Physica A 681 (2026) 131111

Contents lists available at ScienceDirect

Physica A: Statistical Mechanics and its Applications

journal homepage: www.elsevier.com/locate/physa

Exploring crypto-stock risk contagion via directed complex network analytics

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ARTICLE INFO

Keywords:
Cryptocurrency
Risk Spillover
DMST
DPMFG
INFOMAP
TVP-VAR

ABSTRACT

In the context of financial market integration and convergence of investor behavior, the risk contagion between cryptocurrency and traditional financial markets has become increasingly significant. We construct a risk spillover matrix using the Elastic-Net-GFEVD (Generalized Forecast Error Variance Decomposition) method, encompassing major global stock indices and cryptocurrencies. Based on this matrix, we develop a cryptocurrency risk contagion network employing DMST(Directed Minimum Spanning Tree) and DPMFG(Directed Planar Maximally Filtered Graph) techniques. The INFOMAP algorithm is further applied to identify network communities, enabling the tracking of risk spillover effects across time and regions. To capture the dynamic evolution of risk spillovers and network connectivity, we utilize TVP-VAR(Time-Varying Parameter Vector Autoregressive Model) and smoothing techniques. Our findings indicate that U.S. and European markets exhibit the highest risk spillovers to cryptocurrencies among all regions, and Ethereum is the cryptocurrency with the greatest risk spillover. The COVID-19 pandemic has reshaped the dynamics of risk transmission between stock and cryptocurrency markets. Before the pandemic, stock markets were tightly interconnected, while the cryptocurrency market operated largely independently. Post-pandemic, economic uncertainty has intensified risk spillovers, especially from U.S. and European stock markets to cryptocurrencies. LTC was the most impacted index in the latter half of 2021, while Ethereum was most affected by spillovers in mid-2021 and exhibited the highest contagion by the end of 2022. This shift—from risk recipient to active transmitter—underscores the increasing systemic importance of select cryptocurrency indices in the global financial network. This research offers key insights for regulators to mitigate systemic risk contagion between cryptocurrencies and global stock markets.

1. Introduction

Cryptocurrencies, powered by blockchain technology, have become a focal point in modern financial markets. While their full potential remains untapped [1], They demonstrate functionalities similar to traditional assets, such as serving as a store of value and medium of exchange [2]. By mid-2024, cryptocurrency market capitalization exceeded $2 trillion, with Bitcoin comprising over 50 %. This has garnered substantial attention from investors, regulators, and academics [3]. The model by Allen and Gale (2000) indicates that financial contagion, as an equilibrium phenomenon, can rapidly spread through financial networks, with even minor initial shocks potentially causing widespread vulnerability [4]. The high volatility and decentralized nature of cryptocurrencies make them prone to

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https://doi.org/10.1016/j.physa.2025.131111
Received 23 December 2024; Received in revised form 23 October 2025; Accepted 5 November 2025
Available online 8 November 2025
0378-4371/

contagion effects during market stress, posing risks to global financial stability [5,6]. These dynamics have fueled academic interest, particularly in cryptocurrencies' role in global financial integration. The interconnectedness between traditional and cryptocurrency markets has deepened, especially during major events such as the COVID-19 pandemic and the Russia-Ukraine conflict [7].

Existing studies primarily explore the interactions between cryptocurrencies and specific financial markets [8–12]. Bouri employed the Cross-Quantilogram approach to analyze cryptocurrencies and the U.S. stock market, uncovering varying hedging and safe-haven effects across industries [13]. Using Quantile Vector Autoregression (QVAR), Khalfaoui identified Bitcoin as a net recipient of volatility spillovers, while green commodities acted as net contributors [14]. Corbet et al. utilized a Rolling Window method to examine cryptocurrencies and China's major stock markets during COVID-19, showing initial safe-haven properties and significant contagion effects [15]. Pham and Nguyen through a Structural Break Vector Autoregression (SB-VAR) model, demonstrated bi-directional causality between China's thermal coal futures and cryptocurrencies [16]. Xie employed a TVP-VAR to investigate dynamic risk spillovers between cryptocurrencies and Chinese financial markets [17]. However, such studies' narrow focus on individual markets often overlooks the broader interconnectedness of this evolving global financial system [18].

An increasing number of scholars have focused on the linkages between cryptocurrencies and multiple financial markets. Techniques such as Vector Autoregression (VAR) [19], Generalized Autoregressive Conditional Heteroskedasticity (GARCH) [20], and the DY and BK frameworks [21,22] have been employed to construct risk spillover matrices. Complex network analysis further elucidates the relationships between cryptocurrencies and traditional financial systems [23,24]. For example, Papadimitriou et al. utilized the TW-MDS (Threshold Weighted-Minimum Dominating Set) method to study the topological properties of 112 cryptocurrencies, confirming price synchronization within the cryptocurrency market [25]. Yu applied entropy-based complex networks to show that traditional financial assets act as information transmitters, while cryptocurrencies mostly serve as receivers, with extreme events correlating to abnormally high values in dynamic network curves [26]. Gong et al. combined the QVAR and BK methods to examine tail risk spillovers between cryptocurrencies and global stock markets, constructing networks from both time- and frequency-domain perspectives using conditional quantiles as thresholds [27]. Zieba et al. used the Minimum Spanning Tree (MST) method to analyze cryptocurrency market structures and assessed Bitcoin's influence on the volatility of other cryptocurrencies through a VAR model [28]. Hong and Yoon utilized mutual information and correlation coefficients to construct a cryptocurrency network. Using MST and PMFG methods, they found that the pandemic altered relationships and heightened complexity, demonstrating mutual information's effectiveness in capturing non-linear dependencies [29]. Zhuang et al. integrated MST and Planar Maximally Filtered Graph (PMFG) approaches, demonstrating that PMFG adds complementary insights to MST [30]. Despite these advancements, threshold-based methods face inherent subjectivity; small thresholds may introduce noise, while large thresholds isolate nodes and lose valuable information. MST and PMFG mitigate subjectivity and effectively simplify networks, they typically yield undirected networks, restricting their ability to capture the directional nature of risk spillovers. Furthermore, the association between cryptocurrency and global stock markets remains underexplored, hindering a comprehensive understanding of risk propagation pathways. This gap complicates the evaluation of cryptocurrencies' direct impact on traditional financial markets and their indirect transmission of risk via other markets. Additionally, studies on dynamic network evolution often emphasize extreme-event peaks, neglecting noise filtering for non-extreme peaks, which could obscure meaningful insights.

Building on this, we first utilize the Elastic-Net [31] and GFEVD [21] models to construct a risk spillover matrix between the cryptocurrency market and global stock markets. This approach facilitates an investigation of risk contagion mechanism and spillover effects across different time periods (before, during, and after extreme events). To uncover risk transmission paths and identify key nodes, we apply DMST [32] and DPMFG to construct a static directed graph representing the complex network between cryptocurrencies and global stock markets. Subsequently, we use the INFOMAP algorithm to analyze the network's community structure and integrate these findings with the DMST and DPMFG methods to examine risk contagion patterns. This integrated approach enhances the accuracy of network analysis and improves the interpretability of network structures. Finally, by employing a TVP-VAR technique, we track the dynamic evolution of total spillover within the cryptocurrency network and the topological properties of individual nodes, capturing both network-wide and node-specific dynamic behaviors. In summary, using the TVP-VAR [33] technique, we track total spillover and node dynamics in the cryptocurrency network, offering a comprehensive view of risk contagion between cryptocurrencies and global stock markets. These insights are crucial for devising more effective risk management strategies and policies.

The remainder of this paper is structured as follows: Section 2 introduces the methodology; Section 3 presents the data and descriptive statistics; Section 4 discusses the empirical results and analysis; and Section 5 concludes with a summary and discussion.

