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Heterogeneity in the volatility spillover of cryptocurrencies and exchanges

Meiyu Wu[1], Li Wang[1] and Haijun Yang[1,2*]

*Correspondence:
navy@buaa.edu.cn

[1] School of Economics and Management, Beihang University, No.37 Xueyuan Road, Haidian District, Beijing 100191, China
[2] Key Laboratory of Complex System Analysis, Management and Decision, Beihang University, Ministry of Education, Beijing, China

Abstract

This study examines the volatility spillovers in four representative exchanges and for six liquid cryptocurrencies. Using the high-frequency trading data of exchanges, the heterogeneity of exchanges in terms of volatility spillover can be examined dynamically in the time and frequency domains. We find that Ripple is a net receiver on Coinbase but acts as a net contributor on other exchanges. Bitfinex and Binance have different net spillover effects on the six cryptocurrency markets. Finally, we identify the determinants of total connectedness in two types of volatility spillover, which can explain cryptocurrency or exchange interlinkage.

Keywords: Cryptocurrency, Cryptocurrency exchanges, Volatility spillover, Heterogeneity of volatility spillover

Introduction

Cryptocurrencies can be cross-listed on various exchanges, and research interest in the heterogeneity of cryptocurrency volatility spillovers across exchanges has recently emerged. The same portfolio can express diverse volatility spillover mechanisms across different exchanges, owing to the different features of trading regulations, trading attributions (Dimpfl and Peter 2021), and exchange reserves (Hoang and Baur 2021). Investors and regulators must identify the volatility connectedness[1] among cryptocurrencies on different exchanges. The volatility spillover of cryptocurrencies on one exchange can provide investors with potential diversification benefits at a specific venue based on net pairwise directional connectedness, which might offer a unique premium compared with other exchanges. Furthermore, the volatility spillover of cryptocurrencies reveals the net emitting effect of future uncertainty (Diebold and Yılmaz 2014), which can help supervisors perform risk management for specific exchanges. However, the current literature on cryptocurrency volatility spillovers sets the scope as the global market, except for one specific exchange (Caporale et al. 2021). The volatility spillover of cryptocurrencies stems from a special crisis and is driven by investor trading (Diebold and Yılmaz 2014), which could differ across exchanges. The heterogeneity of exchange features should not be neglected when analyzing the mechanism underlying cryptocurrency volatility spillovers. Baur and Hoang (2022) have investigated the volatility connectedness

[1] We use the terms "volatility spillover" and "volatility connectedness" interchangeably.

among ten cryptocurrencies in Binance and Bitfinex, emphasizing a similar connectedness estimation for both exchanges rather than the volatility transmission. In contrast, our study aims to explore the volatility transmission in representative exchanges, which can fill the gap in knowledge on the heterogeneity of cryptocurrency volatility spillovers.

Triggered by the same cryptocurrency exhibiting various features across different exchanges, the heterogeneity of exchange volatility spillovers is under debate. The price discrepancy has been observed across exchanges (Baur and Dimpfl 2020; Borri and Shakhnov 2019; Dimpfl and Peter 2021; Giudici and Abu-Hashish 2019; Tsang and Yang 2020). The price difference creates an arbitrage opportunity for investors to obtain excess profits by trading across exchanges (Augustin et al. 2023; Makarov and Schoar 2021). When arbitrage occurs, the price co-movement across markets causes volatility spillover (Liu and Gong 2020), which can exacerbate the volatility of the cryptocurrency market. Constructing the exchange volatility spillover network in specific cryptocurrency markets is beneficial for regulators when identifying the exchange that serves as the source of the contagion. An exchange volatility network can also provide quantitative analysis for arbitrageurs to construct portfolios based on the high-/low- connected exchange pairs. Studies have investigated the return or volatility transmission among Bitcoin (BTC) exchanges (Alexander and Heck 2020; Carol et al. 2021; Dimpfl and Elshiaty 2021; Dyhrberg 2020; Gillaizeau et al. 2019; Giudici and Abu-Hashish 2019; Hoang and Baur 2021; Ji et al. 2021). Nevertheless, research remains scarce on volatility generation across exchanges (Dimpfl and Elshiaty 2021). With the development and acceptance of Ether and Litecoin, the volatility transmission of altcoins should also be considered. By examining the volatility transmission in altcoin markets with high capitalization, our study can enrich the current research on exchange volatility spillovers.

This study examines the heterogeneity of exchange volatility spillovers within one cryptocurrency market and the cryptocurrency volatility spillovers within an exchange in both the time and frequency domains. We focus on specific exchanges, rather than global cryptocurrency markets, to provide practical suggestions for regulators, arbitrators, and diversified investors. Based on the high-frequency trading data and connectedness approach Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) have proposed, we examine the connectedness matrix among representative exchanges (cryptocurrencies) statically and dynamically. Volatility spillover reveals the net transmitter and net pairwise connectedness, which can benefit cryptocurrency market participants by identifying the risk core and highly related pairs. Volatility spillover estimation is also important for regulators when formulating risk minimization strategies.

Volatility spillover is a method for measuring contagion among interlinked economies, from pairwise to system-wide. With this method, a spillover matrix is constructed to reveal which entities emit (receive) spillover to (from) others on average and in what relative contributions. A set of dynamic spillover indices can illustrate the time-varying nature of contagion risk among entities. This method has been widely applied in research on risk contagion in traditional financial markets (Diebold and Yilmaz 2012; Diebold and Yılmaz 2014), financial institutions (Diebold and Yılmaz 2014), and 21st-century technological assets (Le et al. 2021). Compared with traditional financial markets, cryptocurrencies can be listed on different exchanges (Augustin et al. 2023), which provides us with a unique market to explore how cryptocurrencies export volatility across different venues. Our empirical results can help differentiate between theoretical explanations of volatility spillovers in both traditional assets and newly developed cryptocurrencies (Liu et al. 2022). Cryptocurrencies have more volatile prices than traditional assets. This inherently volatile asset can transmit its volatility to traditional equity exchanges, commodity and foreign exchange markets, Fintech companies, and green bonds (Dyhrberg et al. 2018; Grobys and Sapkota 2019; Kumar et al. 2022; Le et al. 2021). Cryptocurrency is generally considered to have evolved into an investment rather than a medium of exchange (Maghsoodi 2023), which enhances its interconnection and contagion with traditional financial markets. Therefore, understanding the dynamics of cryptocurrency volatility spillovers is essential for managing investor risk and creating public policy.

Correlation-based measures have revealed the increasing interconnection among fast-growing cryptocurrency markets. Griffin and Shams (2020) combined clustering algorithms and capital flow analysis to reveal that Tether flows can largely explain Bitcoin prices. Scholars have also explored higher linkages among cryptocurrencies based on methodologies such as GARCH type, the detrended cross-correlation analysis correlation coefficient, and wavelet coherence (Caporale et al. 2021; Ferreira and Pereira 2019; Katsiampa et al. 2019, 2022; Qiao et al. 2020; Xu et al. 2021). The connectedness measures of Diebold and Yilmaz (2009, 2012, 2014) have been widely used to reveal the more substantial spillover among cryptocurrencies for their pairwise informative meaning and close linkage to network theory (Baruník and Křehlík, 2018). Koutmos (2018) has revealed the growing interdependence among cryptocurrencies based on the work of Diebold and Yilmaz (2009), applying the Cholesky decomposition of the covariance matrix. Yi et al. (2018) have applied the LASSO-VAR and connectedness estimation method of Diebold and Yılmaz (2014), finding the typical 52 cryptocurrencies grew closer from December 2016 to April 2018. Antonakakis et al. (2019) investigated the transmission mechanism among nine cryptocurrencies based on TVP-FAVAR and the same connectedness approach, finding that the market gradually becomes more complex. Li and Yang (2022) examined the return connectedness between leading cryptocurrencies and memecoins based on TVP-VAR, revealing that leading coins influence memecoins by falling, whereas memecoins drive leading coins by rising. Hasan et al. (2022) introduced liquidity connectedness based on Diebold and Yilmaz (2012) to explore the increasing interconnections among cryptocurrencies. Therefore, the connectedness framework of Diebold and Yilmaz (2009, 2012, 2014) can effectively reveal the risk spillover mechanism of cryptocurrencies in the time domain.

The decomposition of volatility spillover into the frequency domain can provide insights for cryptocurrency market participants. Scholars have applied the modified method of Diebold and Yilmaz (2012), as proposed by Baruník and Křehlík (2018) to decompose the time-domain results into frequencies. This frequency decomposition can measure long-, medium-, and short-run connectedness to provide precise suggestions for diverse-term investors. Mensi et al. (2021) employed a frequency-decomposed connectedness network across cryptocurrencies from August 2015 to February 2019, finding heterogeneity in volatility spillovers in the short, medium, and long term. A stronger short-term volatility spillover implies asymmetry behavior in risk spillover. Kumar et al. (2022) found structural changes in volatility connectedness among ten major cryptocurrencies during the COVID-19 outbreak, reporting that the short-term component of volatility connectedness increased during the COVID-19 period. Hence, the frequency-decomposed connectedness measurement proposed by Baruník and Křehlík (2018) can provide more information in the frequency domain.

Furthermore, some researchers are interested in identifying the determinants of total connectedness. Ji et al. (2019) found that the cryptocurrency trading volume, global finance, investment substitution, and market uncertainty affect cryptocurrency market integration. Andrada-Félix et al. (2020), in applying a general-to-specific stepwise modeling strategy to select the determinants of total connectedness within cryptocurrencies, have found that the cryptocurrency-specific variables covering market capitalization and trade volume of sample cryptocurrencies overwhelmingly account for total connectedness. Charfeddine et al. (2022) introduced a linear regression model to investigate the determinants of total connectedness considering the trading volume of cryptocurrency, traditional macroeconomic and financial factors into consideration. The above-mentioned studies indicate that the total connectedness in cryptocurrency volatility spillovers is sensitive to financial and macroeconomic indicators. However, these studies neglect the influence of Internet concern and the underlying technology. Social media activity and blockchain performance can significantly affect the cryptocurrency market significantly (Ante 2023; Pagnotta 2021; Shen et al. 2019). Our research considers the effects of Internet concern and blockchain-related technical indicators on the total volatility connectedness of both cryptocurrencies and exchanges. We find that these indicators have diverse effects on the volatility spillovers of different exchanges (cryptocurrencies), supporting the argument that Internet concern and blockchain-related characteristics can influence cryptocurrency markets (Ante 2023; Hoang and Baur 2022).

Our study has two research objectives. The first objective is to examine the heterogeneity of cryptocurrency volatility spillovers and the exchange volatility spillovers. Heterogeneity could exist in different exchanges serving as volatility emitters or receivers in one cryptocurrency market and could be the same portfolio expressing various volatility connectedness in different exchanges. Based on high-frequency trading data acquired from Kaiko, we select six liquid cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and EOS) and four representative exchanges (Binance, OKEx, Coinbase, and Bitfinex). We use the connectedness measurement framework proposed by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) to estimate the volatility spillover in the time and frequency domains. The second objective is to explore the determinants of total connectedness obtained from estimating the volatility spillover of cryptocurrencies and exchanges. The sample period is from April 13, 2019, to January 24, 2021, which includes January 2021, when Bitcoin smashed its 2020 price record, and March 2020, when Bitcoin experienced an extreme price plunge. Our empirical findings provide insights into the volatility spillover heterogeneity of exchanges.

We address that cryptocurrencies in the same portfolio express various volatility spillovers in different exchanges. On one exchange, the selected cryptocurrencies are highly interconnected with an average total connectedness of 76.12%. The difference in volatility spillover among the four exchanges exists in XRP, which plays a net receiver role in Coinbase, but a net contributing role in the other three exchanges. The analysis based on Baruník and Křehlík (2018) reveals the frequency decomposition of cryptocurrency volatility spillover. Low frequency constitutes most of the total connectedness, indicating that investors' anticipation dominantly and durably influences spillovers. For the total connectedness in cryptocurrency volatility spillovers, the Internet concern of ETH, electricity prices in the US, and global economic uncertainty significantly affect the total connectedness.

Furthermore, we reveal the heterogeneity of exchange volatility spillovers across different cryptocurrency markets. In the six selected cryptocurrency markets, four exchanges are highly connected, with 74.7% total connectedness on average. Regarding the role exchanges play in the six coins, Coinbase continues to be the net contributor, whereas OKEx continues to be the net receiver. Bitfinex and Binance shift their contributing or receiving roles in distinct cryptocurrencies. The largest net contributors differ across the six sample cryptocurrency markets. Low frequency accounts for most of the total connectedness, and an exchange can change its emitting or receiving role with frequency and time variance. The most significant net trigger for the six cryptocurrencies also varies over time. We apply stepwise regression to select the relevant empirical determinants of total connectedness in exchange volatility spillovers. Three Proof-of-Working (PoW) coins have different indicators. BTC's total volatility connectedness is affected by exchange returns and trading volumes. In addition to the above variables, the macroeconomic effect, volatility of some exchanges, and technical indicators of ETH are also determinants of ETH's total volatility connectedness. LTC's total volatility connectedness shows persistence in the time series and is determined by the Internet concern of OKEx and LTC.

Our study contributes to the literature in two ways. First, we examine the heterogeneous volatility spillovers in the cryptocurrency market, in which the same assets listed on different venues are widely seen. This characteristic distinguishes cryptocurrency markets from traditional financial markets and provides a perfect market for examining heterogeneity in volatility spillovers from the perspective of specific exchanges. Based on 5-min high-frequency data, we explore the dynamic contagion features among cryptocurrencies and exchanges in the time and frequency domains. Crisis-sensitive volatility spillover bursts imply that distinct exchange-specific events can drive cryptocurrency and exchange volatility spillovers. Second, we enrich our understanding of the determinants of total volatility spillover in the cryptocurrency market from an exchange-based perspective. We investigate the influence of Internet concern and blockchain performance on the total volatility connectedness of both cryptocurrencies and exchanges. The different mechanisms of determinants affecting the total volatility connectedness across different venues highlight the heterogeneity in cryptocurrency and exchange volatility spillovers.

Our findings reveal the heterogeneity among exchanges in volatility spillover, which has several implications for investors and supervisors. Investors should consider the heterogeneity of volatility spillovers in the cryptocurrency market. The potential risk exchange for different coins or the most volatile assets on different exchanges can be diverse. Investors are urged to consider exchange-specific events that can influence cryptocurrency volatility spillovers at a specific venue. Moreover, the increasing popularity of cryptocurrency trading and dramatic pricing volatility have attracted the attention of regulators. On March 9, 2022, US President Biden signed an executive order to regulate cryptocurrencies and conducted a study on US Central Bank Digital Currency (CBDC).[2] Supervisors can understand the volatility spillovers of cryptocurrencies or exchanges, which is beneficial for mitigating contagion-related risks and digital currency usage (Iqbal et al. 2021; Yousaf and Ali 2020). The heterogeneous influence of factors on total volatility spillover can also inform investment decisions and policymaking. Investors should note that unregulated exchanges substantially affect exchange volatility spillovers in the BTC market. Investors and regulators must distinguish among the effects of traditional financial market factors on cryptocurrency volatility spillovers. Although the MSCI World index and S&P 500 index are stock market indicators, the prices of large- and mid-cap stocks across countries with developed markets can mitigate cryptocurrency volatility connectedness, whereas an increase in the price of large-cap stocks in the US can aggravate the connectedness of cryptocurrencies in the four exchanges. Higher Internet concern of ETH can decrease investors' fear of cryptocurrency uncertainty. Developers and regulators are encouraged to promote the widespread adoption of well-developed blockchain trading architecture to foster a cryptocurrency market and enhance investor confidence. The positive relationship between electricity prices and the total connectedness of exchanges underlines the need for a more efficient consensus to decouple energy consumption from the cryptocurrency market.

The remainder of this paper is organized as follows. Sect. "Methodology" introduces the connectedness calculation approach based on Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). Sect. "Data and preliminary analysis" presents the empirical data and provides an overview of the heterogeneity of cryptocurrency volatility across exchanges. Sect. "Empirical results" explores the volatility spillovers among different cryptocurrencies on specific exchanges, based on the connectedness decomposition matrix and network. The exchange volatility spillovers for the selected coins is also examined. Furthermore, we explore the factors affecting total connectedness. Finally, Sect. "Conclusion" summarizes the findings and provides some insights.

Methodology

This study applies time- and frequency-domain connectedness measurement approaches to analyze connectedness (Baruník and Křehlík, 2018; Diebold and Yilmaz 2012). Diebold and Yilmaz (2012) proposed a framework for conceptualizing and empirically measuring volatility connectedness from pairwise to system-wide levels, based on variance decomposition. Then, Baruník and Křehlík (2018) modified this framework for measuring connectedness by introducing heterogeneous frequency responses to shocks. These two connectedness measurement frameworks are widely used to reveal spillover mechanisms (Andrada-Félix et al. 2020; Shahzad et al. 2021; Yarovaya et al. 2016; Zhang and Hamori 2021).

Estimation of shocks in the time and frequency domains

For the time-domain connectedness estimation, Diebold and Yilmaz (2012) have introduced a generalized forecast error variance decomposition (GFEVD) into the vector

[2] https://www.whitehouse.gov/briefing-room/statements-releases/2022/03/09/fact-sheet-president-biden-to-sign-executive-order-on-ensuring-responsible-innovation-in-digital-assets/ [Accessed on 2020–5-22].

autoregression (VAR). Estimating the forecast error variance decomposition (FEVD) from generalized vector autoregression paves the way for computing connectedness.

Assume a stationary covariance K-variable VAR (p) model as follows:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t, \tag{1}$$

where y_t is the $K \times 1$ vector of the sample cryptocurrency realized volatility at time t, and Φ_i is the $K \times K$ autoregressive coefficient matrix. The vector of error terms ε_t is assumed to be white noise with a possible non-diagonal covariance matrix Σ. Equation (1) can be transformed into a moving average ($MA(\infty)$) representation, which is represented as follows:

$$y_t = \Psi(L)\varepsilon_t, \tag{2}$$

where $\Psi(L)$ is a $K \times K$ coefficient matrix of infinite lag polynomials subjected to recursion of the form $\Phi(L) = [\Psi(L)]^{-1}$. By combining the moving-average framework with the GFEVD proposed by Koop et al. (1996) and Pesaran and Shin (1998), the variance decomposition is independent on the order of the variables. The H-step-ahead GFEVD is expressed as follows:

$$\theta_{jk}^{H} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left((\Psi_h \Sigma)_{jk} \right)^2}{\sum_{h=0}^{H} (\Psi_h \Sigma \Psi_h')_{jj}}, \tag{3}$$

where the estimation of θ_{jk}^{H} is based on assessing the share of the forecast error variation of one entity owing to shocks arising elsewhere. θ_{jk}^{H} denotes the directed pairwise connectedness from cryptocurrency k to cryptocurrency j at horizon H, which represents the contribution of innovations in cryptocurrency k to cryptocurrency j's H-step forecast error variance. Its own and others' contributions are defined by the main diagonal and off-diagonal elements, respectively, in the $D^H = \left[\theta_{jk}^{H}\right]$ matrix. To straightforwardly express the contribution, each element in D^H is standardized by the row sum, which can be expressed as follows:

$$\widetilde{\theta}_{jk}^{H} = \frac{\theta_{jk}^{H}}{\sum_{k=1}^{N} \theta_{jk}^{H}}, \tag{4}$$

where $\widetilde{\theta}_{jk}^{H}$ is the contribution after standardization. Therefore, $\sum_{k=1}^{N} \widetilde{\theta}_{jk}^{H} = 1$ and $\sum_{j,k=1}^{N} \widetilde{\theta}_{jk}^{H} = N$.

