue to serve as net receivers of shocks.

The TCI and NET results underscore the critical role that extreme market conditions play in amplifying the interconnectedness among these assets. These results not only align with previous studies but also highlight unique contributions, particularly the influence of intraday data in capturing real-time market dynamics. The insights from the extreme quantiles provide a deeper understanding of market dynamics during periods of financial turmoil, offering valuable guidance for risk management and policy formulation. Specifically, investors can leverage these insights to optimize their portfolio strategies, particularly by reducing exposure to assets that act as net receivers of shocks during volatile market conditions. For instance, during bull markets, the S&P500's role as a transmitter of shocks to commodities like gold and oil suggests that a balanced portfolio may benefit from reducing reliance on equity markets during periods of economic expansion. Policymakers, on the other hand, can utilize these findings to monitor systemic risks more effectively. By identifying assets that are prone to receiving shocks, such as Brent oil and gold during bear and bull markets, regulatory bodies can design targeted interventions to mitigate potential market disruptions. Additionally, understanding the distinct behavior of cryptocurrencies as volatility transmitters can inform the development of regulatory frameworks tailored to the unique risks posed by digital assets, thereby enhancing overall financial stability.

Understanding the roles of cryptocurrencies, traditional commodities like gold and oil, and stock indices in transmitting volatility shocks is vital for portfolio diversification and risk management strategies. Investors can adjust their portfolios based on the observed net transmitter and receiver roles of these assets across different market phases. Policymakers can use the obtained insights to assess systemic risks and formulate policies that aim to stabilize financial markets during volatile periods. For instance, identifying assets that are more vulnerable to receiving shocks can inform regulatory measures or intervention strategies.

However, this study is subject to certain limitations that should be acknowledged. First, while the use of intraday data provides a detailed view of market dynamics, it also introduces the challenge of managing noise, which could affect the clarity of the relationships observed. Additionally, the study focuses on a specific set of assets, primarily cryptocurrencies, gold, oil, and US stocks. While these are key assets in the financial markets, the exclusion of other important commodities, currencies, and regional stock indices may limit the generalizability of the findings. Future research could address these limitations by incorporating a more diverse set of financial instruments and further refining the methods to better filter and interpret the nuances captured in high-frequency data.

As a research agenda, we suggest deepening the present study with intraday data of higher frequencies, to verify how very short-term noise could affect some of the conclusions of this text. Another suggestion would be to include a broader class of commodities, such as food commodities, to verify whether there is a relevant distinction in the transmission between the categories of commodities. Such discussions are beyond the scope of this text and are left as possibilities for future work.

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Availability of data and materials Publicly available datasets were analyzed in this study, available at: https://forexsb.com/historical-forex-data.

Code availability The code used in this study are available upon reasonable request from the corresponding author.

Declarations

Conflict of 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.

Ethical approval This article does not contain any studies with human participants performed by the author.

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