2. Method

2.1. Data preprocessing and testing

Before calculating the multivariate correlation, we first transformed the closing prices of each asset into logarithmic returns to ensure the stationarity of the series, using the following formula:

$$r_{m,t} = 100 \bullet \ln(p_{m,t}/p_{m,t-1}) \tag{1}$$

where$r_{m,t}$is the asset return at time$t$for the$m-th$asset, and$p_{m,t}$is the asset price at time$t$for the$m-th$asset$(m=1,2\ldots,M;t=1,2,\ldots,N)$。$M$and Ndenote the number of assets and the length of the asset series, respectively. Then, the ADF test is performed on the data for each asset series [34]:

$$\Delta Y_{m,t} = \alpha_m + \beta_m t + \gamma_m Y_{t-1,m} + \sum_{\lambda=1}^{q_i} \delta_{\lambda,m} \Delta Y_{t-\lambda,m} + \zeta_{t,m} \tag{2}$$

where$\Delta Y_{m,t}$denotes the first-order difference at time$t$for the$m-th$time series,$\alpha_m$is the intercept term, and$\beta_m$represents the time trend coefficient for the$m-th$time series.$\gamma_m$is the coefficient of the first lag, while$\delta_{\lambda,m}$is the coefficient of the$\lambda-th$ order difference.$q_m$denotes the lag order for the$m-th$time series, and$\zeta_{t,m}$is the error term at time.

2.2. Information leakage network based on the elastic-net-GFEVD mode

Currently, with the advancement of the Least Absolute Shrinkage and Selection Operator (LASSO) method and Elastic Net Shrinkage technology, it has become feasible to accurately estimate high-dimensional VAR models by selecting variables and compressing regression coefficients through penalty functions.

The construction of a risk spillover matrix is both a fundamental and essential step in developing a digital financial network encompassing cryptocurrency and traditional financial markets. In this study, we establish a risk spillover network between cryptocurrencies and global stock indices utilizing a high-dimensional VAR model：

$$D_t = \sum\nolimits_{k=1}^{d} (\beta_k D_{t-k}) + \varepsilon_t \tag{3}$$

where$D_t = (D_{1t}, D_{2t}, \cdots, D_{nt})$represents the n-dimensional endogenous variable of the VAR model, encompassing the returns of 7 major cryptocurrencies and 12 global stock indices. $\beta_k$denotes the coefficient matrix, and$\varepsilon_t$is the residual term. To effectively address the "curse of dimensionality", we build upon the methodologies of Gross and Siklos [31], employing the elastic net shrinkage technique to compress the model's coefficient estimations. This approach involves solving the following optimization problem:

$$\widehat{\beta} = \arg\min\left\{\sum\nolimits_{t=1}^{T}\left[D_{it} - \sum\nolimits_{k=1}^{d}(\beta_{ki}D_{it-k})\right]^2 + \gamma\sum\nolimits_{k=1}^{d}\left[(1-\delta)|\beta_{ki}| + \delta|\beta_{ki}|^2\right]\right\}, 0 \le \delta \le 1 \tag{4}$$

Where$\widehat{\beta}$is the matrix of estimated coefficients within the elastic net framework, andD_{it}represents the return of index$i$on day$t$.The penalty function$(1-\delta)|\beta_{ki}| + \delta|\beta_{ki}|^2$is designed to effectively integrate the LASSO technique with ridge regression. Specifically, when$\delta = 0$, the elasticity estimation aligns with LASSO, and when$\delta = 1$, it aligns with ridge regression. The model's shrinkage effect intensifies with a larger parameterγ. In this study, we utilize 10-fold cross-validation to determine the optimal values for the parameters γ andδ.

Building on the high-dimensional VAR model estimation, we reference Diebold and Yilmaz [21] to construct the risk spillover matrix through generalized variance decomposition. Consequently, the high-dimensional VAR process in Eq. (3) is transformed into the following moving average form:

$$D_t = \sum\nolimits_{k=0}^{\infty} A_k \varepsilon_{t-k} \tag{5}$$

where A_k is the $N \times N$ latitude coefficient matrix and A_0 is the unit matrix. If $i < 0$, then $A_k = 0$; if $i \ge 1$, then$A_k = \beta_1 A_{k-1} + \beta_2 A_{k-2} + \cdots + \beta_d A_{k-d}$. Contribution of variable j to the variance of the generalized prediction error of variable $i$for the forward H-periods$\theta_{ij}(H)$:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e'_i A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e'_i A_h \sum A_h^T e_i\right)} \tag{6}$$

where σ_{jj} represents the element in the matrix located in the $j-th$ row and $j-th$ column. The vector e_i denotes an $N \times 1$ dimensional vector, where the $i-th$ element is 1 and all other elements are 0. The symbol H denotes the forecasting horizon, and A_h is the coefficient in Eq. (5).

The dynamic spillover index is calculated to measure the total spillover effects of one variable on all others. The overall spillover index SI is defined as [18]:

$$SI = \frac{\sum_{i \ne j}\theta_{ij}(H)}{\sum_{i,j}\theta_{ij}(H)} \times 100 \tag{7}$$

Directional spillover analyses are conducted to quantify the "spillovers received" and "spillovers transmitted" for each variable [35]. Spillovers Received (From Others):

$$S_i^{from} = \sum\nolimits_{j \ne i}\theta_{ij}(H) \tag{8}$$

where S_i^{from} denotes the total spillover effects received by variable i from all other variables$j$.

Spillovers Transmitted (To Others):

$$S_i^{to} = \sum\nolimits_{j \ne i}\theta_{ji}(H) \tag{9}$$

where S_i^{to}represents the total spillover effect of variable i on other variables$j$.
Net Spillover:

$$S_i^{net} = S_i^{to} - S_i^{from} \tag{10}$$

2.3. Directed minimum spanning tree(DMST)

Due to the complexity of the information within the matrices constructed using generalized variance, it is necessary to filter out noise by building a complex network. Since the associated matrices are directed, the resulting network must also be directed. Therefore, we employ the DMST method to construct the directed network [36]. The DMST algorithm reduces the dense network to a tree structure (n-1 edges for n nodes) that connects all nodes with the minimum total cost, thereby highlighting the most efficient global propagation pathways. Our implementations are as follows:

1. Correlation Matrix Construction: The process begins with the construction of a generalized variance matrix derived from the Elastic-Net-GFEVD model. This matrix systematically characterizes the directed correlation strength between elements, capturing their interaction mechanisms and dependency relationships.
2. Distance Matrix Transformation: To align with the DMST's objective of minimizing total connection cost, the generalized variance matrix is converted into a distance matrix. In this transformation, a higher correlation corresponds to a smaller distance. This establishes "distance" as an effective quantitative metric for measuring similarity, ensuring the algorithm prioritizes the strongest connections.
3. Optimal Tree Construction: A root node, representing the origin of signal propagation, is defined based on the research objectives. The Chu–Liu/Edmonds' algorithm is then applied to optimally solve for the DMST [37]. This algorithm efficiently identifies the set of edges that minimizes the total distance from the root, connecting all nodes without cycles. The result is a structurally optimal directed tree network that delineates the most efficient pathways for signal propagation.