Regarding the frequency-domain spillover measurement, Baruník and Křehlík (2018) employed the Fourier transform $\Psi_h : \Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ (where $i = \sqrt{-1}$) to decompose the time-domain model results into high, medium, and low frequencies. The generalized causation spectrum over frequencies $\omega \in (-\pi, \pi)$ can be expressed as follows:

$$(f(\omega))_{jk} = \frac{\sigma_{kk}^{-1} \left| (\Psi(e^{-i\omega})\Sigma)_{jk} \right|^2}{(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega}))_{jj}}, \tag{5}$$

where $\Psi(e^{-i\omega}) = \sum_h e^{-i\omega h}\Psi_h$ is the Fourier transform of the impulse response, and Ψ_h .$(f(\omega))_{jk}$ presents the contribution of shocks in cryptocurrency k to cryptocurrency j's spectrum at the ω frequency and can be interpreted as within-frequency causation. To construct the decomposition of variance decompositions to frequencies, which can be globally comparable, $(f(\omega))_{jk}$ can be weighted by the frequency share of cryptocurrency j variance as follows:

$$\Gamma_j(\omega) = \frac{(\Psi(e^{-i\omega})\Sigma\Psi\prime(e^{+i\omega}))_{jj}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Psi(e^{-i\lambda})\Sigma\Psi'(e^{+i\lambda}))_{jj}d\lambda}, \tag{6}$$

where $\Gamma_j(\omega)$ implies the dominance of cryptocurrency j at the ω frequency, which amounts to a constant value of 2π through frequencies. The frequency band is defined as $d = (a, b) : a, b \in (-\pi, \pi), a < b$. The generalized variance decomposition at frequency band d is $\theta_{jk}(d) = \frac{1}{2\pi}\int_a^b \Gamma_j(\omega)(f(\omega))_{jk}d\omega$. The effects over the entire range of frequency influences are defined as $(\theta_\infty)_{jk} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\Gamma_j(\omega)(f(\omega))_{jk}d\omega$. The scaled generalized variance decomposition can be defined as follows:

$$\widetilde{\theta}_{jk}(d) = \frac{\theta_{jk}(d)}{\sum_k \theta_{jk}(\infty)}, \tag{7}$$

where $\theta_{jk}(d)$ and $\theta_{jk}(\infty)$ are the generalized variance decompositions at frequency band d and over the entire frequency range, respectively.

Connectedness measures

For the connectedness estimation in the time and frequency domains, the FEVD matrix can be constructed based on Diebold and Yilmaz (2012) and Baruník and Křehlík (2018). The spillover effect between the two markets and the dependency of the cryptocurrencies in the system can be estimated based on the elements in the matrix.

Net pairwise directional connectedness from j to k

$\tilde{\theta}_{jk}^H$ is directed based on the definition of FEVD. The difference between $\tilde{\theta}_{kj}^H$ and $\tilde{\theta}_{jk}^H$ pairwise directional connectedness can reveal the net volatility spillover, which can be more informative than the "gross" pairwise directional connectedness. The net pairwise directional connectedness can be defined as follows:

$$C_{jk}^H = \left(\frac{\tilde{\theta}_{kj}^H - \tilde{\theta}_{jk}^H}{\sum_{j,k=1}^{N}\tilde{\theta}_{jk}^H}\right) \cdot 100 = \left(\frac{\tilde{\theta}_{kj}^H - \tilde{\theta}_{jk}^H}{N}\right) \cdot 100, \tag{8}$$

where C_{jk}^H constructs the net pairwise directional connectedness by taking the difference between $\tilde{\theta}_{kj}^H$ and $\tilde{\theta}_{jk}^H$ as the total variation (N). This standardization is beneficial for comparability among markets. Furthermore, the variance decompositions are networks, each entity can be considered as a node and the net pairwise directional connectedness can be regarded as a directional edge (as in $C_{jk}^H > 0$, the arrow points to k from j).

Total directional connectedness from others to j and to others from k

The variance decomposition matrix can also obtain the total directional connectedness "FROM" and "TO" one market. The total directional connectedness from others to j can be calculated as follows:

$$C_{j\leftarrow\cdot}^{H} = \frac{\sum_{k=1,k\neq j}^{N} \tilde{\theta}_{jk}^{H}}{\sum_{k,j=1}^{N} \tilde{\theta}_{jk}^{H}} \cdot 100 = \frac{\sum_{k=1,k\neq j}^{N} \tilde{\theta}_{jk}^{H}}{N} \cdot 100, (k \neq j), \tag{9}$$

where $C_{j\leftarrow\cdot}^{H}$ denotes j's total directional connectedness FROM others.

Similarly, the total directional connectedness to others from k can be estimated as follows:

$$C_{\cdot\leftarrow k}^{H} = \frac{\sum_{j=1,k\neq j}^{N} \tilde{\theta}_{jk}^{H}}{\sum_{k,j=1}^{N} \tilde{\theta}_{jk}^{H}} \cdot 100 = \frac{\sum_{j=1,k\neq j}^{N} \tilde{\theta}_{jk}^{H}}{N} \cdot 100, (k \neq j), \tag{10}$$

where $C_{\cdot\leftarrow k}^{H}$ denotes k's total directional connectedness TO others. Overall, total directional connectedness is calculated based on the normalized elements of the generalized variance decomposition matrix.

Net total directional connectedness

For one market, the "net" volatility spillover can be found based on a comparison between the total directional connectedness from and to others. Net total directional connectedness can be calculated as $C_{j}^{H} = C_{\cdot\leftarrow j}^{H} - C_{j\leftarrow\cdot}^{H}$. A positive value for C_{j}^{H} indicates that market j exerts a risk-transmitting influence on the system, whereas a negative value for C_{j}^{H} implies that market j bears the spillover in the system.

Total connectedness

In addition to conveying the spillover among entities, the total connectedness of the system can be measured based on the variance decomposition matrix. Hence, we define total connectedness as follows:

$$C^{H} = \frac{\sum_{k,j=1,k\neq j}^{N} \tilde{\theta}_{\mathrm{jk}}^{H}}{\sum_{k,j=1}^{N} \tilde{\theta}_{\mathrm{jk}}^{H}} \cdot 100 = \frac{1 - Tr\left\{\tilde{\theta}\right\}}{N} \cdot 100, (k \neq j), \tag{11}$$

where $Tr\{\cdot\}$ is the trace operator and the denominator is the sum of all elements of the D^{H} matrix. This demonstrates the integration of the entire system.

Data and preliminary analysis

Our sample data are collected from Kaiko, following Makarov and Schoar (2020). Kaiko provides actual traded prices, rather than non-tradable average prices, across multiple exchanges. These high-frequency pricing data support the estimation of actual volatility connectedness (Baur and Hoang 2022). The sample period is from April 13, 2019, to January 24, 2021, which includes the period during which Bitcoin surpassed $40,000 in January 2021 and an extreme price plunge in March 2020. The study period includes 653 observations for each exchange. To assess the volatility spillover variations among

Table 1 Exchanges market share

Exchanges	Binance	OKEx	Coinbase	Bitfinex
Code	BN	OE	CB	BF
Market share (%)	25.95	22.11	1.56	0.69
Coins	297	235	91	130
Markets	1079	428	274	291

Source: https://coinranking.com/exchanges
https://finance.yahoo.com/news/big-three-crypto-exchanges-handle-171755919.html

cryptocurrency exchanges, we select four exchange markets: Binance, OKEx (now known as OKX), Coinbase, and Bitfinex. As Table 1 shows, these four exchanges have a substantial market share of approximately 50.31%.[3] Although they are all centralized cryptocurrency exchanges, they differ in their acceptance of government regulations, user composition, and trading specifications. Binance is the largest cryptocurrency exchange in terms of market capitalization.[4] OKEx was initially headquartered in China; however, under a series of manipulations and regulations, it withdrew from the Chinese mainland market in 2021.[5] Bitfinex also has a substantial market share and is recognized as an important exchange for circulating the authorized stablecoin Tether (Griffin and Shams 2020). Coinbase is the largest US cryptocurrency exchange under the SEC's regulations, whereas the others are self-regulated or unregulated (Alexander and Heck 2020; Carol et al. 2021).

Driven by an interest in analyzing the connectedness of cryptocurrencies and exchange aspects, the existing studies choose to use exchange rates against the US dollar. However, some cryptocurrency exchanges, such as Binance and OKEx, do not support fiat USD pairs trading. The Binance and OKEx markets support Tether (USDT)-backed trading; thus, investors can make trades between USDT and other cryptocurrencies. Tether is a stable coin backed by USD reserves, and one Tether is purported to equal one underlying unit of the currency backing it (e.g., USD). This stable coin overcomes the obstacles to transacting without banking support in many cryptocurrency exchanges (Griffin and Shams 2020). We convert the USDT pairs in Binance and OKEx to the USD quoted. All cryptocurrencies in the sample exchanges are against the USD, making the prices comparable among exchanges.

In terms of cryptocurrency market capitalization on January 24, 2021, and data accessibility, we use six assets in this study: Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC), Stellar (XLM), and EOS (EOS). BTC, ETH, and LTC are mining coins based on the PoW consensus,[6] whereas XRP, XLM, and EOS are non-mining coins (Charfeddine et al. 2022). BTC is the most prominent cryptocurrency with the highest capitalization. Ethereum is a widely used blockchain development platform. ETH has become the second-most popular cryptocurrency for supporting Ethereum's

[3] Refer to https://finance.yahoo.com/news/big-three-crypto-exchanges-handle-171755919.html, https://coinranking.com/exchanges [Accessed on 2021–10-12].

[4] Refer to https://www.binance.com/en-GB/blog/ecosystem/%E2%80%8Bwhat-is-kyc-or-identity-verification-and-how-is-it-increasingly-important-for-crypto-421499824684903785 [Accessed on 2022–5-22].

[5] Refer to https://www.okx.com/support/hc/zh-cn/articles/4411212179853 (in Chinese) [Accessed on 2022–5-22].

[6] ETH switched its consensus from PoW to PoS on Sep., 2022. It is acknowledged that the PoS is less energy-intensive than PoW. But in our sample period, ETH still based on PoW. Therefore, ETH is classified as one of the mining coins in this paper.

community operations. LTC is the fork of BTC; they are similar in their underlying blockchain, except for the encryption algorithm. XRP is a typical cryptocurrency that supports cross-border business payments, and airdrops based on XRP holdings are often launched. XLM was introduced to help individuals transact with different fiat currencies at low fees. EOS is based on the DPoS consensus, which can overcome the high energy consumption and low efficiency caused by PoW. These samples cover 653 daily observations for each coin in one exchange. We exclude other leading cryptocurrencies such as Polkadot and Uniswap because their available price data do not exceed half a year or are not supported in one sample exchange. The six sample cryptocurrencies express 78.35%[7] of the total market capitalization, representing the entire market.

Diebold and Yilmaz (2012) have noted that the reference universe of connectedness measurements is typically either returns or volatilities. We estimate realized volatility based on 5-min-frequency pricing data to capture the daily actual aggregated volatility. For cryptocurrency a on day t, the realized volatility ($rv_{a,t}$) is estimated as $rv_{a,t} = \sqrt{\sum_{n=1}^{N} r_{a,n}^{2}}$, where N is the 5-min time interval in a day, and $r_{a,n}$ is estimated as $100 \times (\ln(P_n) - \ln(P_{n-1}))$, in which P_n is the 5-min closing price of cryptocurrency a.

Each panel in Fig. 1 illustrates the dynamic log-realized volatility of one cryptocurrency on four exchanges during a specific period.[8] Regarding the dynamic log-realized volatility of the six cryptocurrencies, Fig. 8 illustrates that the volatility of each cryptocurrency surged to its peak on March 13, 2020, when Bitcoin lost half of its value in a two-day plunge. Figure 1 also indicates that the log-realized volatility of one cryptocurrency can be distinct among exchanges. For BTC, the log-realized volatility on Bitfinex around July 1, 2020, is lower than that of the others. On July 15, 2020, the log-realized volatility of EOS on Coinbase was higher than that of the log volatility of the other three exchanges. A significant difference in log volatility among the exchanges can also be observed in ETH in March 2020 and in LTC in June 2020. From December 2019 to early 2020, the log volatility of XLM on OKEx and Binance was lower than that on the other two exchanges. The volatility of XRP on Bitfinex was higher than that on the other three exchanges in late December 2020.

Table 2 summarizes the statistics for the daily realized volatility of the six cryptocurrencies in the four exchanges. The most volatile coins differed across the four exchanges. The largest mean of log-realized volatility on Binance and OKEx is LTC (1.462 and 1.458, respectively), whereas on Coinbase and Bitfinex, it is XLM (1.556 and 1.565, respectively). BTC has the lowest mean. One asset in each exchange shows distinct fluctuations. Coinbase and Binance have larger realized volatility for BTC. XLM has the highest mean volatility on Bitfinex (1.565) and the lowest on OKEx (1.443). XRP, which has the highest standard deviation among the four exchanges, is above 0.56. A positive skewness value indicates that the distribution of the log-realized volatility series is asymmetric. The recorded kurtosis values for all examined series exceed the threshold of 3, which illustrates that the log-realized volatility under examination for the sample period has flatter tails than the anticipated normally distributed series shows. The augmented Dickey-Fuller (ADF) test indicates that all volatility series are stationary.

[7] The market share of different coins is from https://www.coingecko.com/en/coins/. The total market share is from https://coinmarketcap.com/historical/20210124/ [Accessed on 2021–01-25].

[8] The comparison of four exchanges' volatility for one coin across the whole sample period is attached in the appendix.

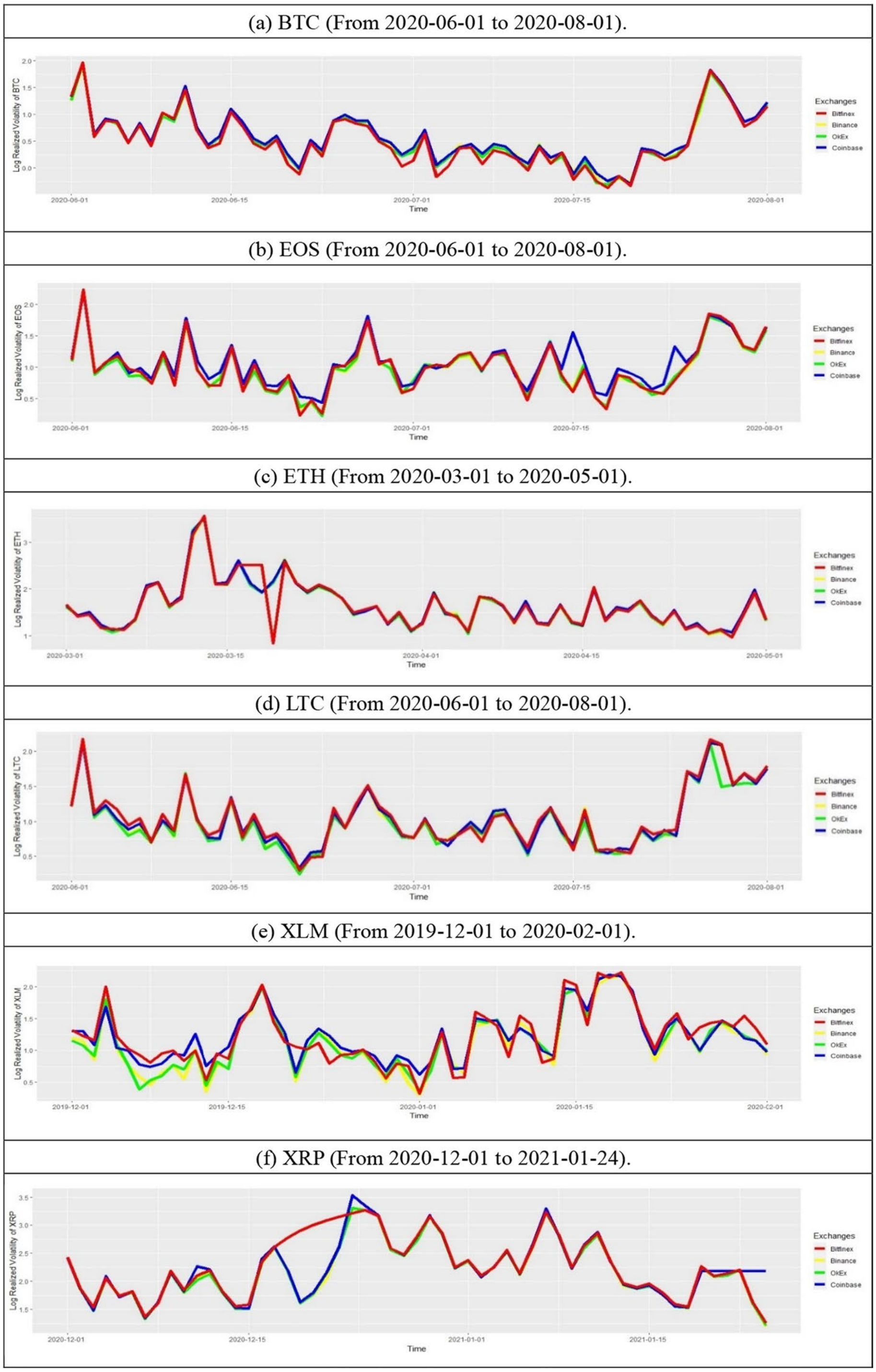

Fig. 1 The comparison of one coin's volatility in four exchanges during a specific period. *Notes*: This figure shows the log realized volatility of 6 cryptocurrencies in four sample exchanges during the selected period. **a–f** depicts BTC, EOS, ETH, LTC, XLM and XRP respectively. In each subgraph, the horizontal axis is time, while the vertical axis is the log realized volatility for one cryptocurrency in a specific exchange

Table 2 Descriptive statistics of the log realized volatility of 6 cryptocurrencies in 4 exchanges