2.4. Directed planar maximally filtered graph (DPMFG)

The network graph generated using DMST is clear and intuitive but retains fewer edges, leading to the loss of key information. To preserve more edges while simplifying the network, it is essential to ensure that sufficient information is retained to analyze network structures and identify critical nodes. Therefore, we adopt the DPMFG method [38], similar to DMST, with the following steps:

1. Matrix Symmetrization Preprocessing: To satisfy the input requirement of the undirected Planar Maximum Filtering Graph (PMFG) algorithm, the original directed generalized variance matrix undergoes symmetrization. This is achieved by adding the matrix to its transpose, resulting in a symmetric, undirected association matrix that serves as the foundation for graph construction [38].
2. Core Connection Selection and PMFG Construction: The PMFG algorithm is executed on the symmetrized matrix. Under the strict topological constraint of planarity, it greedily selects the strongest edges. For a network of n nodes, this process precisely identifies the 3n-6 most critical core connections, forming a sparse, undirected, planar subgraph that retains essential topological information.
3. Weight Restoration and Direction Assignment: This step transforms the undirected PMFG into a directed graph (DPMFG).
   Weight Restoration: The weight of each retained edge is restored from the symmetrized matrix value to its original value in the directed generalized variance matrix, ensuring an accurate representation of the true association strength.
4. Direction Assignment: For each undirected edge between a node pair, the original directional weights in both directions are compared. The edge is assigned a single, dominant direction corresponding to the higher weight, thereby clarifying the primary pathway of signal propagation and removing the weaker reverse connection. This process achieves an organic integration of topological simplicity and explicit directionality.
5. Based on the constructed DPMFG network, build the adjacency matrix and calculate the following metrics for each node. The indegree of each node is calculated as follows [39]:

$$Indegree(i) = \sum\nolimits_{j\in V} G_{ji} \tag{11}$$

where G is the adjacency matrix, $G_{ji} = 1$ if there is an edge from node j to node i, and $G_{ji} = 0$ otherwise. V is the set of all nodes. The Outdegree and Betweenness Centrality of each node are shown in Eqs. (12) and (13)[39]:

$$Outdegree(i) = \sum\nolimits_{j\in V} G_{ij} \tag{12}$$

$$C_B(i) = \sum\nolimits_{s\neq i\neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{13}$$

where σ_{st} is the total number of shortest paths from node$s$ to node t, and $\sigma_{st}(i)$ is the number of shortest paths passing through node i. The PageRank of each node is shown as follow [40] :

$$PR(i) = \frac{1-l}{N} + l\sum_{j\in In(i)} \frac{PR(j)}{L(j)} \tag{14}$$

where $PR(i)$ is the PageRank value of node i, $l$is the damping factor, N is the total number of nodes, $In(i)$ is the set of nodes pointing to i, $L(j)$ is the out-degree of node$j$.

Hubs, also known as "hub scores", are values calculated by the HITS algorithm (Hyperlink - Induced Topic Search) and assigned to each node in the network. These values aim to quantify the importance of each node as a "hub node", which is closely related to the node's ability to point to other authoritative nodes in the network [40,41].

Eigenvector centrality is an extension of the concept of degree centrality. It assigns scores to all nodes in the network based on the idea that connections to high-scoring nodes contribute more to the score of the node than connections to low-scoring nodes [42].

$$x_v = \frac{1}{\kappa}\sum_{j\in V} x_j = \frac{1}{\kappa}\sum_{j\in V} G_{ij}x_j \tag{15}$$

where κ is a constant called eigenvalue. With a slight rearrangement, this is an eigenvector equation, which can be rewritten in vector notation,$Gx = \kappa x$.

2.5. INFOMAP

We use the INFOMAP method proposed by M. Rosval and C.T. Bergstrom to analyze large-scale networks, identify community structures, and pinpoint key nodes [43–45]. The INFOMAP algorithm reveals the community structure in complex networks through the following steps:

1. The Random Walk model simulates the flow of information in the network. In this model, a virtual walker moves among the nodes, with the direction of movement determined by the network's structure and edge weights.
2. The coding length measures the amount of information required to describe the random walk path. The optimal community division is the one that minimizes the coding length.
3. A combination of greedy search and simulated annealing algorithms is used to merge and split communities, minimizing the map equation.
4. Step 3 is repeated until the coding length of the entire network reaches its minimum. The resulting community structure is visualized as a network graph.

2.6. Dynamic risk spillovers

We employ the time-varying parameter vector autoregressive (TVP-VAR) model [33] and estimate it based on the Bayesian information criterion (BIC), as follows:

$$y_t = B_t y_{t-1} + \mu_t, \quad \mu_t \sim N(0, S_t), \tag{16}$$

$$\mathrm{vec}(B_t) = \mathrm{vec}(B_{t-1}) + o_t, \quad o_t \sim N(0, R_t), \tag{17}$$

where y_t and μ_t are $n \times 1$dimensional vectors, B_t is an $n \times n$ dimensional matrix, and both $\mathrm{vec}(B_t)$ and o_t are $n^2 \times 1$ dimensional vectors. The terms μ_t and o_t are modeled as normally distributed with a mean of zero and covariance matrices S_t and R_t, respectively. Additionally, to ensure numerical stability, the model leverages the Kalman filter algorithm integrated with a forgetting factor for computing time-varying coefficients and error covariance.

Table 1
List of global stock indices.

Continent	Full name of stock index	Abbreviation of stock index	Country
Asia	Nikkei 225	Nikkei	Japan
	Taiwan Stock Exchange Index	TAIEX	Taiwan , China
	Shanghai Stock Exchange Composite Index	SSE	China mainland
	Hang Seng Index	HSI	Hong Kong , China
	Korea Composite Stock Price Index	KOSPI	South Korea
Europe	Deutscher Aktienindex	DAX	Germany
	Cotation Assistée en Continu	CAC	France
	Financial Times Stock Exchange	FTSE	UK
Americas	S&P 500 Index	SPX	USA
	National Association of Securities Dealers Automated Quotations	NASDAQ	USA
	Índice Bovespa	Ibovespa	Brazil
Oceania	Australian Securities Exchange	ASX	Australia

3. Data and descriptive statistics

We focus on seven major cryptocurrencies—Bitcoin(BTC),Ethereum(ETH),Litecoin (LTC), Ripple(XRP), Dogecoin(DOGE), Binance Coin (BNB), TRON(TRX)—alongside 12 global stock indices to investigate the risk relationships between the cryptocurrency and global stock markets [24,25]. Notably, BTC and ETH together comprise about 60 % of the total cryptocurrency market capitalization, while BNB, DOGE, and TRX represent popular emerging cryptocurrencies. The 12 stock indices, listed in Table 1, represent major economies, including the United States, Brazil, the United Kingdom, France, Germany, China, Japan, South Korea, and Australia, ensuring broad and diverse market coverage. Our dataset spans November 15, 2017, to October 11, 2024, capturing key phases of cryptocurrency market evolution, such as the 2017 peak, the 2018 decline, the 2020 surge, and the steady growth observed through 2024.

To assess the impact of the COVID-19 pandemic, the data are segmented into three periods: pre-pandemic (November 15, 2017–December 9, 2019), mid-pandemic (December 9, 2019–July 30, 2020), and post-pandemic (July 30, 2020–October 11, 2024). We selected December 9, 2019, to July 30, 2020, as the mid-pandemic analysis period. This timeframe begins with the WHO's first report of unknown pneumonia, capturing the market's initial response to COVID-19. By July 30, markets had begun adapting to uncertainties and entering a "new normal," with volatility stabilizing. This segmentation provides a detailed framework for analyzing the evolution of linkages and risk spillover effects between cryptocurrencies and global stock markets before, during, and after the pandemic. To resolve the issue of inconsistent timestamps, we decided to take the intersection of all data, i.e., only consider dates when all relevant markets were open for trading(see Appendix.5 for the Sensitivity Analysis of Timestamp Alignment). All daily data is sourced from Investing.com [46].

We use Eq. (1) to convert the daily closing prices of cryptocurrencies and stock markets into logarithmic returns, capturing market dynamics while mitigating noise. Table 2 provides descriptive statistics for the cryptocurrency index (Panel A) and the stock market index (Panel B), including metrics such as average return, standard deviation, skewness, and kurtosis. The results reveal that the cryptocurrency market generally experiences positive average returns, accompanied by exceptionally high volatility, particularly for DOGE and TRX. DOGE demonstrates extreme fluctuations, with returns ranging from −415.59–414.18 %, highlighting the market's instability. In contrast, the stock market shows much greater stability, characterized by near-zero average returns, lower volatility, and narrower fluctuations. The cryptocurrency market exhibits a tendency toward left-skewness, whereas the stock market remains almost symmetric. Both markets exhibit heavy-tailed distributions, with the cryptocurrency market having notably higher kurtosis. The Jarque-Bera test indicates substantial deviations from normality in both markets, while the ADF test confirms the stationarity of all time series.

4. Empirical results

4.1. Static network analysis of cryptocurrency indices and global stock markets

We use the Elastic-net-GFEVD method (hyperparameters are set as follows: nlag = 1, nfore = 10, nfolds = 10, alpha = NULL, loss = "mae", n_alpha = 10. Detailed specifications are provided in Appendix.3.) to construct a risk spillover matrix between the

Table 2
Descriptive statistics of returns.

	N	Mean	Std.Dev	Min	Max	Skewness	Kurtosis	Jarque-Bera	ADF
Panel A : Cryptocurrencies									
BTC	1674	0.13	4.54	−49.73	20.72	−0.83	11.85	9923.92***	−17.65***
ETH	1674	0.12	5.88	−58.96	34.81	−0.68	9.64	6575.13***	−27.82***
LTC	1674	0.00	6.28	−48.68	52.77	0.27	10.64	7857.25***	−40.80***
XRP	1674	0.06	7.09	−54.10	62.27	1.39	18.60	24,512.87***	−16.83***
BNB	1674	0.35	6.55	−58.23	53.24	0.38	14.64	14,895.17***	−10.30***
DOGE	1674	0.27	16.77	−415.59	414.18	0.53	452.35	14,186,913.21***	−29.84***
TRX	1674	0.25	7.53	−57.08	97.03	2.60	35.42	88,834.55***	−10.79***
Panel B : Stocks									
Nikkei	1674	0.03	1.31	−13.23	9.74	−0.51	10.71	8021.23***	−42.15***
TAIEX	1674	0.04	1.10	−8.72	6.17	−0.88	6.94	3555.98***	−27.92***
SSE	1674	0.00	1.11	−8.04	7.76	−0.33	6.39	2856.87***	−18.04***
ASX	1674	0.02	1.02	−10.20	6.77	−1.23	14.88	15,772.66***	−9.92***
HSI	1674	−0.02	1.43	−6.57	8.69	0.18	2.90	590.78***	−17.30***
KOSPI	1674	0.00	1.18	−9.18	8.25	−0.44	8.33	4864.27***	−27.01***
DAX	1674	0.02	1.23	−13.05	10.41	−0.59	15.03	15,747.65***	−14.46***
CAC	1674	0.02	1.21	−13.10	8.06	−0.95	14.22	14,262.89***	−10.03***
FTSE	1674	0.01	1.04	−11.51	8.67	−1.09	16.28	18,690.63***	−8.05***
SPX	1674	0.05	1.25	−12.77	8.97	−0.83	15.23	16,260.89***	−10.65***
NASDAQ	1674	0.06	1.48	−13.15	8.93	−0.60	7.62	4125.63***	−10.40***
Ibovespa	1674	0.04	1.57	−15.99	13.02	−1.22	20.53	29,622.28***	−8.98***

Note: The table presents the basic descriptive statistics of the logarithmic returns for seven cryptocurrency indices and global stock market indices. ***, **, and * denote significance at the 1 %, 5 % and 10 % levels, respectively.

cryptocurrency market and global stock markets (and conduct a static comparison with other methods such as QVAR, VAR-GFEVD, and Transfer Entropy [41] in Appendix 1 to test robustness, with sensitivity tests of the GFEVD to variable ordering presented in Appendix.4.). Table 3 shows that the average total spillover effect is 67.02 %, indicating that interactions among variables account for most of the system's variation. However, cryptocurrencies contribute only 8.14 % to stock index variations, reflecting their relatively weak influence, likely due to the diverse information sources and complex drivers in stock markets. Further analysis shows that U.S. and European equity markets generate the strongest positive spillovers to cryptocurrencies and other stock markets. The SPX and CAC indices, with spillovers of 97.89 and 96.68 and net spillovers of 22.44 and 19.79, underscore their central roles in global capital markets. In contrast, the cryptocurrency market has minimal impact on the stock market, with only BTC, ETH (maximum 18.72), and LTC showing positive Net values, while the others, including DOGE with the lowest Net value at −16.14, primarily act as information receivers. Overall, global capital markets are increasingly interconnected, with U.S. and European stock markets dominating due to their liquidity and infrastructure. Cryptocurrency markets, constrained by limited depth, have a weaker influence and remain more affected by traditional markets.

Tables 4, 5, and 6 provide a comprehensive overview of the static risk spillover effects between the cryptocurrency market and the stock market before, during, and after the COVID-19 pandemic, offering insights into the evolution of market interconnections. Table 4 reveals that before the pandemic, the global economy was relatively stable, with the stock market exerting significantly stronger influence on the cryptocurrency market than vice versa. The average spillover effect between the two markets was 63.53, while spillovers from cryptocurrencies to the stock market averaged only 1.41. This reflects weak connections and minimal cryptocurrency impact on the traditional stock market. The U.S. equity market emerged as a dominant force, with the SPX demonstrating a net spillover effect of 21.96, followed by the NASDAQ and CAC, underscoring their pivotal roles in the global financial network. In contrast, the cryptocurrency market, despite its rapid growth, remained relatively independent, with price volatility driven predominantly by internal dynamics rather than external influences from traditional stock markets. Within the cryptocurrency market, BTC and LTC exhibit low risk spillover effects, while ETH stands out with a net spillover value of 18.21, indicating a significant influence on market volatility. However, TRX exhibited a net spillover value of −9.04, indicating a pronounced reverse spillover effect. This means it was more significantly influenced by external market volatility than involved in risk transmission. Such behavior highlights the heterogeneity within the cryptocurrency market, where individual assets respond differently to external shocks.

During the COVID-19 pandemic (see in Table 5), global economic uncertainty and sharp stock market volatility significantly increased spillover effects between the stock and cryptocurrency markets. The average total spillover effect rose to 78.97 %, indicating that market interactions accounted for most of the system's variation. Spillovers from cryptocurrencies to stock markets increased to 20.42 %, showing stronger volatility transmission compared to the pre-pandemic period.European stock markets emerged as the primary risk spillover sources, surpassing those of the U.S. during the pandemic. The DAX, CAC, and FTSE exhibited spillover values of 104.7, 108.48, and 102.57, respectively, marking them as the top contributors to risk transmission across global markets and impacting both cryptocurrency and stock markets. Increased financial policy uncertainty intensified the information flow between cryptocurrency and stock markets. Within the cryptocurrency market, BTC and LTC shifted from being "transmitters" to "receivers", while BNB became a "transmitter". The risk premiums for BTC, ETH, LTC, XRP, BNB, and TRX on Ibovespa yields rose sharply, from 0.2, 0.03, 0.04, 0.05, 0.11, and 0.11–3.58, 4.39, 3.65, 3.86, 4.07, and 3.74, respectively. This trend underscores the heightened interconnectedness of global markets during the pandemic.

As the global economy recovers, investor sentiment and institutional capital flows have improved, stabilizing capital markets. Although spillover effects have decreased from their peak during the pandemic, they remain significant. The spillover effect from the U.S. equity market to cryptocurrencies and other stock markets has not weakened but further intensified. The SPX has risen to 96.12, with a net spillover of 25.74, highlighting its growing post-pandemic influence on global financial markets(see in Table 6). Meanwhile,

Table 3

Static spillover matrix of cryptocurrencies and stock indices during the full sample period.