Variable	N	Mean	SD	Skewness	Kurtosis	Min
Panel 1: Binance						
BTC	653	1.072	0.531	0.553	3.757	−0.246
EOS	653	1.391	0.492	0.531	3.698	0.042
ETH	653	1.316	0.476	0.658	3.96	0.163
LTC	653	1.462	0.473	0.424	3.393	0.232
XLM	653	1.448	0.519	0.832	4.139	−0.096
XRP	653	1.323	0.564	0.908	4.012	−0.108
Panel 2: OKEx						
BTC	653	1.061	0.541	0.521	3.698	−0.313
EOS	653	1.394	0.494	0.585	3.752	0.12
ETH	653	1.316	0.478	0.66	3.993	0.154
LTC	653	1.458	0.476	0.443	3.419	0.25
XLM	653	1.443	0.519	0.837	4.015	−0.018
XRP	653	1.325	0.564	0.938	4.007	−0.024
Panel 3: Coinbase						
BTC	653	1.093	0.545	0.546	3.633	−0.291
EOS	653	1.457	0.473	0.633	3.837	0.353
ETH	653	1.341	0.474	0.677	3.995	0.173
LTC	653	1.485	0.473	0.449	3.521	0.233
XLM	653	1.556	0.496	1.22	5.362	0.625
XRP	653	1.369	0.563	1.024	4.276	0.049
Panel 4: Bitfinexs						
BTC	653	1.051	0.554	0.418	3.536	−0.365
EOS	653	1.422	0.492	0.487	3.652	−0.017
ETH	653	1.328	0.477	0.641	3.985	0.161
LTC	653	1.503	0.463	0.402	3.447	0.3
XLM	653	1.565	0.498	0.728	3.877	0.325
XRP	653	1.372	0.563	0.989	4.117	0.036
Variable	**Max**	**P25**	**Median**	**P75**	**Mean difference**	**ADF test**
Panel 1: Binance						
BTC	3.504	0.714	1.015	1.372	–	−5.139***
EOS	3.549	1.051	1.325	1.707	–	−6.002***
ETH	3.525	0.986	1.266	1.559	–	−5.568***
LTC	3.59	1.141	1.415	1.793	–	−5.418***
XLM	3.557	1.084	1.356	1.743	–	−6.291***
XRP	3.415	0.923	1.216	1.627	–	−5.282***
Panel 2: OKEx						
BTC	3.477	0.683	1.006	1.370	−0.011***	−5.162***
EOS	3.550	1.049	1.318	1.707	0.003**	−6.092***
ETH	3.505	0.990	1.270	1.564	0.000	−5.591***
LTC	3.558	1.125	1.405	1.785	−0.004***	−5.419***
XLM	3.512	1.061	1.365	1.744	−0.005**	−6.285***
XRP	3.405	0.923	1.214	1.632	0.002	−5.348***
Panel 3: Coinbase						
BTC	3.493	0.713	1.038	1.392	0.020***	−4.879***
EOS	3.604	1.126	1.392	1.752	0.065***	−6.126***
ETH	3.53	1.018	1.286	1.610	0.025***	−5.384***
LTC	3.579	1.169	1.436	1.804	0.023***	−5.326***
XLM	3.754	1.220	1.454	1.820	0.107***	−5.758***

Table 2 (continued)

Variable	Max	P25	Median	P75	Mean difference	ADF test
XRP	3.634	0.950	1.262	1.683	0.046***	−4.827***
Panel 4: Bitfinex						
BTC	3.454	0.685	1.003	1.376	−0.021***	−5.167***
EOS	3.539	1.081	1.355	1.734	0.031***	−6.039***
ETH	3.561	0.996	1.281	1.595	0.012***	−5.474***
LTC	3.591	1.195	1.460	1.809	0.041***	−5.427***
XLM	3.552	1.229	1.501	1.862	0.117***	−6.790***
XRP	3.395	0.985	1.269	1.661	0.049***	−5.185***

This Table reports the summary statistics for the logarithm of the daily realized volatility of the research sample. The sample covers Apr. 13th, 2019 to Jan. 24th, 2021, includes 6 coins (BTC, ETH, XRP, LTC, XLM, and EOS) and 4 exchange markets (Binance, OKEx, Coinbase and Bitfinex). For each cryptocurrency in a specific exchange, the *Mean*, standard deviation (*SD*), *Skewness*, *Kurtosis*, minimum (*Min*), maximum (*Max*), *Mean Difference*, *t-statistic for difference* and *ADF test* are calculated. *Mean difference* compares the means of the same cryptocurrency's log realized volatility between Binance and the other three exchanges. *ADF test* is the result of Augmented Dickey and Fuller Unit Root Test (1979), which is used to check the stationarity of time series. As for the *Mean Difference* and *ADF*, ***,** and * indicated significance at the 1%, 5% and 10% levels respectively

Empirical results

This section applies the VAR model to estimate the cryptocurrency volatility spillovers and exchange volatility spillovers. We employ the approaches discussed above (Diebold and Yilmaz 2012; Baruník and Křehlík, 2018) to calculate the direction and magnitude of connectedness in the time and frequency domains. For the frequency-domain volatility spillover, we define three frequency bands based on Cui et al. (2021): 1–5 days (one day to one week, obtained on the bands corresponding to $d_1 \in [3.14, 0.63]$), 5–22 days (one week to one month, obtained on the bands corresponding to $d_2 \in [0.63, 0.14]$), and 22–inf days (more than one month, obtained on the bands corresponding to $d_3 \in [0.14, 0.00]$). The first frequency band demonstrates the shocks disturbed by market noise and abnormal events that occur in the short term (connectedness is created at a high frequency). The second frequency refers to shocks triggered by market movements arising in the medium term (connectedness has arisen at a medium frequency). The third frequency represents shocks that persist for a longer period and connectedness is created at a low frequency (Cui et al. 2021). The lag length of the VAR model is chosen using the Akaike information criterion (AIC). The 12-day forecasting horizon for variance decomposition is set based on Diebold and Yılmaz (2014).

Cryptocurrency volatility spillovers for four exchanges

Cryptocurrency volatility spillovers matrix analysis

Table 3 reports the estimated cryptocurrency volatility connectedness, which reflects the cryptocurrency market interdependence within an exchange. Panels A–D display the Diebold and Yilmaz (2012) connectedness for four exchanges in the time domain, and Panels E–P show the connectedness in the frequency domain. The *jth* row–*kth* column element in the connectedness matrix measures the assessed contribution of the innovations to market k to the forecast error variance of market j, which can be illustrated as $C^H_{j\leftarrow k} = \widetilde{d}^H_{jk}$. The diagonal elements (*jth* row–*jth* column) present the estimations of their variance influence, which measure the percentage of the forecast error variance of

Table 3 Cryptocurrency volatility connectedness matrix for 4 exchanges in a time domain and frequency domain

Diebold and Yilmaz (2012) Connectedness

Panel A: Bitfinex

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	22.86	14.75	18.13	19.08	11.59	13.6	12.86
EOS	10.3	23.42	16.38	21.11	13.21	15.59	12.76
ETH	12.71	16.96	22.82	20.03	12.82	14.67	12.87
LTC	11.04	17.29	17.11	25.68	13.57	15.32	12.39
XLM	8.04	15.99	15.43	19.14	24.36	17.04	12.61
XRP	8.88	15.03	14.71	19.52	15.92	25.94	12.34
TO	8.49	13.33	13.63	16.48	11.19	12.7	**75.82**
NET	−4.36	0.57	0.76	4.09	−1.42	0.36	

Panel B: Binance

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	22.05	14.9	18.74	19.34	11.16	13.8	12.99
EOS	11.17	23.33	17.15	21.28	11.91	15.17	12.78
ETH	13.06	17.22	22.9	20.14	12.07	14.61	12.85
LTC	11.88	17.28	17.75	26.04	12.12	14.93	12.33
XLM	8.83	15.68	16.67	18.47	22.46	17.9	12.92
XRP	9.47	15.46	15.41	19.44	15.6	24.62	12.56
TO	9.07	13.42	14.29	16.45	10.48	12.73	**76.44**
NET	−3.92	0.64	1.44	4.12	−2.45	0.17	

Panel C: Coinbase

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	22.51	14.7	19.18	19.49	10.84	13.29	12.92
EOS	10.89	24.07	16.91	20.91	12.42	14.8	12.65
ETH	13.53	17.26	23.24	19.64	11.96	14.38	12.79
LTC	12.43	17.41	17.82	25.68	12.17	14.49	12.39
XLM	8.17	16.52	15.99	18.1	23.95	17.28	12.68
XRP	9.81	15.27	16	18.66	15.73	24.52	12.58
TO	9.14	13.53	14.32	16.13	10.52	12.37	**76.01**
NET	−3.78	0.87	1.52	3.75	−2.15	−0.21	

Panel D: OKEx

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	22.28	14.68	18.92	19.35	10.85	13.92	12.95
EOS	10.89	23.46	17.15	21.32	11.94	15.24	12.76
ETH	12.95	17.06	23.01	20.22	12.04	14.72	12.83
LTC	11.7	17.24	17.71	26.35	11.82	15.19	12.28
XLM	8.37	15.62	16.52	18.65	22.8	18.04	12.87
XRP	9.27	15.35	15.42	19.51	15.48	24.97	12.5
TO	8.86	13.32	14.29	16.51	10.36	12.85	**76.19**
NET	−4.09	0.57	1.46	4.23	−2.51	0.35	

Baruník and Křehlík (2018) Connectedness

The spillover table for band: 3.14 to 0.63, roughly corresponds to 1 days to 5 days

Panel E: Bitfinex

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	3.76	1.21	1.71	1.27	1.19	0.88	1.04
EOS	1.55	2.94	1.52	1.44	1.31	1.29	1.19
ETH	1.81	1.30	2.57	1.21	1.15	1.01	1.08
LTC	1.35	1.17	1.12	1.78	0.89	0.74	0.88
XLM	1.01	0.68	0.63	0.53	2.02	0.83	0.62
XRP	1.16	1.39	1.09	0.89	1.30	2.66	0.97
TO	1.15	0.96	1.01	0.89	0.97	0.79	**5.77**
NET	0.11	−0.23	−0.07	0.01	0.36	−0.18	

Panel F: Binance

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	3.22	1.10	1.53	1.08	1.26	0.79	0.96
EOS	1.47	2.74	1.54	1.29	1.49	1.24	1.17
ETH	1.64	1.20	2.18	1.04	1.26	0.93	1.01
LTC	1.33	1.13	1.16	1.74	1.11	0.73	0.91
XLM	1.11	0.71	0.74	0.55	2.07	0.96	0.68
XRP	1.19	1.38	1.17	0.89	1.74	2.74	1.06
TO	1.12	0.92	1.02	0.81	1.14	0.77	**5.79**
NET	0.16	−0.25	0.01	−0.10	0.46	−0.29	

Panel G: Coinbase

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	3.60	1.19	1.82	1.39	1.08	1.02	1.08
EOS	1.55	2.96	1.61	1.47	1.44	1.47	1.26
ETH	1.93	1.36	2.54	1.33	1.31	1.25	1.19
LTC	1.64	1.33	1.43	2.18	1.16	1.02	1.10
XLM	1.00	0.69	0.79	0.59	2.30	1.17	0.71
XRP	1.27	1.50	1.33	1.04	1.69	2.99	1.14
TO	1.23	1.01	1.16	0.97	1.11	0.99	**6.47**
NET	0.15	−0.25	−0.03	−0.13	0.40	−0.15	

Panel H: OKEx

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	3.46	1.18	1.70	1.17	1.29	0.84	1.03
EOS	1.57	2.99	1.65	1.39	1.61	1.33	1.26
ETH	1.75	1.25	2.32	1.09	1.29	0.96	1.06
LTC	1.43	1.21	1.27	1.87	1.18	0.81	0.98
XLM	1.11	0.72	0.76	0.53	2.09	0.94	0.68
XRP	1.28	1.46	1.28	0.97	1.80	2.96	1.13
TO	1.19	0.97	1.11	0.86	1.20	0.81	**6.14**
NET	0.16	−0.29	0.05	−0.12	0.52	−0.32	

Table 3 (continued)

The spillover table for band: 0.63 to 0.14, roughly corresponds to 5 days to 22 days

Panel I: Bitfinex

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	1.46	0.37	0.54	0.42	0.39	0.27	0.33
EOS	0.39	0.75	0.31	0.29	0.31	0.29	0.26
ETH	0.60	0.29	0.74	0.28	0.26	0.20	0.27
LTC	0.39	0.26	0.21	0.42	0.16	0.14	0.19
XLM	0.36	0.24	0.29	0.14	0.90	0.26	0.21
XRP	0.41	0.47	0.40	0.16	0.50	0.95	0.32
TO	0.36	0.27	0.29	0.21	0.27	0.20	**1.60**
NET	0.02	0.01	0.02	0.02	0.06	−0.13	

Panel J: Binance

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	1.21	0.31	0.45	0.34	0.40	0.21	0.28
EOS	0.34	0.68	0.32	0.25	0.36	0.30	0.26
ETH	0.48	0.26	0.62	0.24	0.28	0.18	0.24
LTC	0.34	0.23	0.21	0.38	0.19	0.13	0.18
XLM	0.38	0.25	0.31	0.17	0.89	0.32	0.24
XRP	0.37	0.46	0.42	0.15	0.71	1.03	0.35
TO	0.32	0.25	0.29	0.19	0.33	0.19	**1.56**
NET	0.03	−0.01	0.04	0.01	0.09	−0.16	

Panel K: Coinbase

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	1.19	0.42	0.55	0.42	0.36	0.28	0.34
EOS	0.34	0.75	0.38	0.28	0.33	0.38	0.29
ETH	0.61	0.35	0.79	0.31	0.30	0.28	0.31
LTC	0.46	0.34	0.32	0.49	0.22	0.22	0.26
XLM	0.31	0.27	0.41	0.17	0.93	0.40	0.26
XRP	0.36	0.54	0.49	0.17	0.66	1.10	0.37
TO	0.35	0.32	0.36	0.23	0.31	0.26	**1.82**
NET	0.01	0.04	0.05	−0.03	0.05	−0.11	

Panel L: OKEx

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	1.33	0.35	0.51	0.39	0.45	0.24	0.32
EOS	0.40	0.75	0.37	0.28	0.41	0.33	0.30
ETH	0.55	0.28	0.68	0.26	0.30	0.19	0.26
LTC	0.38	0.25	0.24	0.42	0.22	0.15	0.21
XLM	0.39	0.28	0.33	0.18	0.96	0.34	0.25
XRP	0.38	0.48	0.44	0.17	0.73	1.05	0.37
TO	0.35	0.28	0.32	0.21	0.35	0.21	**1.71**
NET	0.03	−0.02	0.05	0.01	0.10	−0.16	

The spillover table for band: 0.14 to 0.00, roughly corresponds to 22 days to Inf days

Panel M: Bitfinex

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	17.63	13.17	15.88	17.39	10.02	12.44	11.48
EOS	8.36	19.73	14.55	19.37	11.59	14.01	11.31
ETH	10.3	15.37	19.51	18.54	11.41	13.45	11.51
LTC	9.3	15.86	15.78	23.48	12.51	14.44	11.31
XLM	6.67	15.07	14.5	18.48	21.45	15.95	11.78
XRP	7.32	13.16	13.22	18.48	14.12	22.33	11.05
TO	6.99	12.1	12.32	15.38	9.94	11.71	**68.45**
NET	−4.49	0.79	0.81	4.06	−1.84	0.67	

Panel N: Binance

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	17.61	13.49	16.77	17.92	9.5	12.81	11.75
EOS	9.36	19.91	15.29	19.74	10.06	13.63	11.35
ETH	10.94	15.75	20.09	18.87	10.53	13.5	11.6
LTC	0.21	15.91	16.38	23.91	10.82	14.07	11.23
XLM	7.34	14.72	15.62	17.76	19.49	16.62	12.01
XRP	7.91	13.62	13.81	18.41	13.15	20.85	11.15
TO	7.63	12.25	12.98	15.45	9.01	11.77	69.08
NET	−4.12	0.90	1.38	4.22	−3.00	0.62	

Panel O: Coinbase

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	17.72	13.09	16.81	17.67	9.41	11.99	11.5
EOS	9	20.35	14.91	19.16	10.65	12.95	11.11
ETH	11	15.55	19.91	18	10.35	12.84	11.29
LTC	10.33	15.74	16.07	23.01	10.8	13.25	11.03
XLM	6.86	15.56	14.78	17.34	20.71	15.71	11.71
XRP	8.19	13.23	14.18	17.46	13.38	20.42	11.07
TO	7.56	12.19	12.79	14.94	9.1	11.12	**67.71**
NET	−3.93	1.08	1.50	3.91	−2.61	0.05	

Panel P: OKEx

	BTC	EOS	ETH	LTC	XLM	XRP	FROM
BTC	17.48	13.15	16.7	17.79	9.11	12.84	11.6
EOS	8.92	19.72	15.13	19.65	9.93	13.58	11.2
ETH	10.65	15.53	20.02	18.87	10.45	13.56	11.51
LTC	9.89	15.78	16.19	24.07	10.43	14.23	11.09
XLM	6.86	14.62	15.43	17.94	19.75	16.77	11.94
XRP	7.6	13.41	13.7	18.37	12.95	20.96	11.01
TO	7.32	12.08	12.86	15.44	8.81	11.83	**68.34**
NET	−4.28	0.88	1.35	4.35	−3.13	0.83	

This table presents the volatility spillovers among 6 cryptocurrencies in 4 exchanges in the time domain and frequency domain. This result uses the daily realized volatility data for each market. Each item in *j-th* row of the *k-th* column indicates the influence of the *k-th* market's innovations on the *j-th* market's forecast error variance. The "FROM" ("TO") in Baruník and Křehlík (2018) refer to the FROM_ABS (TO_ABS) market j that stems from its shocks. The last column of each panel, *FROM*, is estimated by the mean of row elements except the diagonal one, which demonstrates the scaled volatility spillover from all other markets. The *TO* row in each panel is the scaled mean of specific column elements apart from the diagonal value, which indicates the spillover to other markets. The total connectedness is bold in the matrix.

The total connectedness in Panels A–D indicates that the volatility of the six cryptocurrencies is highly connected in the sample exchanges. On average, the total connectedness in the four exchanges is 76.12%. Decomposing the time domain results into three frequency bands, and the long-lasting shock effects are dominant. The total spillover for low-frequency accounts for the largest portion (90.28% on Bitfinex, 90.37% on Binance, 89.08% on Coinbase, and 89.70% on OKEx). These results are consistent with the findings of Kumar et al. (2022). This low-frequency dominance originates from investor confidence in the future (Balke and Wohar 2002) and indicates long-term connectedness (Baruník and Křehlík, 2018). Volatility is generated after a return and takes much more time to be emitted from one coin to another, which causes most volatility spillovers to develop at a low frequency (Zhang and Hamori 2021).

As for the gross directional spillovers in the time domain, LTC is the largest contributor to other cryptocurrencies in four exchanges, with over 16%. In the frequency domain, the "FROM_ABS & TO_ABS" in the Baruník and Křehlík (2018) connectedness matrix evaluates the total connectedness that is received from or contributes to the entire system in the absolute sense. "FROM_WTH & TO_WTH" measures the connectedness within the specific frequency band (Cui et al. 2021). For convenience in comparing among frequency bands and the time domain, "FROM_ABS & TO_ABS" is explained in detail. At a high frequency, BTC transmits the most in Bitfinex and Coinbase, whereas the contributions of BTC and XLM are similar in Binance and OKEx. At a low frequency, the greatest transmitter among the four exchanges is LTC. This is consistent with the results obtained in the time domain. Therefore, the largest volatility spillover emitter varies among different exchanges when the frequency domain is introduced.