	BTC	ETH	LTC	XRP	BNB	DOGE	TRX	From	To	Net
Nikkei	0.55	0.77	0.56	0.32	0.49	0.04	0.3	68.57	47.85	−20.72
TAIEX	0.33	0.5	0.42	0.38	0.32	0.02	0.16	68.01	55.51	−12.5
SSE	0.06	0.31	0.3	0.25	0.21	0	0.11	51.4	33.21	−18.19
ASX	0.77	1.14	0.76	0.41	0.69	0.04	0.38	67.61	58.21	−9.4
HSI	0.16	0.42	0.38	0.33	0.22	0	0.14	64.24	58.01	−6.23
KOSPI	0.24	0.51	0.3	0.31	0.24	0.02	0.13	70.97	67.65	−3.32
DAX	1.03	1.3	0.89	0.49	0.84	0.08	0.45	76.35	93.86	17.52
CAC	1.11	1.3	0.9	0.44	0.92	0.09	0.39	76.89	96.68	19.79
FTSE	0.93	1.23	0.98	0.6	0.91	0.1	0.35	75.5	88.84	13.34
SPX	1.88	2.1	1.53	1.12	1.49	0.16	0.71	75.45	97.89	22.44
NASDAQ	2.33	2.45	1.9	1.35	1.73	0.17	0.78	72.29	82.58	10.28
Ibovespa	1.66	1.77	1.2	1.08	1.26	0.1	0.87	63.6	50.88	−12.72
From	72.3	74.54	71.87	65.17	68.21	27.71	62.65	Total spillover = 67.02		
To	81.66	93.26	79.86	58.04	66.24	11.57	51.53	Total spillover from Cryptocurrencies to stocks = 8.14		
Net	9.36	18.72	7.99	−7.13	−1.97	−16.14	−11.12			

Note: "From Others" (Eq. (8)) shows the total spillover received by an index, while "To Others" (Eq. (9)) indicates the total spillover transmitted by an index. "Net" (Eq. (10)) reflects the net spillover between the two. "Total spillover" is the average of all spillovers, and "Total spillover from Cryptocurrencies to stocks" is the average spillover from the seven cryptocurrencies to the stock market.

Table 4
Static spillover matrix of cryptocurrencies and stock indices before the COVID-19 pandemic.

	BTC	ETH	LTC	XRP	BNB	DOGE	TRX	From	To	Net
Nikkei	0.2	0.05	0.04	0.05	0.11	0.05	0.11	68.77	46.8	−21.97
TAIEX	0.34	0.02	0.03	0.21	0.05	0.05	0.02	66.9	61.5	−5.41
SSE	0.02	0.09	0.21	0.13	0.02	0	0.05	59.28	46.58	−12.7
ASX	0.12	0.28	0.35	0.03	0.29	0.11	0.11	55.92	24.49	−31.43
HSI	0.04	0.09	0.12	0.11	0	0	0.13	69.54	76.93	7.38
KOSPI	0.24	0	0.01	0.05	0.01	0.07	0.02	66.27	63.3	−2.97
DAX	0.01	0.16	0.2	0.05	0.07	0.11	0.1	71.15	83.75	12.61
CAC	0.03	0.13	0.15	0.04	0.07	0.09	0.04	73.43	96.66	23.23
FTSE	0	0.17	0.25	0.16	0.05	0	0	68.82	72.93	4.11
SPX	0.02	0.15	0.09	0.13	0.2	0.19	0.11	66.67	88.63	21.96
NASDAQ	0.03	0.2	0.22	0.14	0.19	0.24	0.1	65.7	82.46	16.76
Ibovespa	0.2	0.05	0.04	0.05	0.11	0.05	0.11	68.77	16.21	−12.57
From	66.71	70.66	65.39	61.78	62.26	60.75	58.21	Total spillover = 63.53		
To	71.62	88.87	66.27	57.18	58.23	55.43	49.17	Total spillover from Cryptocurrencies to stocks = 1.41		
Net	4.92	18.21	0.88	−4.61	−4.04	−5.32	−9.04			

Table 5
Static spillover matrix between cryptocurrencies and stock indices during the COVID-19 pandemic.

	BTC	ETH	LTC	XRP	BNB	DOGE	TRX	From	To	Net
Nikkei	0.5	0.7	0.36	0.31	0.85	0	0.49	75.81	55.72	−20.08
TAIEX	0.24	0.39	0.09	0.16	0.27	0	0.18	78.11	67.26	−10.85
SSE	0.19	0.32	0.04	0.23	0.63	0.02	0.15	71.51	46.06	−25.45
ASX	2.13	2.56	2.2	1.9	2.79	0.01	2.01	82.05	75.79	−6.26
HIS	0.27	0.44	0.22	0.35	0.59	0	0.4	81.3	83.21	1.91
KOSPI	0.06	0.14	0.04	0.06	0.13	0.01	0.12	79.24	73	−6.24
DAX	2.86	3.08	2.32	2.43	3.36	0.02	2.8	86.48	104.7	18.22
CAC	3.12	3.3	2.51	2.67	3.63	0.01	3	86.92	108.48	21.56
FTSE	3.18	3.14	2.52	2.68	3.54	0.04	3.1	86.38	102.57	16.19
SPX	3.1	3.91	3.1	3.42	3.82	0.01	3.27	85.37	91.97	6.6
NASDAQ	3.67	4.41	3.44	3.73	4.26	0.01	3.63	84.43	83.9	−0.53
Ibovespa	3.58	4.39	3.65	3.86	4.07	0.01	3.74	84.92	89.46	4.53
From	84.96	85.85	84.79	84.73	85.43	6.97	85.13	Total spillover = 78.97		
To	84.26	91.64	83	82.84	89.57	1.12	85.85	Total spillover from Cryptocurrencies to stocks = 20.42		
Net	−0.7	5.79	−1.8	−1.89	4.14	−5.85	0.72			

Table 6
Static spillover matrix between cryptocurrencies and stock indices after the COVID-19 pandemic.

	BTC	ETH	LTC	XRP	BNB	DOGE	TRX	From	To	Net
Nikkei	0.9	1.11	0.95	0.49	0.75	0.21	0.39	60.83	40.74	−20.09
TAIEX	0.69	0.65	0.72	0.47	0.6	0.12	0.26	59.91	46.77	−13.14
SSE	0.14	0.44	0.49	0.35	0.31	0.02	0.19	39.67	26.93	−12.74
ASX	1.31	1.65	1.1	0.95	0.9	0.44	0.51	68.63	40.79	−27.85
HIS	0.46	0.73	0.75	0.57	0.48	0.09	0.18	54.62	49.77	−4.85
KOSPI	0.52	0.97	0.6	0.58	0.44	0.14	0.19	64.58	59.6	−4.98
DAX	1.18	1.44	0.99	0.55	0.82	0.39	0.37	70.59	85.42	14.83
CAC	1.17	1.4	1	0.41	0.93	0.47	0.29	70.81	85.74	14.93
FTSE	0.86	1.26	1.1	0.63	0.97	0.41	0.26	67.87	72.96	5.09
SPX	3.5	3.21	2.59	1.8	2.18	1.21	1.07	70.38	96.12	25.74
NASDAQ	4.1	3.51	2.92	2.07	2.56	1.05	1.27	67.77	83.22	15.45
Ibovespa	1.88	1.4	1.15	1.29	1.42	0.78	0.65	43.65	28.07	−15.59
From	74.6	75.62	74.91	66.73	70.06	57.27	67.26	Total spillover = 64.52		
To	90.59	96.23	92.34	60.86	70.09	38.64	60.91	Total spillover from Cryptocurrencies to stocks = 11.76		
Net	15.99	20.61	17.43	−5.87	0.03	−18.63	−6.35			

the risk spillovers of BTC, ETH, and LTC have remained relatively high, reaching 90.59, 96.23, and 92.34, respectively.