Cryptocurrency volatility spillovers network analysis

Sect. "Cryptocurrency volatility spillovers matrix analysis" presents the analyses of gross connectedness. Based on directed pairwise connectedness, the net connectedness between two cryptocurrencies and the net contribution of a specific cryptocurrency on one exchange can be estimated.

Figure 2 illustrates the net pairwise directional connectedness, net emitters, and net receivers for the four exchanges in the time domain. The frequency-decomposition network is shown in Fig. 9. The magnitude and direction of cryptocurrency volatility spillovers in the four exchanges are similar, except for specific cryptocurrencies. In the four exchanges, LTC always transmits the highest net pairwise connectedness compared to BTC, which is consistent with the findings of Corbet et al. (2018). However, in contrast to the global cryptocurrency market research of Corbet et al. (2018), we consider four exchange markets. BTC is the largest net receiver. LTC is the dominant contagion

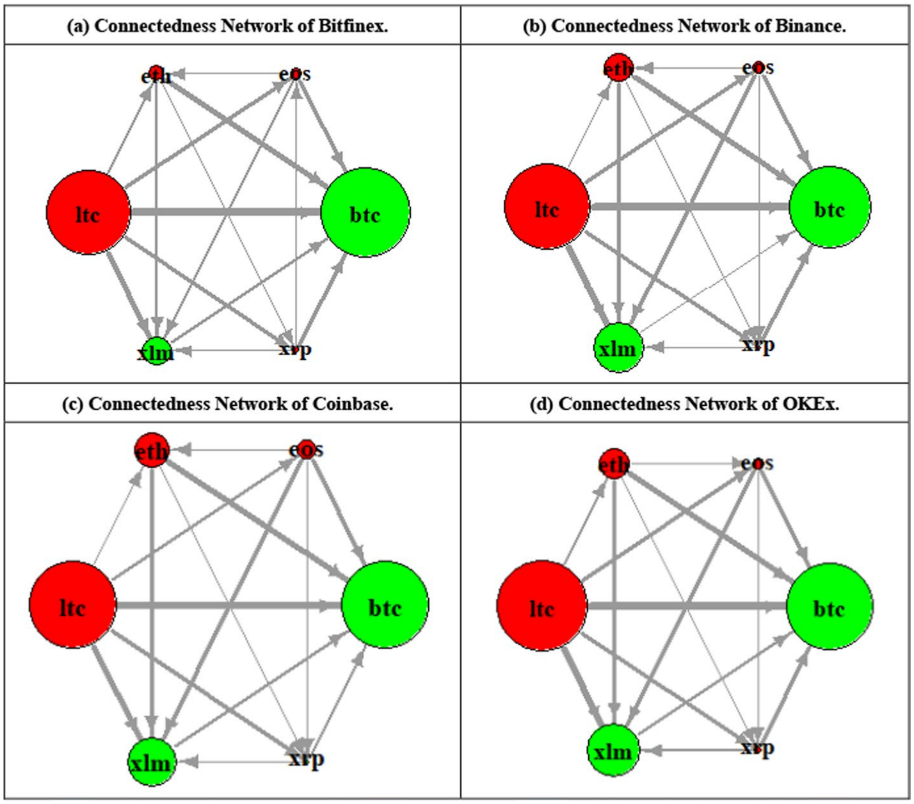

Fig. 2 Cryptocurrency volatility connectedness network for 4 exchanges based on Diebold and Yilmaz (2012). Notes: This figure shows the cryptocurrency volatility connectedness network for 4 exchanges in the time domain. The red node in a network denotes the net emitter, which indicates that the value of net total directional connectedness is positive. The green node in a network denotes the net receiver, which means the net total directional connectedness is negative. The size of the node represents the magnitude of a net emitter to other cryptocurrencies or a net receiver from the others. The thickness of the directional arrows denotes the magnitude of the net pairwise directional volatility connectedness. The thicker the arrow, the stronger the volatility spillover. These NET indexes are measured in Table 3 based on Sect. "Connectedness measures". The net pairwise directional connectedness is defined as Eq. (8), which can illustrate the net spillover direction between two coins

source in the four sample exchanges, which is consistent with the findings of Mensi et al. (2021), Bouri et al. (2021), Ji et al. (2019), and Zięba et al. (2019). Unexpected shocks in LTC can export possible future uncertainty to other cryptocurrencies. Although LTC is considered a Bitcoin fork, their encryption algorithms differ. The underlying algorithm is relevant to the mining process. BTC depends on the SHA-256 algorithm, which requires more computational power to mine cryptocurrency. This expensive resource constrains Bitcoin distribution. Approximately 2.1% of BTC addresses hold more than one BTC in their balance.[9] Only top accounts can manipulate Bitcoin's flow following a price downturn (Griffin and Shams 2020). Therefore, the net emitting of BTC originating from demand shocks is limited. LTC is based on the Scrypt algorithm, which is less resource-consuming. This easy mining algorithm allows for a broader distribution. Of the LTC addresses, 16.91% hold more than one LTC.[10] Shocks originating from a sudden

[9] Refer to https://bitinfocharts.com/bitcoin-distribution-history.html.

[10] Refer to https://bitinfocharts.com/litecoin-distribution-history.html.

unexpected event for LTC are widespread among investors and have spillovers to other cryptocurrencies. The difference among the exchanges is that XRP, which serves as a net receiver in Coinbase, has a net transmitting effect on the other three exchanges. This illustrates that the same asset in different exchanges can play a distinct role in volatility spillover. On different exchanges, the direction and influence of the net pairwise volatility connectedness can vary. Regarding the net pairwise connectedness of ETH and EOS, the arrow points to EOS in OKEx; however, in the other three exchanges, the edge direction is inverted. This implies that the same cryptocurrency pairs have various net effects on different exchanges.

Fig. 9 introduces frequency bands to decompose the volatility connectedness network of Diebold and Yilmaz (2012) into high, medium, and low frequencies. At medium frequencies, the net connectedness of a specific cryptocurrency varies across exchanges. The LTC is a net receiver in Coinbase but acts as an emitter in the other three exchanges. At a high frequency, ETH is a net receiver in Bitfinex and Coinbase but plays a net transmitting role in Binance and OKEx. These distinctions demonstrate that investors with different investment horizons should consider the heterogeneity of cryptocurrency volatility connectedness in terms of exchange aspects.

Cryptocurrency dynamic volatility spillovers

The above static analysis summarizes the volatility spillover of the cryptocurrencies; however, the time variation in the spillover mechanism has not been considered. Figure 3 shows the dynamic total volatility spillovers of the cryptocurrencies in the time and frequency domains. The estimation window is set to 180 days (Kumar et al. 2022). This moderate estimation window ensures that the curves are neither excessively smooth nor coarse. To better understand the evolution of cryptocurrency volatility spillovers, Fig. 3 shows the S&P Cryptocurrency Top 10 Equal Weight Index (SPCC10), revealing the dynamics of the cryptocurrency market.

As Fig. 3 shows, the evolution and composition of overall connectedness for the four exchanges display both similarities and distinctions. The overall cryptocurrency volatility spillover for four exchanges fluctuates over the sample period, ranging approximately between 70 and 80%. For the four exchanges, the total low-frequency connectedness accounts for most of the overall connectedness. The overall connectedness of the four exchanges declined in January 2020 and from July 2020 to January 2021, driven by the decline in low-frequency connectedness. The analysis period can be divided into two phases combined with the SPCC10. Before July 2020, the dynamics of the SPCC10 and low-frequency connectedness were similar. Subsequently, total connectedness decreased from 80% to a minimum of 71%. Thus, the evolution of the SPCC10 is inverse to that of low-frequency connectedness.

To reveal the evolution of one cryptocurrency's role in the volatility spillover of cryptocurrencies for different exchanges, the net connectedness results for sample cryptocurrencies are conducted. Figure 4 shows a dynamic comparison of net directional connectedness in the time domain. As demonstrated in Sect. "Connectedness measures", positive values indicate that this cryptocurrency in a specific exchange serves as a net

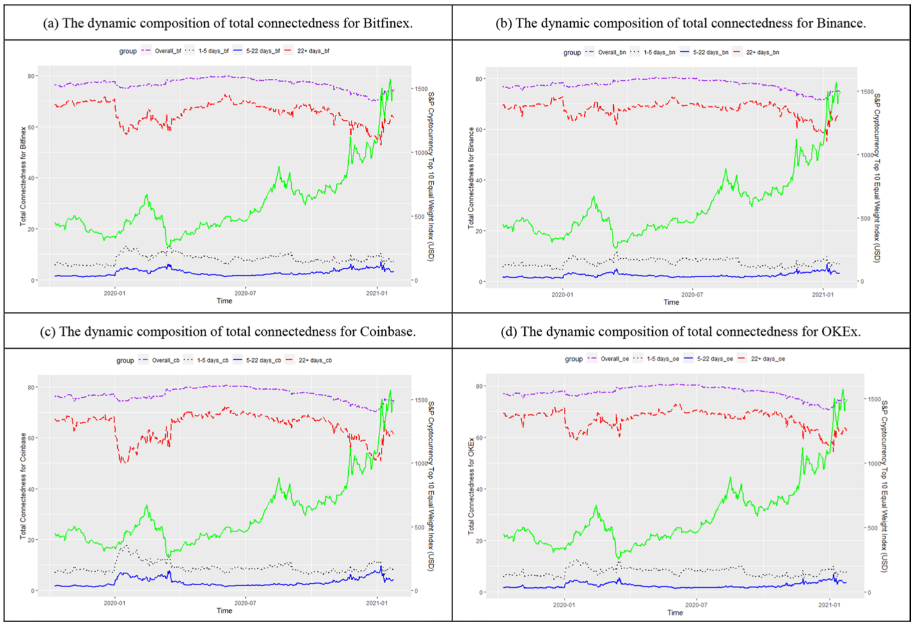

Fig. 3 The dynamic composition of total cryptocurrency volatility connectedness for 4 exchanges. Notes: This figure illustrates the moving-window estimation of total connectedness for Bitfinex, Binance, Coinbase and OKEx in the time domain and frequency domain. The estimation window is set at 180 days (half a year). The green line is the S&P Cryptocurrency Top 10 Equal Weight Index (USD). The *Overall* connectedness is estimated based on Diebold and Yilmaz (2012). The total connectedness can be decomposed into *1–5 days*, *5–22 days* and *22 + days* terms based on Baruník and Krehlík (2018), corresponding to high-frequency, medium-frequency and low-frequency band respectively

transmitter, whereas negative values indicate that this cryptocurrency serves as a net receiver.

Figure 4 indicates that some cryptocurrencies have the same role in spillover, while other cryptocurrencies switch their roles over time. The different roles of the same cryptocurrency on the four exchanges are revealed. For most of the research period, BTC served as a net receiver, except for on Coinbase, where BTC became a net emitter from November 7–9, 2020. A similar situation also occurred for LTC, which is always a net emitter, except for when it was the net receiver on Coinbase in November 2019. ETH persistently acts as the net contributor on the four exchanges, except for the oscillation around zero on Bitfinex before July 2020.

Exchange volatility spillovers for six cryptocurrencies

Exchange volatility spillovers matrix analysis

As shown in Fig. 8, the same asset shows varying volatility among exchanges. For arbitrageurs and regulators, identifying the most dominant volatility-transmitting exchange for one cryptocurrency is noteworthy. Table 4 presents the volatility connectedness. Panels A–F show the results for exchange volatility connectedness for the six coins using the framework of Diebold and Yilmaz (2012). Panels G–X are the results for the frequency decomposition of the time domain table based on the framework of Baruník and Křehlík (2018). The average total volatility connectedness for the six coins is 74.7%. This illustrates that the four exchanges are closely connected. Low frequency accounts over 86%

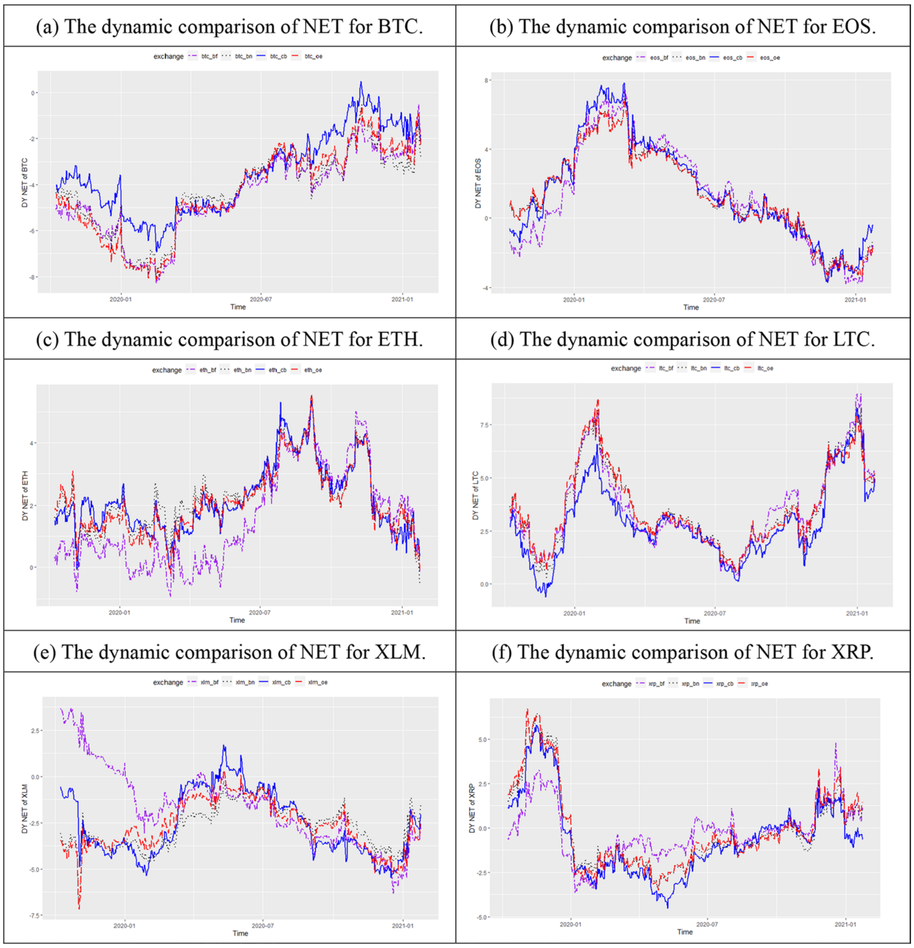

Fig. 4 The dynamic comparison of one cryptocurrency's net directional connectedness in 4 exchanges. Notes: This figure shows the dynamic comparison of *NET* connectedness for each cryptocurrency in 4 exchanges. The *NET* index is the moving-window estimation based on Diebold and Yilmaz (2012) in the time domain. The estimation window is set at 180 days (half a year). The positive values indicated that this cryptocurrency in a specific exchange serves as the net transmitter, while the negative values mean that this coin serves as the net receiver

for the volatility spillover of six coins, indicating that the volatility spillover transmissions among the exchanges for the six coins mainly comprise long-term market factors. The *FROM* and *TO* of the four exchanges show similarities in the specific cryptocurrency market. This finding demonstrates that the contributing and receiving roles of different exchanges on a specific cryptocurrency market are approximately equivalent.

Exchange volatility spillovers network analysis

Figure 5 illustrates the exchange volatility spillovers network for six cryptocurrencies based on Diebold and Yilmaz (2012). The frequency domain results based on Baruník and Křehlík (2018) are shown in Fig. 10. The meanings of the nodes and edges are the same as those in Fig. 2.

Figure 5 shows the distinct volatility spillover roles of exchanges in different cryptocurrency markets. Bitfinex and Binance play diverse spillover roles for these six

Table 4 Exchanges' volatility connectedness matrix for 6 coins in the time domain and frequency domain

Diebold and Yilmaz (2012)

Panel A: BTC

	BF	BN	CB	OE	FROM
BF	24.44	25.63	25.04	24.90	18.89
BN	23.92	25.96	25.11	25.01	18.51
CB	24.02	25.75	25.32	24.91	18.67
OE	24.00	25.83	25.09	25.08	18.73
TO	17.99	19.30	18.81	18.70	**74.80**
NET	−0.90	0.79	0.14	−0.02	

Panel B: EOS

	BF	BN	CB	OE	FROM
BF	25.22	24.56	25.98	24.24	18.69
BN	25.05	24.68	25.95	24.31	18.83
CB	24.96	24.42	26.49	24.12	18.38
OE	25.04	24.63	25.97	24.36	18.91
TO	18.76	18.40	19.48	18.17	**74.81**
NET	0.07	−0.43	1.10	−0.74	

Panel C: ETH

	BF	BN	CB	OE	FROM
BF	24.72	25.04	25.53	24.70	18.82
BN	24.39	25.20	25.58	24.83	18.70
CB	24.44	25.13	25.67	24.76	18.58
OE	24.39	25.17	25.57	24.87	18.78
TO	18.31	18.84	19.17	18.57	**74.89**
NET	−0.51	0.14	0.59	−0.21	

Panel D: LTC

	BF	BN	CB	OE	FROM
BF	25.87	24.63	24.98	24.53	18.53
BN	25.64	24.76	25.00	24.60	18.81
CB	25.67	24.65	25.12	24.56	18.72
OE	25.62	24.70	24.99	24.70	18.83
TO	19.23	18.49	18.74	18.42	**74.89**
NET	0.70	−0.32	0.02	−0.40	

Panel E: XLM

	BF	BN	CB	OE	FROM
BF	27.78	23.14	25.70	23.39	18.06
BN	25.46	24.39	25.30	24.84	18.90
CB	26.35	23.39	26.57	23.69	18.36
OE	25.48	24.28	25.18	25.05	18.74
TO	19.32	17.70	19.05	17.98	**74.05**
NET	1.27	−1.20	0.69	−0.76	

Panel F: XRP

	BF	BN	CB	OE	FROM
BF	26.47	24.33	25.08	24.12	18.38
BN	25.94	24.60	25.17	24.29	18.85
CB	25.90	24.37	25.60	24.13	18.60
OE	25.95	24.52	25.16	24.37	18.91
TO	19.45	18.31	18.85	18.13	**74.74**
NET	1.06	−0.54	0.25	−0.77	

Baruník and Křehlík (2018)

The spillover table for band: 3.14 to 0.63, roughly corresponds to 1 days to 5 days

Panel G: BTC

	BF	BN	CB	OE	FROM
BF	3.06	2.77	2.86	2.88	2.13
BN	2.63	2.56	2.56	2.61	1.95
CB	2.85	2.69	2.82	2.79	2.08
OE	2.79	2.67	2.71	2.78	2.04
TO	2.07	2.03	2.03	2.07	**8.20**
NET	−0.06	0.08	−0.05	0.03	