Next, we analyze the risk transmission network between the cryptocurrency and global stock markets using the DMST, DPMFG, and INFOMAP algorithms for denoising and community structure analysis. This allows us to thoroughly examine changes in the network structure and risk transmission mechanisms across the pre-, mid-, and post-pandemic periods. Figs. 1–3 illustrate the directed network structures during these three phases, clearly revealing the evolving trends in risk transmission.

Before the COVID-19 pandemic, the DPMFG spillover network (Fig. 1(a)) shows a tenuous link between the global stock and cryptocurrency markets, with a decentralized yet locally clustered architecture. Via the INFOMAP algorithm, global stock indices and

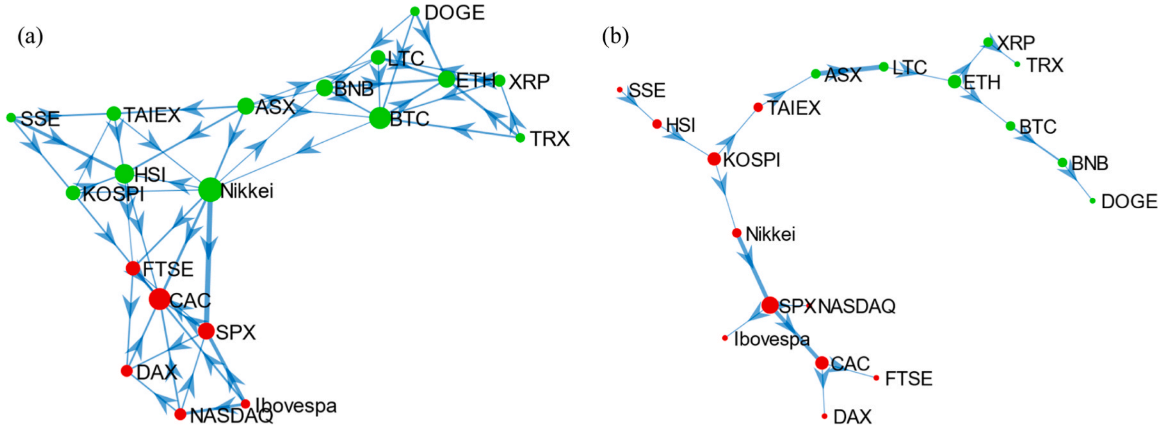

Fig. 1. Risk Spillover Networks between Cryptocurrencies and Stock Markets before the COVID-19 Pandemic:(a) Constructed using the DPMFG method;(b) Constructed using the DMST method. In the network, nodes sharing the same color indicate membership in the same group, while the thickness of the edges reflects the weight of the connections, with thicker edges signifying higher weights.

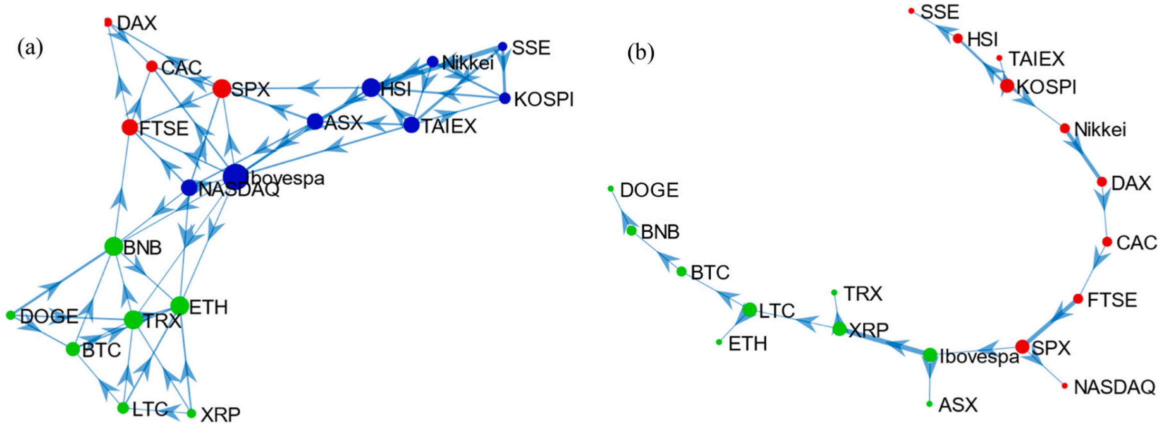

Fig. 2. Risk spillover networks between cryptocurrencies and stock markets during the COVID-19 Pandemic: (a) constructed using the DPMFG method; (b) constructed using the DMST method. In the network, nodes sharing the same color indicate membership in the same group, while the thickness of the edges reflects the weight of the connections, with thicker edges signifying higher weights.

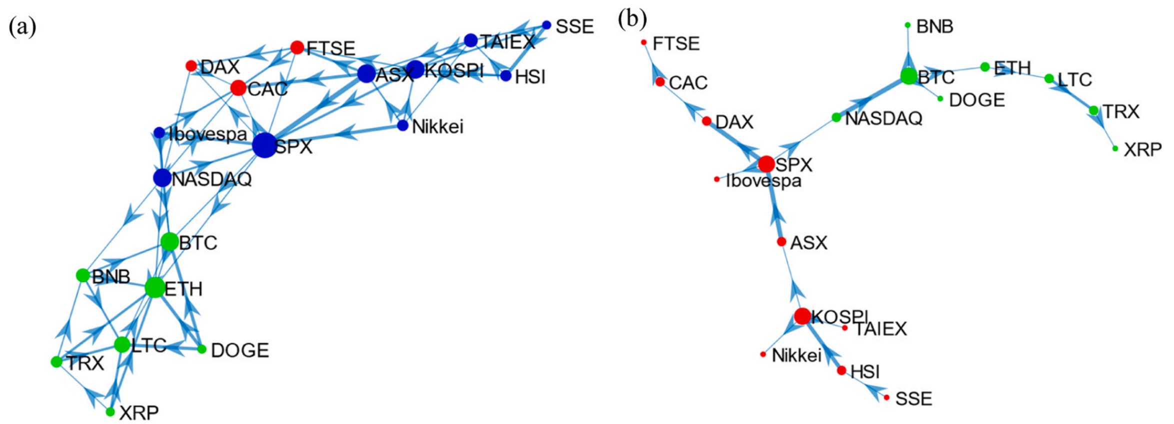

Fig. 3. Risk spillover networks between cryptocurrencies and stock markets after the COVID-19 Pandemic: (a) constructed using the DPMFG method; (b) constructed using the DMST method. In the network, nodes sharing the same color indicate membership in the same group, while the thickness of the edges reflects the weight of the connections, with thicker edges signifying higher weights.

cryptocurrencies fall into two major communities: European and American stock markets (e.g., SPX, CAC, FTSE) form a tightly connected core community, rarely interacting with the cryptocurrency. Within this community, CAC, as a core node for risk transmission and information interaction, has a higher total weight of internal edges. This is due to the Paris stock market's pivotal role in Europe's financial system and its strong influence on capital flows and market sentiment in European and American regions. Major Asian indices (e.g., SSE, Nikkei, HSI) and ASX, along with cryptocurrencies, form another community with strong internal connectivity. Cryptocurrencies such as BTC, ETH, and BNB have limited connections with stock markets in the same community while maintaining close internal ties. Connections between some Asian indices (e.g., ASX, Nikkei) and cryptocurrencies in this community stem from supportive policies in Australia (recognizing crypto as legal tender and ending Bitcoin double taxation) and Japan (classifying Bitcoin as a prepaid payment instrument in 2017 to boost merchant acceptance). This suggests that pre-pandemic cryptocurrencies were more affected by internal community factors than external stock market dynamics.

The DMST network (Fig. 1(b)) further underscores the decoupled cross-community risk transmission structure. Global stock indices and cryptocurrencies are split into two distinct communities: traditional stock indices and cryptocurrency-dominated ones. Within the traditional stock index community, regional clustering is prominent—one led by SPX-centered Euro-American markets and the other by KOSPI-driven Asian markets—with risk transmission mainly intra-regional. The cryptocurrency community, dominated by digital assets, remains relatively independent. Notably, ASX (in the same community as cryptocurrencies) acts as a critical cross-community connector, while ASX-linked LTC bridges the cryptocurrency and stock market communities. Overall, the pre-pandemic network features intra-regional risk transfer, weak inter-community links, and high decoupling and autonomy between stock and cryptocurrency communities.

During the COVID-19 pandemic, heightened global economic uncertainty and severe stock market volatility strengthened linkages between stock and cryptocurrency markets, intensifying information flow, risk transmission, and reshaping the risk network architecture. The DPMFG network (Fig. 2(a)) shows that global stock indices and cryptocurrencies evolved from two pre-pandemic communities to three: a Euro-American stock index community (e.g., SPX, FTSE); another stock index community centered on Ibovespa and Hang Seng Index (notably, NASDAQ—unlike SPX—is grouped with Ibovespa, ASX, and Asian indices); and a cryptocurrency community. The cryptocurrency market, via ETH and BNB, established direct ties with Ibovespa and NASDAQ, integrating into the global risk network. It maintained dense internal connections while expanding external risk transmission, reflecting stronger coupling. European stock markets enhanced their risk transmission capacity. Ibovespa emerged as a key cross-regional node—surpassing SPX in centrality, linking crypto and traditional markets—underscoring the rising importance of emerging markets driven by Brazil's Normative Directive No. 1888. Increased Asian-Euro-American market interactions boosted global interconnectedness. Asian markets (e.g., Hang Seng Index, SSE, Nikkei, KOSPI) strengthened internal links, with the Hang Seng Index expanding its influence and regional reach.

As shown in the DMST network (Fig. 2(b)), during the pandemic, the global financial risk structure shifted from a tree-like to a chain-like form, indicating heightened interdependence where disruptions in one segment could rapidly propagate across the network. Similar to the pre-pandemic period, the network remains divided into two communities. However, a key difference emerges: Ibovespa, previously part of the stock index community, now clusters with the cryptocurrency community. XRP, with direct links to Ibovespa and LTC, acted as a bridge between cryptocurrencies and traditional stock markets, enabling risk transmission to the crypto market. The Ibovespa node's centrality has markedly improved, emerging as a key channel for risk transmission between the cryptocurrency and traditional stock markets. The SPX remains a global hub, sustaining close connections with the FTSE and Ibovespa, facilitating cross-regional risk flow. While the KOSPI contributes to cross-regional risk transmission, its influence is less pronounced compared to European and American markets. Overall, the pandemic made the global financial risk network more interconnected and complex, amplifying systemic risks. Risk transmission was concentrated in core markets such as SPX and Ibovespa and diffused to peripheral markets, with the cryptocurrency market primarily acting as a risk receiver.

From the post-pandemic risk network diagram (Fig. 3), as the global economy recovered and the capital market stabilized, the correlation between cryptocurrencies and the stock market increased. The DPMFG network (Fig. 3(a)) shows a complex structure with risks spreading across markets, reflecting higher systemicity. Similar to the pandemic period, it is divided into three communities: a cryptocurrency community (including ETH, BTC, BNB), a separate community of European stock indices (DAX, CAC, FTSE), and another community centered on SPX (with American, ASX, and Asian indices like KOSPI, TAIEX). ETH and BTC act as key bridges for risk transmission between cryptocurrencies and stocks. Developed indices (led by NASDAQ and SPX) form a two-way risk hub, while emerging markets (e.g., SSE, HSI) connect via KOSPI, highlighting regional traits. This trend comes from U.S. efforts in crypto regulation, Bitcoin futures ETFs, and strategic reserves, boosting integration with traditional finance.

From the DMST network (Fig. 3(b)), BTC has replaced ETH as the core node of the cryptocurrency community that includes NASDAQ. By virtue of its connection with NASDAQ, it builds a crucial bridge between the cryptocurrency community and the stock market community. Within the cryptocurrency community, nodes such as ETH, BNB, and LTC take BTC as the hub to realize the internal circulation of risks, which are then transmitted to the stock market community through NASDAQ. Within the stock community, KOSPI and SPX serve as key nodes, playing a core role in cross-market connectivity and internal risk transmission.

Table 7 presents the topological characteristics of the cryptocurrency DPMFG across periods. ETH maintained an outdegree of 0 in pre-pandemic, pandemic, and post-pandemic phases, with its indegree rising from 6 to 8, highlighting its role as a critical risk input node. In contrast, DOGE showed an indegree of 0 and a stable outdegree of 3 across all phases, indicating its nature as a risk output node. TRX saw its indegree surge to 5 during the pandemic but drop to 1 post-pandemic, likely due to market dynamics or policy adjustments.The SPX and NASDAQ exhibited growing outdegrees and total degrees, reflecting their increasing influence in the global financial network. Nikkei, ASX, and KOSPI had high hub scores (Nikkei reached 0.429 pre-pandemic), acting as risk output nodes with spillover effects via connections to authoritative nodes. Cryptocurrencies, however, showed near-zero hub scores in pre-pandemic and

Table 7
Topological structures of cryptocurrency financial networks across periods.

	outdegree			indegree			degree			betweenness			pagerank			hubs			eigenvector		
	Pre	Mid	Post	Pre	Mid	Post	Pre	Mid	Post	Pre	Mid	Post	Pre	Mid	Post	Pre	Mid	Post	Pre	Mid	Post
BTC	2	3	2	6	2	5	8	5	7	0.141	0.059	0.036	0.053	0.026	0.078	0.000	0.000	0.002	0.28	0.18	0.29
ETH	0	0	0	6	7	8	6	7	8	0.000	0.000	0.000	0.143	0.119	0.208	0.000	0.000	0.000	0.18	0.28	0.30
LTC	2	3	1	3	1	5	5	4	6	0.036	0.023	0.007	0.032	0.022	0.066	0.000	0.000	0.001	0.19	0.13	0.19
XRP	3	3	3	1	0	0	4	3	3	0.029	0.000	0.000	0.027	0.021	0.022	0.000	0.000	0.011	0.13	0.11	0.10
BNB	3	2	3	3	5	2	6	7	5	0.046	0.137	0.010	0.027	0.052	0.025	0.000	0.000	0.014	0.25	0.30	0.20
DOGE	3	3	3	0	0	0	3	3	3	0.000	0.000	0.000	0.024	0.021	0.022	0.000	0.000	0.030	0.12	0.12	0.13
TRX	3	2	3	0	5	1	3	7	4	0.000	0.000	0.007	0.024	0.038	0.022	0.000	0.000	0.012	0.10	0.25	0.13
Nikkei	5	4	3	4	0	1	9	4	4	0.216	0.000	0.026	0.043	0.021	0.023	0.429	0.235	0.163	0.41	0.14	0.18
TAIEX	2	4	3	3	2	2	5	6	5	0.000	0.062	0.010	0.036	0.028	0.030	0.003	0.169	0.005	0.23	0.21	0.15
SSE	3	3	3	0	0	0	3	3	3	0.000	0.000	0.000	0.024	0.021	0.022	0.010	0.494	0.004	0.13	0.09	0.09
ASX	6	3	3	0	3	4	6	6	7	0.000	0.016	0.000	0.024	0.039	0.052	0.005	0.006	0.340	0.29	0.27	0.27
HSI	2	3	3	5	4	1	7	7	4	0.101	0.033	0.000	0.076	0.075	0.033	0.019	0.006	0.005	0.31	0.25	0.12
KOSPI	4	1	3	1	3	4	5	4	7	0.033	0.003	0.092	0.028	0.034	0.058	0.033	0.089	0.104	0.24	0.11	0.24
DAX	1	1	1	3	2	3	4	3	4	0.000	0.015	0.000	0.059	0.050	0.042	0.036	0.000	0.002	0.16	0.12	0.21
CAC	0	0	0	8	4	6	8	4	6	0.000	0.000	0.000	0.224	0.176	0.100	0.000	0.000	0.000	0.31	0.18	0.28
FTSE	2	2	3	3	4	2	5	6	5	0.039	0.085	0.118	0.037	0.083	0.040	0.059	0.000	0.040	0.24	0.27	0.23
SPX	3	3	4	3	4	6	6	7	10	0.007	0.007	0.114	0.062	0.075	0.109	0.040	0.000	0.004	0.23	0.30	0.42
NASDAQ	3	5	6	1	1	1	4	6	7	0.010	0.023	0.007	0.031	0.029	0.027	0.073	0.002	0.086	0.14	0.30	0.32
Ibovespa	3	6	4	0	4	0	3	10	4	0.000	0.111	0.000	0.024	0.070	0.022	0.294	0.000	0.177	0.12	0.43	0.22