Panel H: EOS

	BF	BN	CB	OE	FROM
BF	1.35	1.35	1.22	1.37	0.99
BN	1.33	1.43	1.26	1.43	1.01
CB	1.14	1.19	1.19	1.21	0.89
OE	1.39	1.47	1.32	1.51	1.05
TO	0.96	1.00	0.95	1.00	**3.92**
NET	−0.02	0.00	0.07	−0.04	

Panel I: ETH

	BF	BN	CB	OE	FROM
BF	1.02	0.91	0.90	0.93	0.68
BN	0.86	0.94	0.90	0.95	0.68
CB	0.84	0.89	0.89	0.92	0.66
OE	0.89	0.96	0.93	0.98	0.69
TO	0.65	0.69	0.68	0.70	**2.72**
NET	−0.04	0.01	0.02	0.01	

Panel J: LTC

	BF	BN	CB	OE	FROM
BF	0.88	0.89	0.88	0.89	0.67
BN	0.94	1.02	0.99	1.00	0.73
CB	0.94	0.99	1.01	0.99	0.73
OE	0.96	1.03	1.01	1.06	0.75
TO	0.71	0.73	0.72	0.72	**2.88**
NET	0.04	0.00	−0.01	−0.03	

Panel K: XLM

	BF	BN	CB	OE	FROM
BF	0.74	0.69	0.56	0.66	0.48
BN	0.58	0.91	0.71	0.84	0.53
CB	0.53	0.83	0.83	0.78	0.54
OE	0.57	0.87	0.69	0.87	0.53
TO	0.42	0.60	0.49	0.57	**2.08**
NET	−0.06	0.07	−0.05	0.04	

Panel L: XRP

	BF	BN	CB	OE	FROM
BF	0.83	0.86	0.79	0.87	0.63
BN	0.93	1.06	0.95	1.05	0.73
CB	0.87	0.97	0.97	0.97	0.70
OE	0.99	1.10	1.01	1.14	0.78
TO	0.70	0.73	0.69	0.72	**2.84**
NET	0.07	0.00	−0.02	−0.06	

Table 4 (continued)

The spillover table for band: 0.63 to 0.14, roughly corresponds to 5 days to 22 days

Panel M: BTC

	BF	BN	CB	OE	FROM
BF	0.95	0.82	0.84	0.89	0.64
BN	0.82	0.75	0.74	0.81	0.59
CB	0.88	0.78	0.81	0.85	0.63
OE	0.87	0.79	0.79	0.86	0.61
TO	0.64	0.60	0.59	0.64	**2.47**
NET	0.00	0.00	−0.03	0.03	

Panel N: EOS

	BF	BN	CB	OE	FROM
BF	0.34	0.34	0.27	0.34	0.24
BN	0.33	0.36	0.28	0.36	0.24
CB	0.26	0.27	0.25	0.28	0.20
OE	0.36	0.38	0.30	0.39	0.26
TO	0.24	0.25	0.21	0.25	0.**94**
NET	0.00	0.01	0.01	−0.02	

Panel O: ETH

	BF	BN	CB	OE	FROM
BF	0.22	0.21	0.21	0.22	0.16
BN	0.20	0.22	0.21	0.23	0.16
CB	0.19	0.20	0.20	0.21	0.15
OE	0.21	0.22	0.21	0.24	0.16
TO	0.15	0.16	0.16	0.17	**0.63**
NET	−0.01	0.00	0.01	0.00	

Panel P: LTC

	BF	BN	CB	OE	FROM
BF	0.18	0.20	0.19	0.21	0.15
BN	0.21	0.25	0.24	0.25	0.17
CB	0.19	0.23	0.23	0.23	0.16
OE	0.22	0.26	0.24	0.27	0.18
TO	0.15	0.17	0.17	0.17	**0.67**
NET	0.00	0.00	0.00	−0.01	

Panel Q: XLM

	BF	BN	CB	OE	FROM
BF	0.21	0.21	0.15	0.22	0.15
BN	0.20	0.35	0.26	0.35	0.20
CB	0.15	0.28	0.26	0.28	0.18
OE	0.19	0.33	0.24	0.36	0.19
TO	0.13	0.21	0.16	0.21	**0.71**
NET	−0.01	0.01	−0.01	0.02	

Panel R: XRP

	BF	BN	CB	OE	FROM
BF	0.17	0.20	0.17	0.20	0.14
BN	0.18	0.28	0.25	0.28	0.18
CB	0.14	0.22	0.24	0.23	0.15
OE	0.19	0.28	0.26	0.30	0.18
TO	0.13	0.18	0.17	0.18	**0.65**
NET	−0.01	0.00	0.02	−0.01	

The spillover table for band: 0.14 to 0.00, roughly corresponds to 22 days to Inf days

Panel S: BTC

	BF	BN	CB	OE	FROM
BF	**20.43**	22.04	21.34	21.13	16.13
BN	**20.48**	22.65	21.81	21.59	15.97
CB	**20.29**	22.28	21.69	21.28	15.96
OE	**20.34**	22.38	21.59	21.44	16.08
TO	**15.28**	16.67	16.18	16.00	**64.13**
NET	**−0.85**	0.71	0.22	−0.08	

Panel T: EOS

	BF	BN	CB	OE	FROM
BF	23.54	22.87	24.49	22.53	17.47
BN	23.39	22.89	24.41	22.52	17.58
CB	23.57	22.96	25.06	22.63	17.29
OE	23.30	22.77	24.34	22.46	17.60
TO	17.56	17.15	18.31	16.92	**69.94**
NET	0.09	−0.43	1.02	−0.68	

Panel U: ETH

	BF	BN	CB	OE	FROM
BF	23.48	23.93	24.43	23.54	17.98
BN	23.33	24.05	24.47	23.65	17.86
CB	23.41	24.04	24.59	23.64	17.77
OE	23.30	24.00	24.42	23.64	17.93
TO	17.51	17.99	18.33	17.71	**71.54**
NET	−0.46	0.13	0.56	−0.22	

Panel V: LTC

	BF	BN	CB	OE	FROM
BF	24.81	23.54	23.90	23.43	17.72
BN	24.49	23.48	23.77	23.35	17.90
CB	24.54	23.43	23.88	23.34	17.83
OE	24.44	23.41	23.73	23.37	17.89
TO	18.37	17.59	17.85	17.53	**71.34**
NET	0.65	−0.31	0.02	−0.37	

Panel W: XLM

	BF	BN	CB	OE	FROM
BF	26.83	22.24	24.99	22.51	17.43
BN	24.69	23.13	24.34	23.66	18.17
CB	25.67	22.28	25.48	22.63	17.64
OE	24.73	23.08	24.25	23.83	18.01
TO	18.77	16.90	18.39	17.20	**71.26**
NET	1.34	−1.27	0.75	−0.81	

Panel X: XRP

	BF	BN	CB	OE	FROM
BF	25.47	23.28	24.12	23.05	17.61
BN	24.82	23.26	23.96	22.97	17.94
CB	24.88	23.18	24.39	22.93	17.75
OE	24.76	23.13	23.89	22.94	17.95
TO	18.62	17.40	17.99	17.24	**71.24**
NET	1.00	−0.54	0.25	−0.71	

This table presents the volatility spillover among 4 exchanges for 6 cryptocurrency markets in the time domain and frequency domain. Panel A to Panel F is the volatility spillover result for BTC, EOS, ETH, LTC, XLM and XRP based on the Diebold and Yilmaz (2012) approach. Panel G, Panel M, and Panel S are the frequency decomposition of Panel A. Panel H, Panel N, and Panel T are the frequency decomposition of Panel B. Panel I, Panel O, and Panel U are the frequency decomposition of Panel C. Panel J, Panel P, and Panel V are the frequency decomposition of Panel D. Panel K, Panel Q, and Panel W are the frequency decomposition of Panel E. Panel L, Panel R, and Panel X are the frequency decomposition of Panel F. This result uses the daily realized volatility data for each market. Each item in j-th row of the k-th column indicates the influence of the k-th market's innovations on the j-th market's forecast error variance. The "FROM" ("TO") in Baruník and Křehlík (2018) refer to the FROM_ABS (TO_ABS)

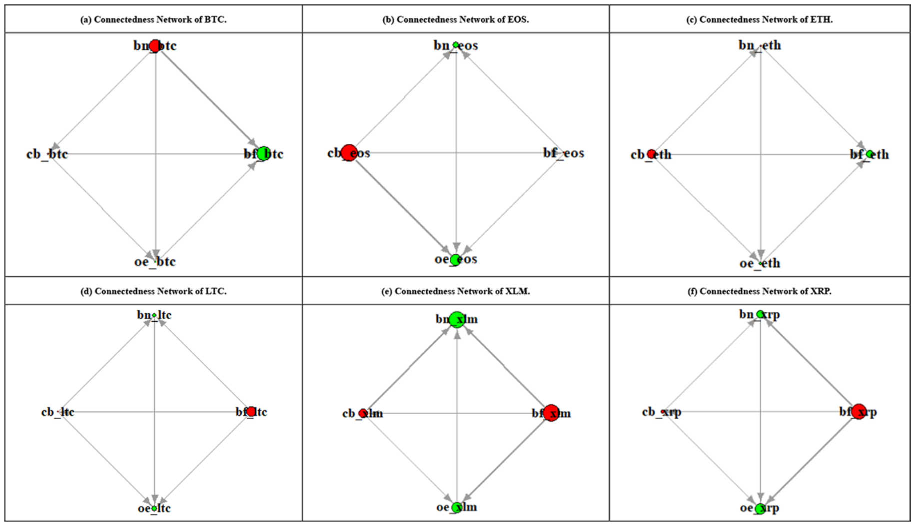

Fig. 5 Exchange volatility connectedness network for 6 coins based on Diebold and Yilmaz (2012). *Notes*: This figure shows the exchange volatility connectedness network for 6 coins in the time domain. The red node in a network denotes the net emitter, the green node denotes the net receiver. The size of the node represents the magnitude of a net emitter to other exchanges, or a net receiver from the others. The thickness of the directional arrows denotes the magnitude of the net pairwise directional volatility connectedness

cryptocurrencies. Coinbase plays a net contributing role, whereas OKEx always acts as a net receiver. This may be explained by the economic environment of these two exchanges are located. We can map the US stock market onto Coinbase and regard the Chinese stock market as OKEx. It has been shown that the established US market has strong volatility spillovers to the emerging Chinese market. Therefore, in the cryptocurrency market, Coinbase continues to emit shocks and OKEx receives them.

The largest net emitters can be identified among the market participants. Binance is the largest net emitter for BTC. Coinbase is the largest net transmitter for EOS and ETH. Bitfinex exerts the highest net contributing effect for XRP, which is inconsistent with its volatility discovery leading effect found by Dimpfl and Elshiaty (2021). Fig. 10 shows that exchanges can change their net effects according to frequency. Taking BTC as an example, as the frequency decreases, Coinbase shifts from a net receiver to a net emitter, whereas OKEx acts contrarily. The net pairwise spillover magnitude and direction reveal the spillover path, which provides asset allocation suggestions for the arbitrager and a regulating focus for the supervisor. For BTC, the net pairwise volatility connectedness transmitted from Binance to Bitfinex is the largest, implying a strong correlation. However, for XLM, the inverse path has the largest spillover magnitude. The strongest net connectedness pairs can also be identified in other cryptocurrency markets.

Exchange dynamic volatility spillovers

Figure 6 illustrates the time-varying frequency decomposition of the total exchange volatility spillover index for BTC, EOS, ETH, LTC, XLM, and XRP.[11] The connectedness decomposition into three frequency bands is shown in each panel. The price of each cryptocurrency is displayed as a green line in each panel.

[11] The dynamic total exchanges' volatility connectedness for 6 coins is shown in Fig. 11.

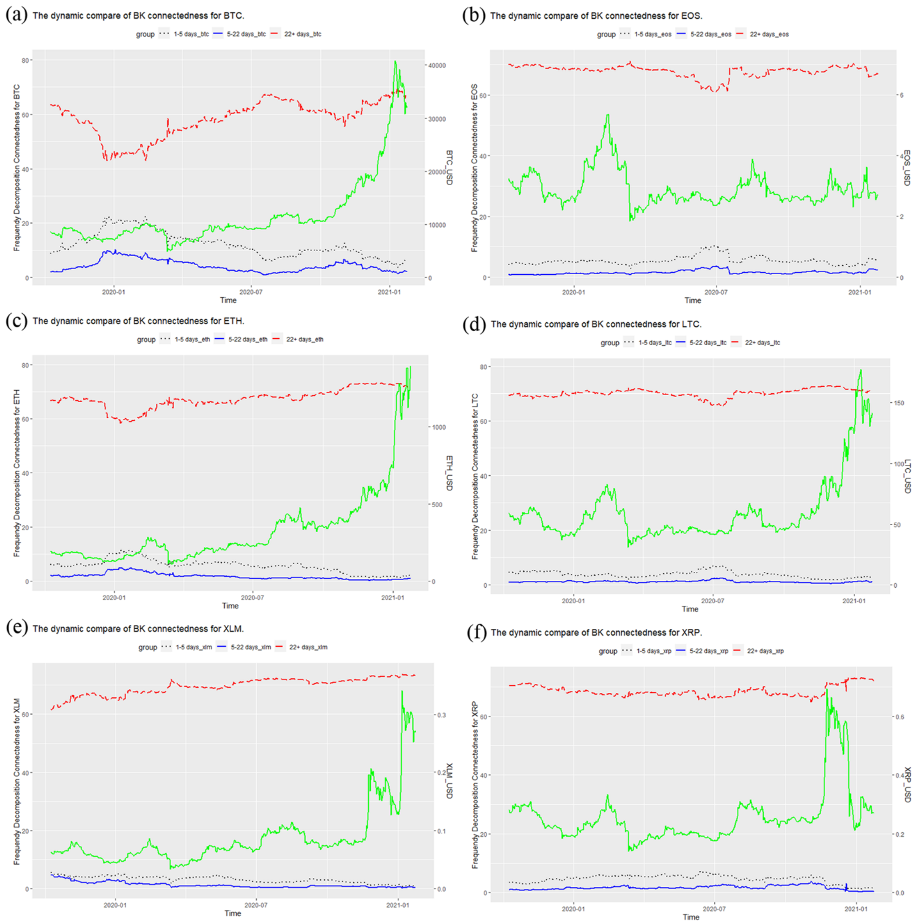

Fig. 6 The dynamic composition of total exchange volatility connectedness for 6 coins. *Notes*: This figure illustrates the moving-window estimation of total connectedness for BTC, EOS, ETH, LTC, XLM, and XRP in the frequency domain. The estimation window is set at 180 days (half a year). The total connectedness decomposed into *1–5 days*, *5–22 days*, and *22 + days* terms are estimated in the same way as Fig. 3. The green line in each panel is the specific cryptocurrency price in USD

For the six coins, the dynamic spillovers in the frequency domain change remarkably, although, in Fig. 11, we capture the same comprehensive system stability as Ji et al. (2021) and Kumar et al. (2022). The cryptocurrency crash on March 12, 2020, brought about a peak of low-frequency connectedness. In contrast, low-frequency connectedness was relatively stable when the prices of BTC, LTC, ETH, and XLM reached a record high and volatile level and XRP dropped in January 2021.

Figure 7 shows that, in a specific cryptocurrency market, the volatility spillover role of one exchange can be maintained or shift dynamically. Exchanges, which are the greatest net contributors, vary over time. Regarding the BTC market, as shown in Fig. 7, Bitfinex retains its net receiver role. Binance remains a net emitter, except for during a short

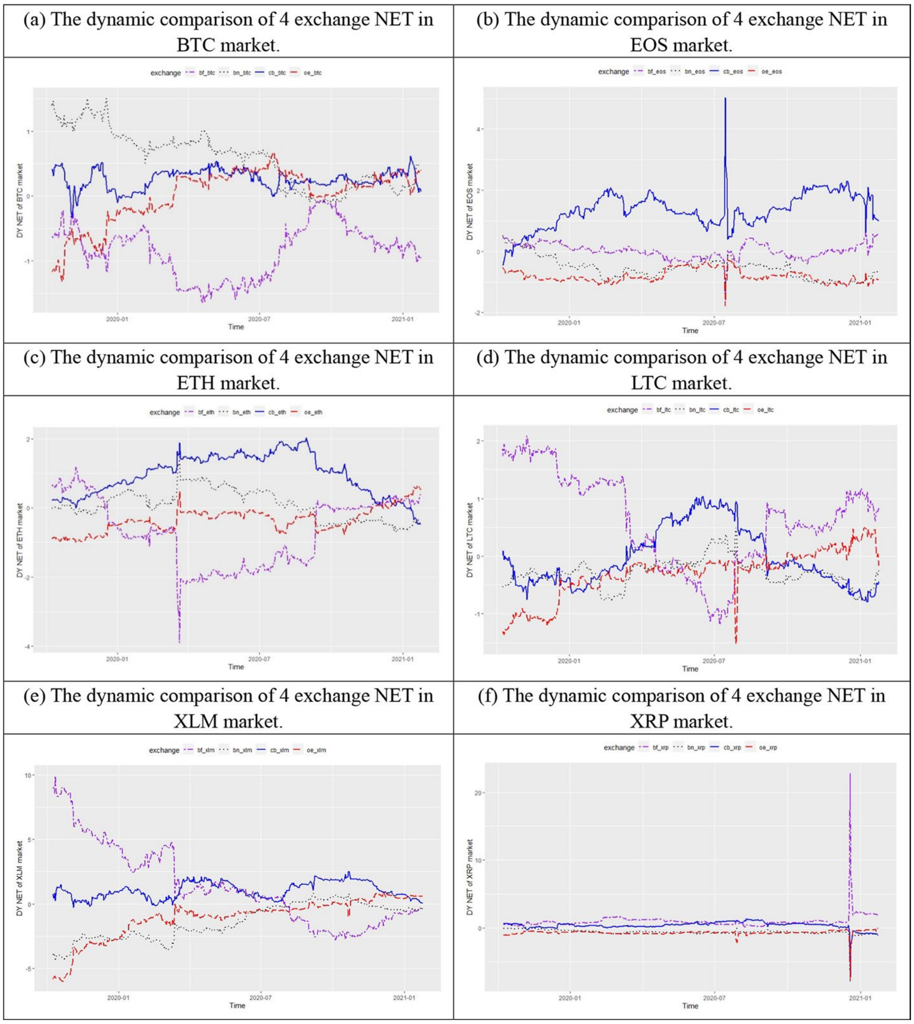

Fig. 7 The dynamic comparison of 4 exchange net directional connectedness in 6 cryptocurrency markets. *Notes*: This figure shows the dynamic comparison of 4 exchanges' *NET* connectedness for each cryptocurrency market. The estimation of *NET* index, estimation window and the value implications are same as Fig. 4

period. When BTC is under price pressure, Bitfinex prints Tether to purchase BTC to manipulate prices, and BTC flows from major Tether-based exchanges, such as Binance (Griffin and Shams 2020). BTC outflows from Binance spread volatility. A large inflow of BTC to Bitfinex creates an avenue for receiving spillovers. In ETH, Bitfinex started as a net emitter and then became a prominent net receiver until September 2020. The salient receiving effect may be attributed to optimistic traders on Bitfinex's Ethereum market. A strong inflow of Ethereum longs in March 2020.[12] In May 2020, the number of ETH long positions on Bitfinex rocketed to over 1.6 million contracts, which is more than three times that at the start of 2020.[13] For XRP, on December 19, 2020, the net directional connectedness of exchanges surged (or plummeted). From November 25 to December 6,

[12] Cryptoslate. Bitfinex whale "claims" $1.7 billion Ethereum long opened in March 2020. https://cryptoslate.com/bitfinex-whale-claims-1-7-billion-ethereum-long-opened-in-march-2020/ [Accessed on 2022–6-16].

[13] Bitcoinist.com. Ethereum Long Positions Hit $300 M on Bitfinex, And It Can Trigger a Major Correction. https://bitcoinist.com/ethereum-long-positions-pass-300m-bitfinex-why-this-could-end-badly/ [Accessed on 2022–6-16].

2020, four exchanges announced that they would successively support the Spark Airdrop Program for XRP holders.[14] The airdropped SPARK amount is calculated based on the amount of XRP held by users. In addition, Bitfinex promotes more XRP products. For example, Bitfinex users can use XRP as collateral to obtain loans in USDT or USD on Bitfinex Borrow,[15] and Bitfinex introduces XRP/USDT trading pairs.[16] These exchange-specific events accumulate as greater shocks to Bitfinex, resulting in prominent volatility emitting.

Determinants of the cryptocurrency and exchange total volatility spillover

Exploring the determinants of total connectedness in cryptocurrency or exchange volatility spillovers is essential for market participants. Here, we consider the influence of cryptocurrency (exchange) importance in the financial market and network, macro-financial influence, the investment substitution effect, and the uncertainty effect to explain the total connectedness in cryptocurrency and exchange volatility spillovers.

Determinants of the total connectedness in cryptocurrency volatility spillovers

Following Ji et al. (2019), Andrada-Félix et al. (2020), Charfeddine et al. (2022), Demiralay and Golitsis (2021), and Liu and Tsyvinski (2020), we construct a linear regression model to explore the determinants of total connectedness in cryptocurrency volatility spillovers. For each exchange, we construct the following model:

$$\begin{aligned} Total_t = \beta_0 &+ \alpha_1 Total_{t-1} + \alpha_2 RES\_LTC_{t-1} + \alpha_3 RES\_XLM_{t-1} + \alpha_4 Vol\_LTC_{t-1} \\ &+ \alpha_5 Vol\_XLM_{t-1} + \alpha_6 Vol\_XRP_{t-1} + \alpha_7 PV\_ETH_{t-1} + \alpha_8 MSCI\_World_{t-1} \\ &+ \alpha_9 SP500_{t-1} + \alpha_{10} LMBA\_Gold_{t-1} + \alpha_{11} GEPU_{t-1} + \alpha_{12} Ele\ Price_{t-1} + \mu_t \end{aligned} \tag{12}$$

where $Total_t$ is the total connectedness for an exchange, which is obtained in Sect. "Cryptocurrency dynamic volatility spillovers". RES is the simple return, which is estimated in $100\% \times [(P_t - P_{t-1})/P_{t-1}]$. Vol is a cryptocurrency's trading volume in one exchange, which excludes coin-to-coin trading due to limited liquidity (Makarov and Schoar 2020). The simple return and trading volume for LTC are involved in its largest net emitting effect. Considering the growing liquid and dominance of ETH (Kumar et al. 2022), the Wikipedia search for the keyword "Ethereum" is included and denoted by PV_ETH. The sample period is set from September 12 to December 2, 2020, when the trend of cryptocurrency total connectedness in the four exchanges decreased but the

[14] Binance Announcement. Binance Will Support the Spark (SPARK) Airdrop Program for XRP (XRP) holders. https://www.binance.com/en/support/announcement/78c11feba44d443998cf7a5329539e91. [2020–11-25, Accessed on 2022–6-16],
Bitfinex. Bitfinex Will Support Spark Airdrop Program for XRP Holders. https://www.bitfinex.com/posts/568 [2020–11-29, Accessed on 2022–6-16];
OKx Support. OKEx to support XRP's SPARK token snapshot and airdrop. https://www.okx.com/support/hc/en-us/articles/360053069811-OKEx-to-support-XRP-s-SPARK-token-snapshot-and-airdrop [2020–11-30, Accessed on 2022–6-16],
The Coinbase Blog. Coinbase to support Flare Network's Spark Airdrop. https://blog.coinbase.com/coinbase-to-support-flare-networks-spark-airdrop-5205ad889463 [2020–12-6, Accessed on 2022–6-16].

[15] Bitfinex. Bitfinex Borrow Adds XRP (XRP), Litecoin (LTC), EOS (EOS), Polkadot (DOT) as Collateral Options. https://www.bitfinex.com/posts/576 [2020–12-14, Accessed on 2022–6-16].

[16] Bitfinex. Bitfinex Adds Trading Pairs for EURt/USDt, XRP/USDt and XMR/USDt. https://www.bitfinex.com/posts/578 [2020–12-18, Accessed on 2022–6-16].

SPCC10 index increased. During this period, the XLM simple return varies and the XRP trading volume slowly increases for its Airdrop promotion; therefore, we add *RES_XLM*, *Vol_XLM*, and *Vol_XRP* to the model. To control for the influence of the macroeconomy and traditional finance market, we introduce the MSCI World index, S&P500 index, LBMA Gold price, Global Economy Policy Uncertainty, and electricity prices in the US. Following Andrada-Félix et al. (2020), we also consider the one-period lag of *Total* connectedness in the independent variables. All independent variables are logged (except *RES*) and lagged by one period in the regression. Based on Liew et al. (2022), Eq. (12) is estimated in OLS with heteroscedasticity and an autocorrelation-corrected (HAC) standard error on daily data. Table 5 shows the regression results.

Table 5 shows the determinants of total connectedness for four exchanges. The significant coefficient of the lagged dependent variable implies high persistence in the dynamic total cryptocurrency connectedness series. For traditional financial market factors, notably, the lagged MSCI World index exhibits a negative effect on the four exchanges, whereas the lagged S&P 500 index and LBMA_Gold have positive effects. This indicates that the traditional financial market affects volatility spillover in the cryptocurrency market. An increase in the prices of large- and mid-cap stocks across developed-countries can mitigate the uncertainty connectedness of cryptocurrencies. An increase in the prices of gold and large-cap equities in the US can aggravate the connectedness of cryptocurrencies in the four exchanges. ETH's pageviews on Wikipedia is negative for total connectedness in the four exchanges. This implies that the rising Internet concern about ETH, relative to the widely accepted cryptocurrency development platform Ethereum, can alleviate investors' suspicions regarding uncertainty in the cryptocurrency market. Global economic uncertainty is significantly positive to total connectedness in four exchanges, which is consistent with Demiralay and Golitsis (2021). This indicates that rising economic policy uncertainty increases the interlinkage of cryptocurrencies on one exchange. Electricity prices in the US show a significant positive influence on the total connectedness in the four exchanges, which supports Liu and Tsyvinski (2020) and indicates that cryptocurrency productional factors affect the cryptocurrency market. This is consistent with Hayes (2017), in that the rising costs of mining cryptocurrencies drive the prices of volatile cryptocurrencies.[17]

Determinants of the total connectedness in exchange volatility spillovers

In this section, we identify the potential drivers of the detected dynamic total connectedness in the three PoW-consensus cryptocurrencies.[18] No consensus has been reached on the determinants of exchange volatility spillovers for one cryptocurrency. Therefore, we introduce relevant variables and adopt a stepwise regression to select the determinants,

[17] We also conduct the robustness test to validate the above results in Table 11. We replace several variables. For Eq. (12), we choose log return, GEPU in current GDP, and the electricity price of the industry section in the USA to replace simple return, GEPU in PPP GDP and the electricity price for all sections, respectively. These robustness checks yield similar results.

[18] The PoW-consensus cryptocurrency can provide us with comparable and abundant indexes in the technical specifications. For PoW-consensus cryptocurrencies like BTC, ETH, and LTC, we choose average block time in minutes, hashrate, number of transactions in the blockchain, and average transaction fee in USD to measure the speed, the mining activity, the amount and the cost of the on-chain transactions. On the contrary, cryptocurrencies based on another consensus cannot be evaluated in the same way. For EOS, which is based on the DPoS consensus, its block time is set in the 0.5 s. This constant cannot reflect the time-varying on-chain trading features. XLM is based on the Stellar Consensus Protocol (SCP), and XRP is based on its unique Ledger Consensus Protocol. These two consensuses eliminate the nonce calculation, which depends on the computer capacity and is measured by hashrate. In conclusion, we only analyze the determinants of total connectedness in three PoW cryptocurrencies.

Table 5 The determinants of net connectedness in four exchanges

	BF	BN	CB	OE
	LnTotal	*LnTotal*	*LnTotal*	*LnTotal*
Lagged LnTotal	0.725***	0.777***	0.851***	0.796***
	(7.70)	(9.50)	(12.01)	(9.91)
Lagged RES_LTC	0.000174**	0.000124*	− 0.0000757	0.0000986
	(2.06)	(1.85)	(− 0.59)	(1.45)
Lagged RES_XLM	− 0.000244***	− 0.000223***	− 0.0000748	− 0.000192**
	(− 3.02)	(− 3.20)	(− 1.01)	(− 2.43)
Lagged LnVolLTC	− 0.000587	− 0.000107	0.000397	0.000179
	(− 0.98)	(− 0.14)	(0.35)	(0.17)
L.LnVolXLM	0.00184**	0.000719	0.00145***	0.000602
	(2.32)	(0.79)	(2.66)	(0.72)
Lagged LnVolXRP	− 0.0000447	0.000877	− 0.00207	0.000530
	(− 0.15)	(0.82)	(− 1.40)	(0.71)
Lagged LnPV_ETH	− 0.00642**	− 0.00722**	− 0.00607	− 0.00744***
	(− 2.25)	(− 2.41)	(− 1.19)	(− 2.74)
Lagged LnMSCI_World	− 0.285**	− 0.258**	− 0.0522	− 0.242**
	(− 2.41)	(− 2.16)	(− 0.46)	(− 2.33)
Lagged LnSP_500	0.284**	0.278**	0.0892	0.266**
	(2.33)	(2.16)	(0.84)	(2.38)
Lagged LnLBMA_Gold	0.0811***	0.0607***	0.0269	0.0571***
	(2.84)	(2.75)	(1.17)	(2.64)
Lagged LnGEPU	0.0146**	0.0134**	0.0125**	0.0117**
	(2.54)	(2.51)	(2.41)	(2.09)
Lagged LnElePrice	0.254**	0.212**	0.178**	0.206**
	(2.61)	(2.30)	(2.47)	(2.31)
_cons	− 0.184	− 0.300	− 0.336	− 0.363
	(− 0.56)	(− 0.81)	(− 0.98)	(− 0.96)
R-squared	0.987	0.985	0.984	0.986
Adjusted R-squared	0.985	0.983	0.982	0.984
Observations	99	99	99	99

This table shows the OLS regression results with heteroscedasticity and autocorrelation corrected (HAC) standard errors for the determinants of total volatility connectedness in four sample exchanges. The *t* statistics are reported in parentheses

*, **, *** Denote the significance at the 10%, 5% and 1% levels

as in Andrada-Félix et al. (2020). The set of potential drivers is mainly based on research on total connectedness among cryptocurrencies, which includes the lagged dependent variable, macroeconomic variables, traditional financial markets, and exchange- and cryptocurrency-specific variables (Andrada-Félix et al. 2020; Demiralay and Golitsis 2021; Ji et al. 2019).[19] Blockchain links cryptocurrency trading across exchanges for BTC, ETH, and LTC (Baur and Dimpfl 2020). On-chain trading is affected by underlying technical indicators. We introduce some technical indicators to explain the total connectedness among exchanges.

Table 6 summarizes the stepwise regression results for three PoW cryptocurrencies. The first two columns show the actual and predicted means of the dependent variables, respectively. The predicted means are close to the actual values in the three panels, demonstrating the good forecasting power of the stepwise models.

[19] In Table 10 we offer a summary of the explanatory variables used in the empirical analysis.

Table 6 Predicted power and relative contributions of explanatory variables

Panel 1: BTC's total volatility connectedness as dependent variable

Actual	**Predicted**		***Lagged RES_OE_BTC***	***Lagged RES_CB_BTC***	***Lagged VolBF***	***Lagged VolOE***
4.11E-06	4.04E-06	Individual Contribution(%)	25.39%	23.34%	24.18%	27.10%
		Category	Exchanges-Return		Exchanges-Trading volume	
		Aggregate contribution(%)	48.72%		51.28%	

Panel 2: ETH's total volatility connectedness as dependent variable

Actual	**Predicted**		***Lagged GSCI_Energy***	***Lagged RV_BN_ETH***	***Lagged RV_OE_ETH***	***Lagged VolCB***	***Lagged RES_CB_ETH***	***Lagged RES_BN_ETH***	***Lagged bt_ETH***
1.15E-06	1.13E-06	Individual Contribution(%)	10.59%	14.46%	11.98%	17.77%	17.83%	17.92%	9.44%
		Category	Macroeconomy	Exchanges-volatility		Exchanges-Trading volume	Exchanges-Return		ETH-Technical
		Aggregate contribution(%)	10.59%	26.45%		17.77%	35.75%		9.44%

Panel 3: LTC's total volatility connectedness as dependent variable

Actual	**Predicted**		***Lagged Total_LTC***	***Lagged PV_OE***	***Lagged PV_LTC***
1.15E-06	1.13E-06	Individual Contribution(%)	46.48%	28.23%	25.29%
		Category	Lagged DV	Exchanges-Internet Concern	LTC-Internet Concern

(1) The variables in stepwise models are all in logarithm, except *RES* (the simple return). All independent variables are lagged in one order

(2) In three panels, some variables require first differences for their non-stationary. We use the Augmented Dickey-Fuller (ADF) tests to test a unit root in time series. Some variables are stationary in levels, including *RES_BF_NTC*, *RES_BN_BTC*, *RES_CB_BTC*, *RES_OE_BTC*, *RV_BF_BTC*, *RV_BN_BTC*, *RV_CB_BTC*, *RV_OE_BTC*, *BTC_Volatility*, *bt_BTC*, and *tx_BTC* in Panel 1. *RES_BF_ETH*, *RES_BN_ETH*, *RES_CB_ETH*, *RES_OE_ETH*, *RV_BF_ETH*, *RV_CB_ETH*, *ETH_Volatility*, *bt_ETH* in Panel 2. *RES_BF_LTC*, *RES_BN_LTC*, *RES_CB_LTC*, *RES_OE_LTC*, *LTC_Volatility*, *bt_LTC* in Panel 3. Other variables are in the first differences. After the appropriate transformation, all the dependent and independent variables are stationaries

(3) All variables are winsorized at 5th and 95th percentiles

(4) To control the heteroskedasticity, we use OLS and the robust standard error in the stepwise regression. We use HAC standard error to estimate the optimal model to overcome the heteroscedasticity and serial correlation, which is illustrated in Table 12

(5) The relative contributions of the optimal explanatory variables are estimated by the standardized coefficients proposed by Bring (1994)

Stepwise regression empirically assessed the relevance of different determinants to the total connectedness of the three PoW coins. The exchange total volatility spillover of BTC is explained by the exchange return (48.72%) and exchange trading volume (51.82%). OKEx showed a highly aggregated contribution, accounting for 52.49% of the total contribution. This confirms OKEx's influence on BTC markets' volatility spillover, which expands the research of Alexander and Heck (2020) and reveals that unregulated exchanges strongly lead to price discovery in the BTC market. The macroeconomy, exchange volatility, and technical indicators of ETH can also explain the changes in the total volatility connectedness for ETH. Ethereum-mining requires large energy input

(Krause and Tolaymat 2018). A doubled hash rate[20] implies that ETH-mining becomes more dependent on energy consumption. The stepwise regression results indicate that higher energy costs for mining ETH can increase future market uncertainty. The average block time of ETH is 0.2 min, which is shorter than that of BTC at 10 min or LTC at 2.5 min. This lower latency can advance the correlation among exchanges (Baur and Dimpfl 2020), making the ETH market more interdependent. The lagged dependent variable contributes almost 50% to the total volatility connectedness of LTC, implying high persistence in this time series. The optimal regression model and contributions of each category differ across the three panels. The determinants of exchange volatility spillovers for different cryptocurrencies are inconsistent.

Conclusion

It is acknowledged that cryptocurrencies can cross-list on different exchanges. However, the heterogeneity of exchanges in volatility spillover has been overlooked. Therefore, this study focuses on specific exchanges rather than the global market. Based on high-frequency trading data covering April 13, 2019, to January 24, 2021, we investigate cryptocurrency volatility spillovers and exchange volatility spillovers based on 653 daily observations. We select Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and EOS as six representative cryptocurrencies (expressing 78.35% of the total market capitalization), and four typical exchanges, including Binance, OKEx, Coinbase, and Bitfinex (accounting for approximately 50.31% of the market share). We adopt the connectedness measurement proposed by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) to estimate the interconnection in the time and frequency domains. We construct a linear regression model to explore the determinants of total connectedness in cryptocurrency volatility spillovers and exchange volatility spillovers.

Our study shows the heterogeneity of exchanges in terms of volatility spillover. First, we reveal the heterogeneity of cryptocurrency volatility spillovers in different exchanges. Regarding cryptocurrency volatility spillovers for the four exchanges, the selected cryptocurrencies are highly interconnected within one exchange. The average total connectedness for the four exchanges is 76.12%, with the low frequency being the majority. This is determined by volatility generation and reveals that investor anticipation is essential for cryptocurrency volatility spillovers. The cryptocurrency net spillover magnitude and direction are similar on the four exchanges. LTC–BTC has the strongest correlation among the four exchanges, and the net spillover direction is from LTC to BTC. This highly relative spillover pair can provide suggestions for investors and regulators. Owing to the different underlying encryption algorithms, BTC emerges as the principal net receiver and LTC is the contagion core in the four exchanges. XRP plays different roles in distinct exchanges: a net receiver in Coinbase but a net contributor in the other three exchanges. This finding addresses different risk emitters in sample exchanges for regulators. For the same asset, XRP, regulators should consider its possible volatility emitting in Binance, Bitfinex, and OKEx. Across the frequency domains, the net emitting effect of one cryptocurrency among the exchanges is different. Thus, it would be appropriate for investors with different investment horizons to consider the heterogeneity of

[20] During our sample period, the Ethereum Network Hashrate grew from 200 k to nearly 400 k. The details are based on https://etherscan.io/chart/hashrate.

cryptocurrency volatility connectedness from an exchange perspective. Considering the time variation in cryptocurrency volatility spillovers, the overall connectedness of the four exchanges decreased in Jan. 2020 and then again later in 2020. The steep declines in low-frequency band connectedness drive this decrease. In these four exchanges, some cryptocurrencies can consistently serve as either a net trigger or receiver, whereas others can change their roles over time.

Second, we examine the exchange volatility spillovers in different cryptocurrency markets to investigate the heterogeneity of exchanges. The four exchanges are highly interlinked in six cryptocurrencies, with the average total connectedness of the four exchanges at almost 75%. Low frequency accounts for the majority, implying that long-term market factors have the strongest influence on exchange volatility spillovers. Coinbase continues to play the role of the net contributor in six cryptocurrency markets, while OKEx remains the net receiver. Considering the countries of these two exchanges are located, this situation is similar to the developed US market and has strong volatility spillover to the emerging Chinese market. Binance, Bitfinex, and Coinbase are the most significant net contributors for some coins; thus, regulators should focus on the volatility spillover contributions of these three exchanges in most cryptocurrency markets. The exchange pairs with the strongest correlations differ across the six cryptocurrency markets. Therefore, arbitrators and regulators in different cryptocurrency markets should consider the heterogeneity of exchanges. As the frequency changes, exchanges can shift their emitting or receiving roles. For the evolution of total connectedness, the overall connectedness in the time domain is stable for the six cryptocurrencies; however, the decline in the low-frequency band connectedness for these cryptocurrencies occur at a different time and magnitude. The core contagion exchange for the six cryptocurrencies varies over time.

Third, we explore the determinants of total connectedness. We construct a linear regression model to explain the total connectedness in cryptocurrency volatility spillovers. The growing Internet concern regarding ETH can relieve investors' suspicions of cryptocurrency uncertainty for four exchanges. Electricity prices in the US positively affect the total connectedness in four exchanges, which indicates that cryptocurrency production factors affect the cryptocurrency market. We apply stepwise regression to select the determinants of total connectedness in exchange volatility spillovers. Some exchange returns and trading volumes account for BTC's total volatility connectedness. For ETH, the macroeconomic influence, volatility of some exchanges, and technical indicators of ETH can also affect its total connectedness. LTC's total volatility connectedness shows persistence in its time series and is influenced by the Internet concern of OKEx and LTC.

Cryptocurrencies can be listed on different exchanges simultaneously, which provides a perfect market in which to explore the heterogeneity of volatility spillovers, revealing risk contagion among assets. Our findings suggest that market participants should consider the heterogeneity of exchanges, which can be expressed through cryptocurrency pricing and volatility spillover mechanisms. Investors should note that a single asset cannot continue to serve as a safe haven in every exchange. Volatility-hedging portfolios may vary across exchanges. Likewise, venues can exhibit different risk features depending on the cryptocurrency market, given an exchange-specific crisis. Investors also need to distinguish between the determinants' influences on volatility spillovers. Supervisors should identify the precise source of contagion within the scope of the exchange rather than looking at the global market alone. In addition, more efficient and environmentally friendly blockchain trading architecture is urgently needed.

Future research should explore the determinants of volatility connectedness for cryptocurrencies or exchanges in the frequency domain. The results based on Baruník and Křehlík (2018) display the various spillovers as the frequency change, emphasizing the necessity of frequency decomposition. The distinction between market noise and fundamental value changes (Andrada-Félix et al. 2020) indicates that macroeconomic or cryptocurrency-specific factors might influence specific frequency bands differently. Therefore, future research should also consider frequency differences.

Appendix

See Figs. 8, 9, 10 and 11.

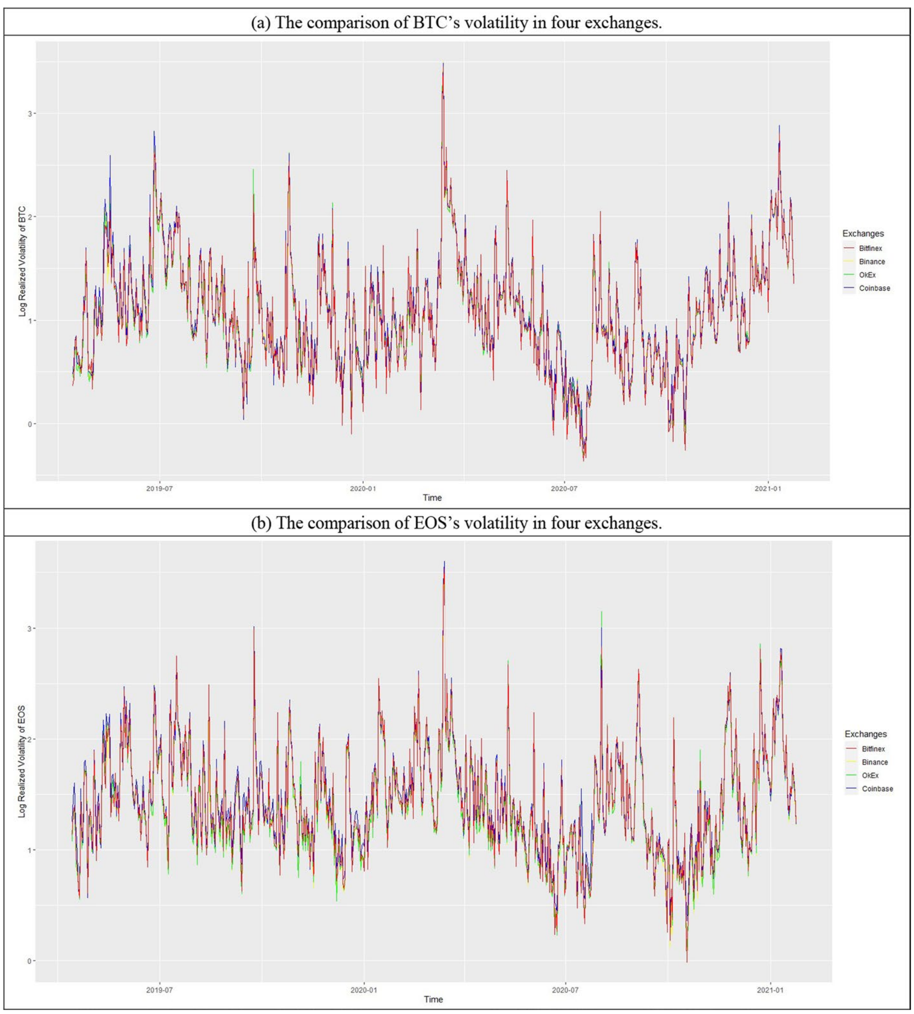

Fig. 8 The comparison of one coin's volatility in four exchanges. Notes: This figure shows the log realized volatility of 6 cryptocurrencies in four sample exchanges. (a)-(f) depicts BTC, EOS, ETH, LTC, XLM and XRP respectively. In each subgraph, the horizontal axis is time, while the vertical axis is the log realized volatility for one cryptocurrency in a specific exchange

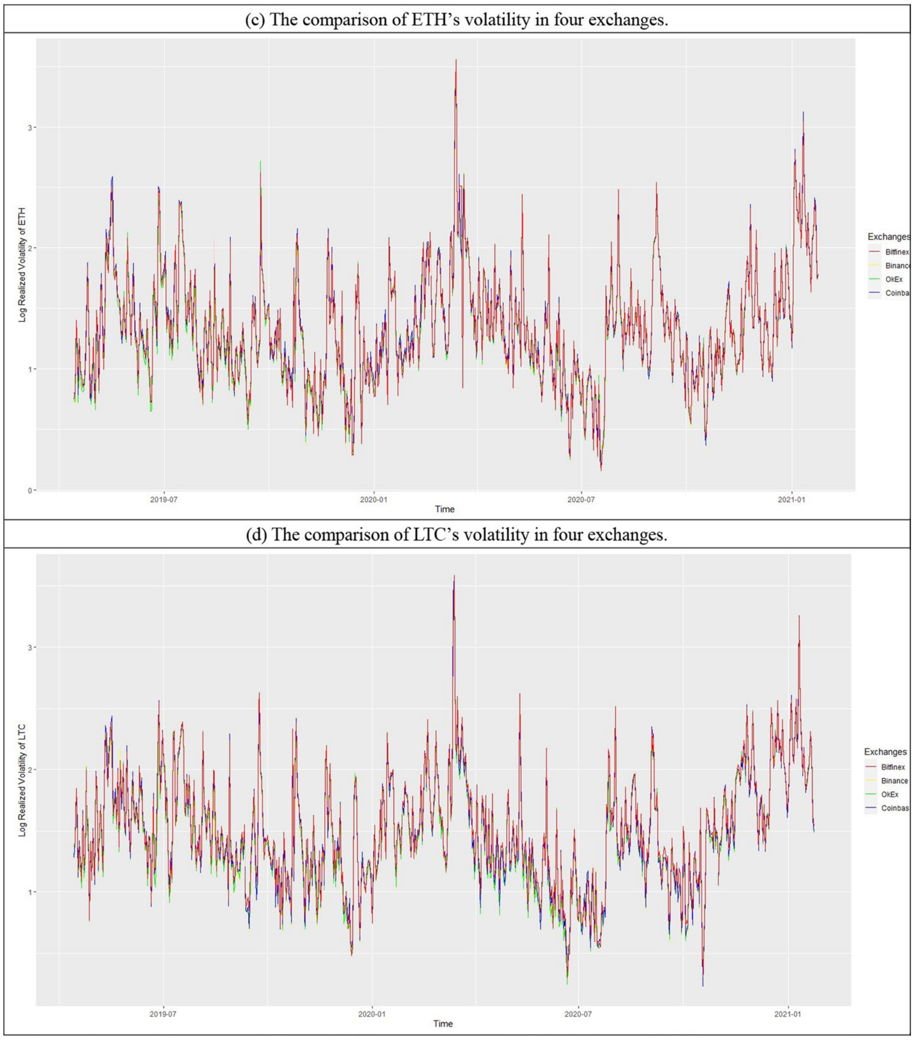

Fig. 8 continued

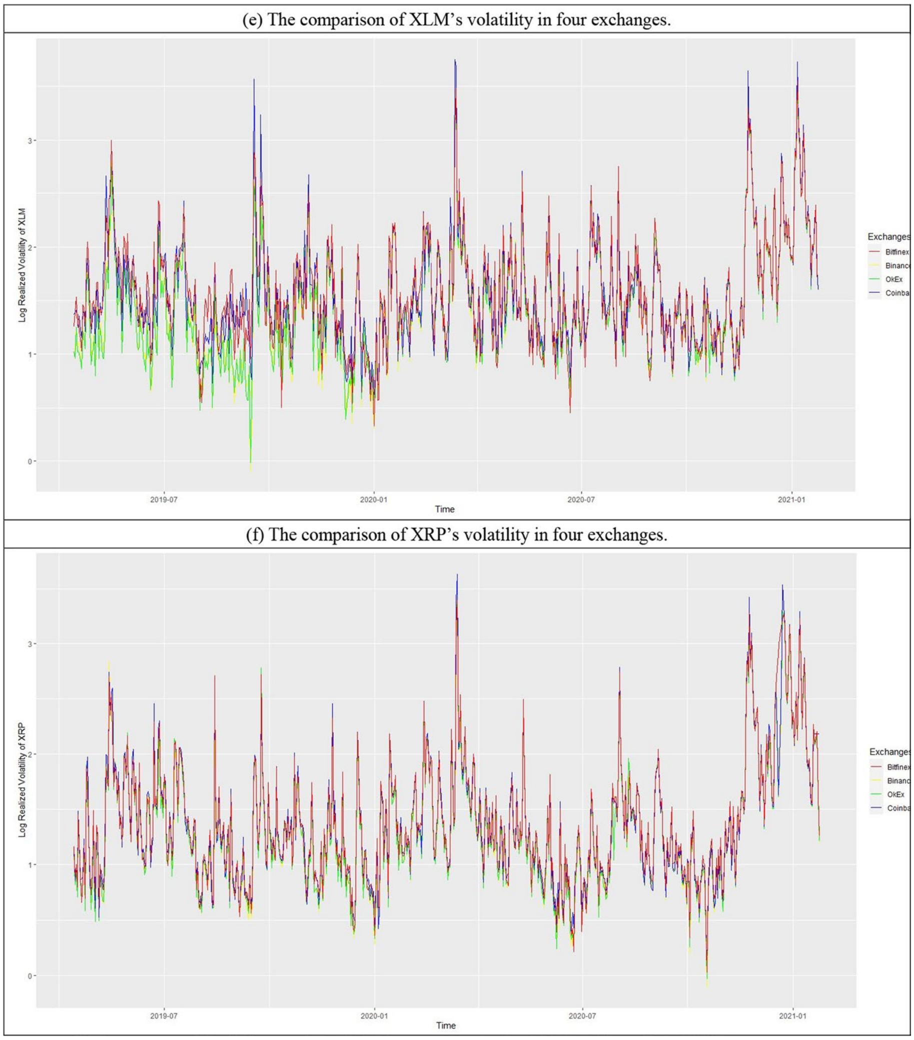

Fig. 8 continued

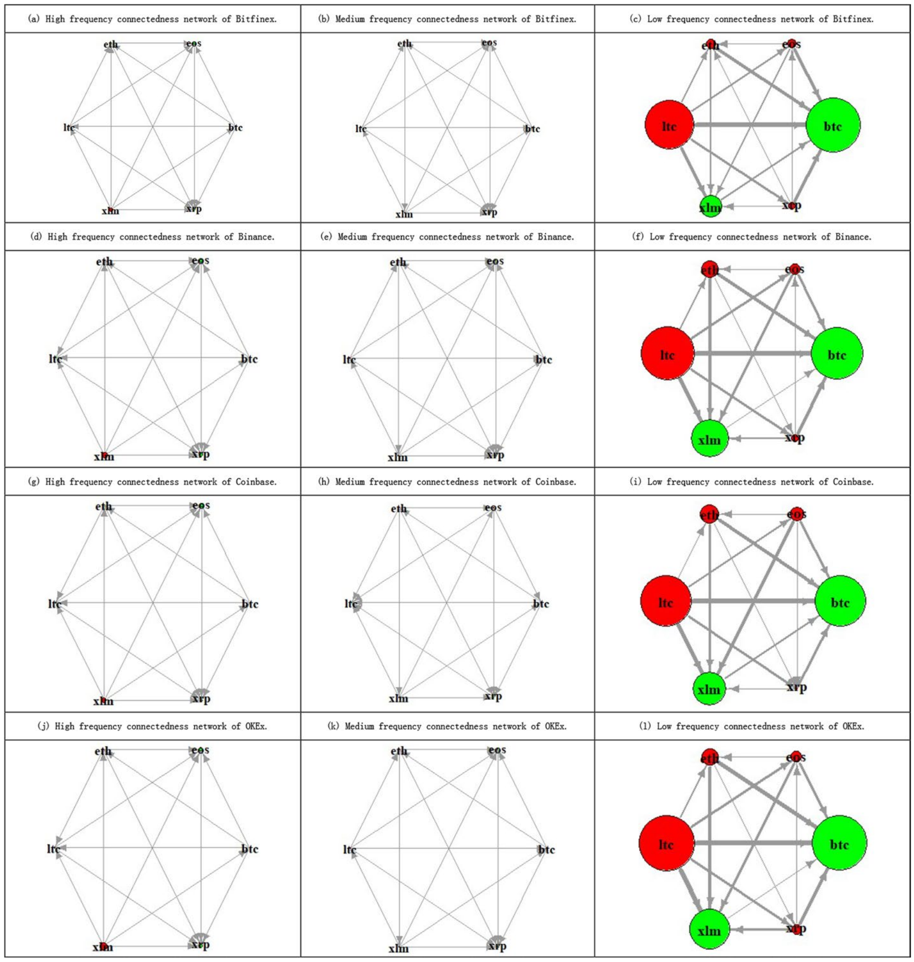

Fig. 9 The frequency decomposition of cryptocurrency volatility connectedness network for 4 exchanges based on Baruník and Křehlík (2018). *Notes*: This figure shows the cryptocurrency volatility connectedness network for 4 exchanges in the frequency domain. The red node in a network denotes the net emitter, the green node in a network denotes the net receiver. The size of the node represents the magnitude of a net emitter to other cryptocurrencies, or a net receiver from the others. The thickness of the directional arrows denotes the magnitude of the net pairwise directional volatility connectedness

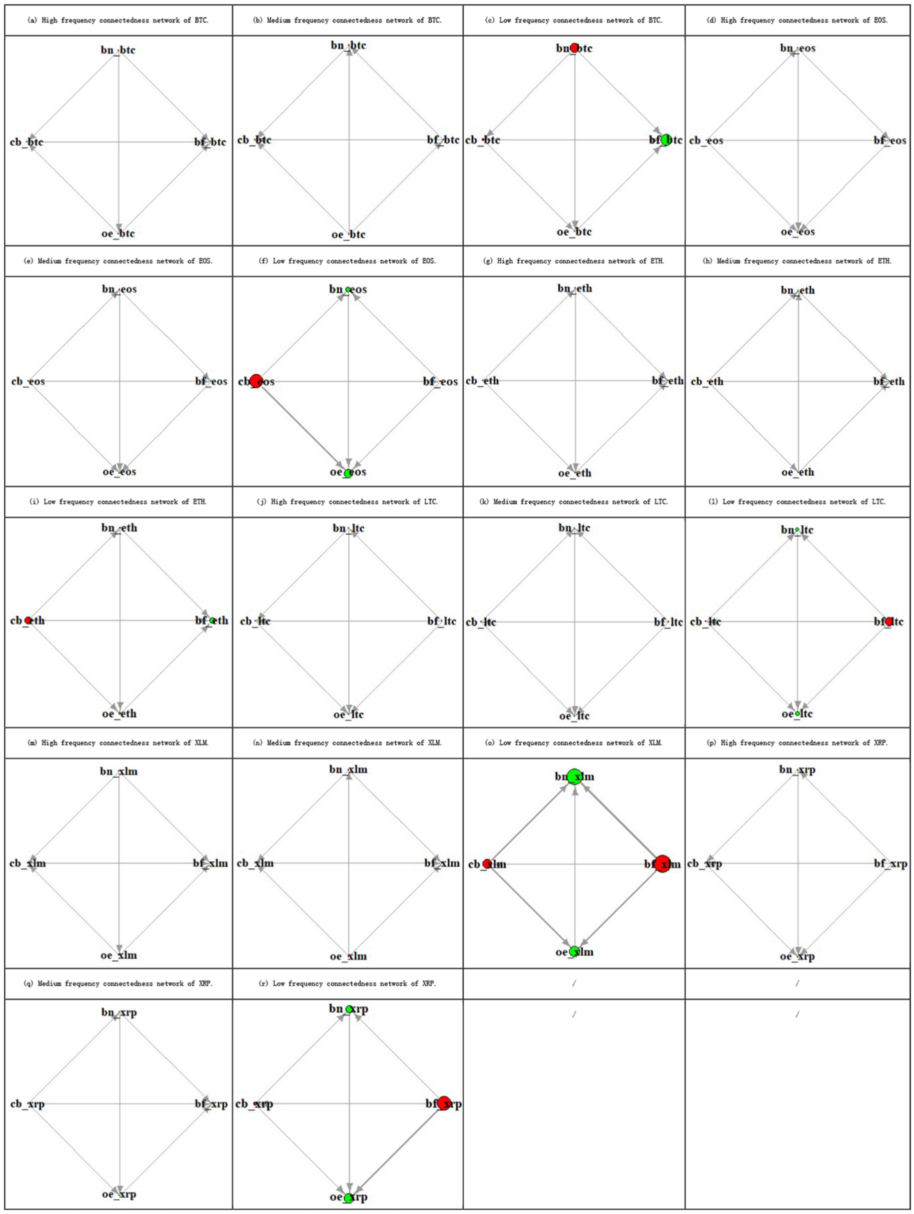

Fig. 10 The frequency decomposition of exchange volatility connectedness network for 6 coins based on Baruník and Křehlík (2018). *Notes*: This figure shows the exchange volatility connectedness network for 6 coins in the frequency domain. The red node in a network denotes the net emitter, the green node in a network denotes the net receiver. The size of the node represents the magnitude of a net emitter to other exchanges, or a net receiver from the others. The thickness of the directional arrows denotes the magnitude of the net pairwise directional volatility connectedness

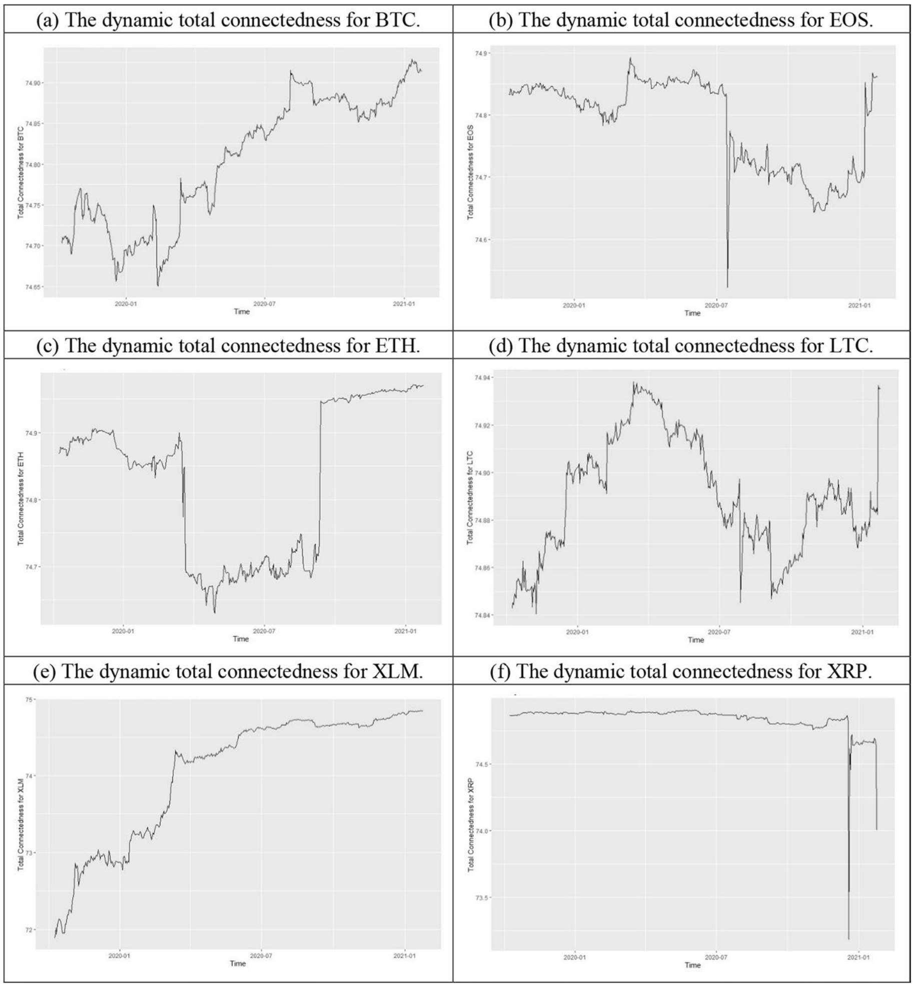

Fig. 11 The dynamic total exchange volatility connectedness for 6 coins. *Notes*: This figure illustrates the moving-window estimation of total connectedness for BTC, EOS, ETH, LTC, XLM and XRP in the time domain. The estimation window is set at 180 days (half a year)

See Tables 7, 8, 9, 10, 11, 12 and 13.

Table 7 Independent variables of total spillovers

Independent Variables	Description
RES	Simple return, which is estimated in $100\% \times [(P_t - P_{t-1})/P_{t-1}]$
Vol	Cryptocurrency's trading volume in one exchange, which excludes coin-to-coin trading
PV	The Wikipedia search for the keyword of corresponding cryptocurrency or exchange, which is collected from https://pageviews.wmcloud.org/
MSCI_World	The Morgan Stanley Capital International World (MSCI_World) index is collected from https://www.msci.com/. This illustrates the large- and mid-cap stock performance across developed-market countries
SP500	The S&P500 index, which is collected from https://www.spglobal.com/spdji/en/indices/equity/sp-500/#overview
LBMA Gold	The LBMA Gold price set at 10:30 in US dollars per fine troy ounce, which is collected from https://www.lbma.org.uk/prices-and-data/precious-metal-prices#/
GEPU	The Global Economic Policy Uncertainty index based on PPP-Adjusted GDP, which is collected from http://www.policyuncertainty.com/global_monthly.html
ElePrice	The average retail price of electricity of all sections in USA, which is collected from https://www.eia.gov/electricity/data/browser/

Table 8 Definition of the potential drivers of total volatility connectedness among exchanges

Category		Variables	Description
Dependent variables		*Total_BTC*	The total exchange connectedness for BTC
		Total_ETH	The total exchange connectedness for ETH
		Total_LTC	The total exchange connectedness for LTC
Exchanges	Trading volume	*VolBF*	The BTC's/ETH's/LTC's trading volume in Bitfinex, which excludes coin-to-coin trading
		VolBN	The BTC's/ETH's/LTC's trading volume in Binance, which excludes coin-to-coin trading
		VolCB	The BTC's/ETH's/LTC's trading volume in Coinbase, which excludes coin-to-coin trading
		VolOE	The BTC's/ETH's/LTC's trading volume in OKEx, which excludes coin-to-coin trading
	Network concern	*PV_BF*	The number of Wikipedia search for the keyword, "Bitfinex"
		PV_BN	The number of Wikipedia search for the keyword, "Binance"
		PV_CB	The number of Wikipedia search for the keyword, "Coinbase"
		PV_OE	The number of Wikipedia search for the keyword, "OKEx" and "OKX"
	Return	*RES_BF_BTC /RES_BF_ETH/ RES_BF_LTC*	The simple return of BTC/ETH/LTC in Bitfinex
		RES_BN_BTC/RES_BN_ETH/ RES_BN_LTC	The simple return of BTC /ETH/LTC in Binance
		RES_CB_BTC/RES_CB_ETH/ RES_CB_LTC	The simple return of BTC /ETH/LTC in Coinbase
		RES_OE_BTC/RES_OE_ETH/ RES_OE_LTC	The simple return of BTC /ETH/LTC in OKEx
	Volatility	*RV_BF_BTC/RV_BF_ETH/RV_BF_LTC*	The realized variance of BTC /ETH/LTC in Bitfinex
		RV_BN_BTC/RV_BN_ETH/RV_BN_LTC	The realized variance of BTC /ETH/LTC in Binance

Table 9 Definition of the potential drivers of total volatility connectedness among exchanges (continued)

Category		Variables	Description
Exchanges	Volatility	*RV_CB_BTC/RV_CB_ETH/RV_CB_LTC*	The realized variance of BTC /ETH/LTC in Coinbase
		RV_OE_BTC/RV_OE_ETH/RV_OE_LTC	The realized variance of BTC /ETH/LTC in OKEx
Cryptocurrency	Network concern	*PV_BTC/PV_ETH/PV_LTC*	The number of Wikipedia search for the keyword, "Bitcoin" / "Ethereum" / "Litecoin"
	Volatility	*BTC_Volatility/ETH_Volatility/LTC_Volatility*	The volatility of BTC /ETH/LTC, which is calculated by the change in the squared log return
	Markets	*SPCC10*	S&P Cryptocurrency Top 10 Equal Weight Index
	Technical indicators	*bt_BTC/bt_ETH/bt_LTC*	Average block time in minutes
		hr_BTC/hr_ETH / hr_LTC	Hashrate
		tx_BTC/tx_ETH / tx_LTC	Number of transactions in blockchain
		fee_BTC/fee_ETH / fee_LTC /	Average transaction fee, USD
Traditional financial markets		*GSCI_Gold*	GSCI_Gold index
		GSCI_Energy	GSCI_Energy index
		VIXCLOSE	VIX daily close price
		MSCI_World	The Morgan Stanley Capital International World (MSCI_World) index
Macroeconomy		*GEPU_ppp*	The Global Economic Policy Uncertainty index
		ElePrice	The average retail price of electricity of all sections in USA

Table 10 Summary statistics for variables in the regression of total connectedness

Exchanges	VarName	Obs	Mean	SD	Min	P25	Median	P75	Max
Bitfinex	*LnTotal*	99	4.333	0.027	4.274	4.307	4.344	4.355	4.366
	RES_BF_LTC	99	0.949	5.120	− 12.956	− 2.221	0.251	3.172	18.352
	RES_BF_XLM	99	1.018	7.808	− 12.857	− 2.828	− 0.097	2.648	48.231
	LnVolLTC	99	15.163	1.111	13.191	14.169	15.079	16.006	17.678
	LnVolXLM	99	12.059	1.486	9.183	10.948	11.618	13.096	16.170
	LnVolXRP	99	15.353	1.567	12.760	14.240	14.832	16.531	19.329
	LnPV_ETH	99	7.682	0.336	7.109	7.418	7.588	7.948	8.484
	LnMSCI_World	99	7.814	0.046	7.738	7.775	7.803	7.860	7.892
	LnSP_500	99	8.159	0.041	8.083	8.121	8.156	8.197	8.222
	LnIBMA_Gold	99	7.541	0.022	7.480	7.530	7.541	7.556	7.584
	LnGEPU_ppp	99	5.790	0.101	5.707	5.714	5.742	5.941	5.941
	LnElePrice	99	2.449	0.020	2.431	2.432	2.432	2.455	2.484
Binance	*LnTotal*	99	4.343	0.025	4.291	4.318	4.351	4.365	4.372
	RES_BN_LTC	99	0.951	5.138	− 12.978	− 2.300	0.219	3.094	18.533
	RES_BN_XLM	99	1.019	7.816	− 12.576	− 2.787	0.010	2.594	47.876
	LnVolLTC	99	17.755	1.023	15.871	16.789	17.707	18.524	19.842
	LnVolXLM	99	16.510	1.194	14.996	15.613	15.988	17.385	19.813
	LnVolXRP	99	18.267	1.290	16.457	17.272	17.737	19.491	21.366
	LnPV_ETH	99	7.682	0.336	7.109	7.418	7.588	7.948	8.484
	LnMSCI_World	99	7.814	0.046	7.738	7.775	7.803	7.860	7.892
	LnSP_500	99	8.159	0.041	8.083	8.121	8.156	8.197	8.222
	LnIBMA_Gold	99	7.541	0.022	7.480	7.530	7.541	7.556	7.584
	LnGEPU_ppp	99	5.790	0.101	5.707	5.714	5.742	5.941	5.941
	LnElePrice	99	2.449	0.020	2.431	2.432	2.432	2.455	2.484
Coinbase	*LnTotal*	99	4.332	0.029	4.273	4.303	4.335	4.357	4.366
	RES_CB_LTC	99	0.953	5.157	− 13.015	− 2.228	0.223	3.231	18.374
	RES_CB_XLM	99	1.023	7.868	− 12.642	− 2.752	− 0.147	2.602	48.538
	LnVolLTC	99	16.372	1.067	14.581	15.417	16.218	17.237	18.708
	LnVolXLM	99	15.653	1.333	13.911	14.634	15.074	16.810	19.339
	LnVolXRP	99	17.032	1.362	15.200	16.025	16.308	18.357	20.345
	LnPV_ETH	99	7.682	0.336	7.109	7.418	7.588	7.948	8.484
	LnMSCI_World	99	7.814	0.046	7.738	7.775	7.803	7.860	7.892
	LnSP_500	99	8.159	0.041	8.083	8.121	8.156	8.197	8.222
	LnIBMA_Gold	99	7.541	0.022	7.480	7.530	7.541	7.556	7.584
	LnGEPU_ppp	99	5.790	0.101	5.707	5.714	5.742	5.941	5.941
	LnElePrice	99	2.449	0.020	2.431	2.432	2.432	2.455	2.484
OKEx	*LnTotal*	99	4.339	0.027	4.283	4.312	4.347	4.363	4.371
	RES_OE_LTC	99	0.950	5.115	− 12.815	− 2.316	0.298	3.165	18.290
	RES_OE_XLM	99	1.020	7.830	− 12.686	− 2.814	− 0.008	2.595	47.586
	LnVolLTC	99	16.920	0.919	15.245	16.168	16.626	17.667	19.002
	LnVolXLM	99	15.908	1.103	14.610	15.130	15.443	16.870	18.813
	LnVolXRP	99	16.146	1.395	13.865	15.190	15.583	17.445	19.171
	LnPV_ETH	99	7.682	0.336	7.109	7.418	7.588	7.948	8.484
	LnMSCI_World	99	7.814	0.046	7.738	7.775	7.803	7.860	7.892
	LnSP_500	99	8.159	0.041	8.083	8.121	8.156	8.197	8.222
	LnIBMA_Gold	99	7.541	0.022	7.480	7.530	7.541	7.556	7.584
	LnGEPU_ppp	99	5.790	0.101	5.707	5.714	5.742	5.941	5.941
	LnElePrice	99	2.449	0.020	2.431	2.432	2.432	2.455	2.484

Table 11 Robust test for determinants of the total volatility connectedness for four exchanges

	BF *LnTotal*	BN *LnTotal*	CB *LnTotal*	OE *LnTotal*
Lagged LnTotal	0.678***	0.730***	0.824***	0.752***
	(6.41)	(7.64)	(10.26)	(7.93)
Lagged RE_LTC	0.0169**	0.0119*	−0.00819	0.00921
	(2.00)	(1.72)	(−0.64)	(1.34)
Lagged RE_XLM	−0.0244***	−0.0217***	−0.00734	−0.0188**
	(−2.96)	(−3.03)	(−0.96)	(−2.39)
Lagged LnVolLTC	−0.000685	−0.000191	0.000331	0.0000793
	(−1.10)	(−0.26)	(0.29)	(0.08)
Lagged LnVolXLM	0.00170**	0.000445	0.00131**	0.000362
	(2.31)	(0.47)	(2.42)	(0.41)
Lagged LnVolXRP	−0.0000615	0.000873	−0.00209	0.000548
	(−0.20)	(0.82)	(−1.43)	(0.74)
Lagged LnPV_ETH	−0.00612**	−0.00685**	−0.00582	−0.00731***
	(−2.06)	(−2.22)	(−1.14)	(−2.64)
Lagged LnMSCI_World	−0.274**	−0.246**	−0.0354	−0.230**
	(−2.55)	(−2.22)	(−0.31)	(−2.41)
Lagged LnSP_500	0.274**	0.267**	0.0729	0.257**
	(2.46)	(2.23)	(0.69)	(2.47)
Lagged LnLBMA_Gold	0.0862***	0.0654***	0.0312	0.0618**
	(2.88)	(2.76)	(1.32)	(2.63)
Lagged LnGEPU_current	0.0120**	0.0118**	0.0104**	0.0102**
	(2.26)	(2.43)	(2.17)	(2.01)
Lagged LnElePrice_ind	0.214***	0.185**	0.147**	0.182**
	(2.77)	(2.41)	(2.56)	(2.37)
_cons	0.185	0.0102	−0.0972	−0.0781
	(0.65)	(0.03)	(−0.26)	(−0.24)
R-squared	0.987	0.986	0.984	0.987
Observations	99	99	99	99

This table shows the OLS regression results with heteroscedasticity and autocorrelation corrected (HAC) standard errors for the determinants of total volatility connectedness in four sample exchanges. The *t* statistics are reported in parentheses

*, **, *** denote the significance at the 10%, 5% and 1% levels

Table 12 Stepwise regression results

Variables	Δ/level	Coefficient	t-Statistics
Panel 1: BTC's total volatility connectedness as dependent variable			
Lagged RES_OE_BTC	Level	0.0000147**	(2.49)
Lagged LnVolBF	Δ	0.0000110**	(2.07)
Lagged RES_CB_BTC	Level	− 0.0000133**	(− 2.29)
Lagged LnVolOE	Δ	− 0.0000223**	(− 2.36)
_cons		0.00000351	(1.28)
R-squared		0.0271	
Adj-r2		0.0188	
Observations		472	
Panel 2: ETH's total volatility connectedness as dependent variable			
Lagged LnGSCI_Energy	Δ	0.000281*	(1.67)
Lagged lnRV_BN_ETH	Δ	− 0.000284***	(− 2.61)
Lagged lnRV_OE_ETH	Δ	0.000234**	(2.16)
Lagged LnVolCB	Δ	0.0000281***	(2.60)
Lagged Lnbt_ETH	Level	− 0.000532**	(− 2.04)
Lagged RES_CB_ETH	Level	− 0.0000214***	(− 3.20)
Lagged RES_BN_ETH	Level	0.0000219***	(3.20)
_cons		0.000111**	(2.06)
R-squared		0.0596	
Adj-r2		0.0454	
Observations		472	
Panel 3: LTC's total volatility connectedness as dependent variable			
Lagged LnTotal_ltc	Δ	− 0.202***	(− 4.20)
Lagged LnPV_OE	Δ	− 0.00000734**	(− 2.57)
Lagged LnPV_LTC	Δ	0.0000306**	(2.22)
_cons		0.00000131	(0.80)
R-squared		0.068	
Adj-r2		0.062	
Observations		472	

(1) Three panels are estimated in OLS with heteroscedasticity and autocorrelation corrected (HAC) standard errors on daily data to overcome the heteroscedasticity and serial correlation in OLS

(2) The *t* statistics are reported in parentheses

*, **, *** denote the significance at the 10%, 5% and 1% levels

Table 13 The diagnostic tests for the spurious regression issue

Model	Lags for ADF test	Test statistic	Interpolated Dickey–Fuller			MacKinnon approximate *p*-value for Z(t)
			1% Critical value	5% Critical value	10% Critical value	
BF	3	− 6.274	− 3.517	− 2.894	− 2.582	0.0000
BN	1	− 8.640	− 3.514	− 2.892	− 2.581	0.0000
CB	2	− 7.188	− 3.516	− 2.893	− 2.582	0.0000
OE	1	− 8.646	− 3.514	− 2.892	− 2.581	0.0000

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MW: Data curation, writing-original draft preparation, writing-reviewing and editing. LW: Conceptualization, supervision. HY: Conceptualization, methodology, writing-reviewing and editing, supervision.

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Declarations

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The author declares no competing interests.

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