Note: "Pre" refers to the pre-COVID-19 phase, "Mid" denotes the COVID-19 pandemic period, and "Post" indicates the post-pandemic phase.

pandemic phases, indicating limited hub functionality. BTC and HSI saw declining betweenness centrality; Nikkei's betweenness dropped from 0.216 pre-pandemic to 0 during the pandemic, weakening its mediating role. Conversely, BNB and Ibovespa achieved betweenness values of 0.137 and 0.111 during the pandemic, emerging as key intermediaries. In terms of PageRank and eigenvector centrality, ETH and CAC maintained PageRank above 0.1, indicating high influence. Eigenvector centrality shifted: Nikkei led with 0.41 pre-pandemic, Ibovespa peaked at 0.43 during the pandemic, and SPX reached 0.42 post-pandemic, reflecting the migration of core node influence amid the crisis. Overall, Western stock markets showed strong connectivity during the pandemic, stabilizing risk transmission. Cryptocurrencies' linkage with traditional markets deepened, gaining prominence in global crises, which underscores strengthened complementary effects in the global financial ecosystem.

4.2. Dynamic network analysis between the cryptocurrency market and global stock markets

We analyzed the dynamic tail risk spillover between cryptocurrencies and global equity markets using a TVP-VAR model, employing a TVP-VAR approach with a 100-day window size (and conducted a robustness comparison between the original Elastic Net rolling window method and the TVP-VAR method in Appendix.2). Fig. 4 presents the average total spillover index between cryptocurrency and stock market returns, as well as the average spillover from cryptocurrencies to stock returns. Two notable periods of temporal variance were observed: (1) From March 2020 to September 2020, the spillover index from cryptocurrencies to stock returns remained elevated, likely driven by the outbreak of the COVID-19 pandemic, which increased financial market uncertainty and asset correlations. (2) From February 2022 to January 2023, the Russia-Ukraine conflict amplified the transmission of risk from cryptocurrencies to equity returns.

To demonstrate the robustness of the dynamic evolution results for the cryptocurrency network, we also applied window lengths of 200 and 300 days. The choice of a dynamic window length of 100, 200, or 300 days depends on research objectives and data characteristics. A 100-day window captures short-term market dynamics and seasonal or quarterly fluctuations. A 200-day window offers a medium-term perspective, smoothing short-term noise and aligning with the trading year to capture annual cycles. A 300-day window is ideal for long-term trends and structural changes, particularly in volatile markets.

Fig. 5 shows that the overall trend of the dynamic network remains consistent across all three windows. The shorter window (100 days) is more sensitive to volatility but prone to short-term noise. The medium window (200 days) strikes a balance between capturing short-term fluctuations and long-term trends, effectively filtering out noise. In contrast, the longer window (300 days) smooths market variations and reduces short-term disturbances but may overlook critical market dynamics. The differences in the curves in the early stage reflect the influence of different prior choices, while their convergence in the later stage indicates that the model's estimation results become robust after sufficient data accumulation and are no longer sensitive to the selection of priors.

To further examine the relationship between the cryptocurrency dynamic network and extreme events, we applied Gaussian smoothing to the rolling spillover index (gray line) computed with a 100-day window (and we specifically used high-frequency data (hourly) as the research object in Appendix.3 to analyze the sudden risk changes between stocks and cryptocurrencies caused by flash crash events). The smoothed curve (blue line in Fig. 6) effectively suppresses short-term volatility and noise, revealing clearer long-term trends. From 2017–2024, the total spillover index of the cryptocurrency market exhibited significant temporal fluctuations, driven by five major global events.

The period from 2017 to 2018 marked a significant market boom, fueled by widespread recognition of blockchain technology and growing participation from diverse investors. However, this rapid expansion was accompanied by sharp volatility and concerns over

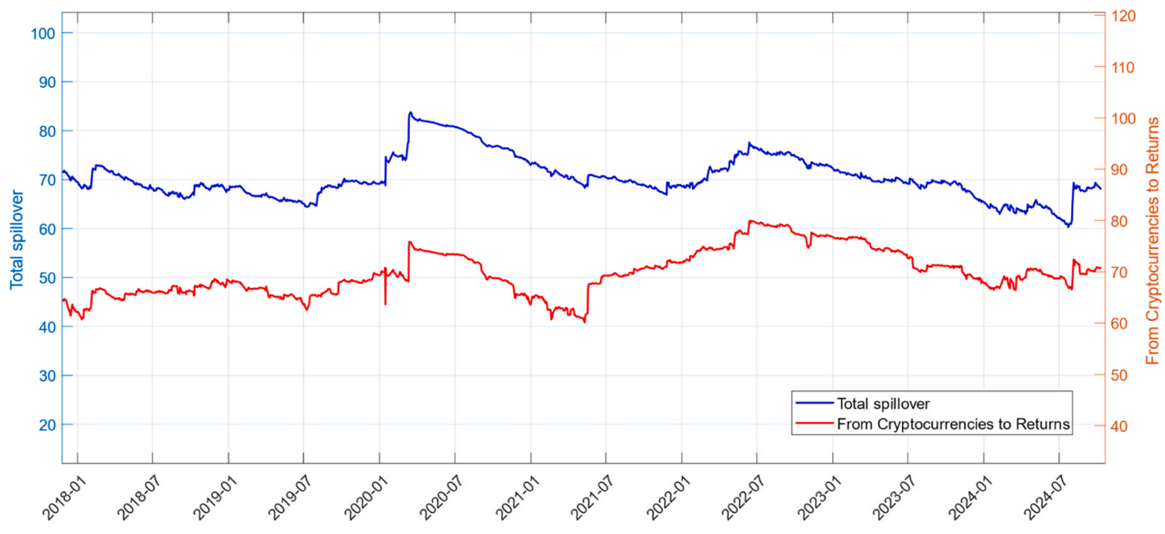

Fig. 4. Evolution of Total Spillovers in the Cryptocurrency Network. The blue curve shows the dynamic total spillover between cryptocurrencies and stock markets, while the red curve represents the average dynamic spillover from the four cryptocurrencies to the stock markets.

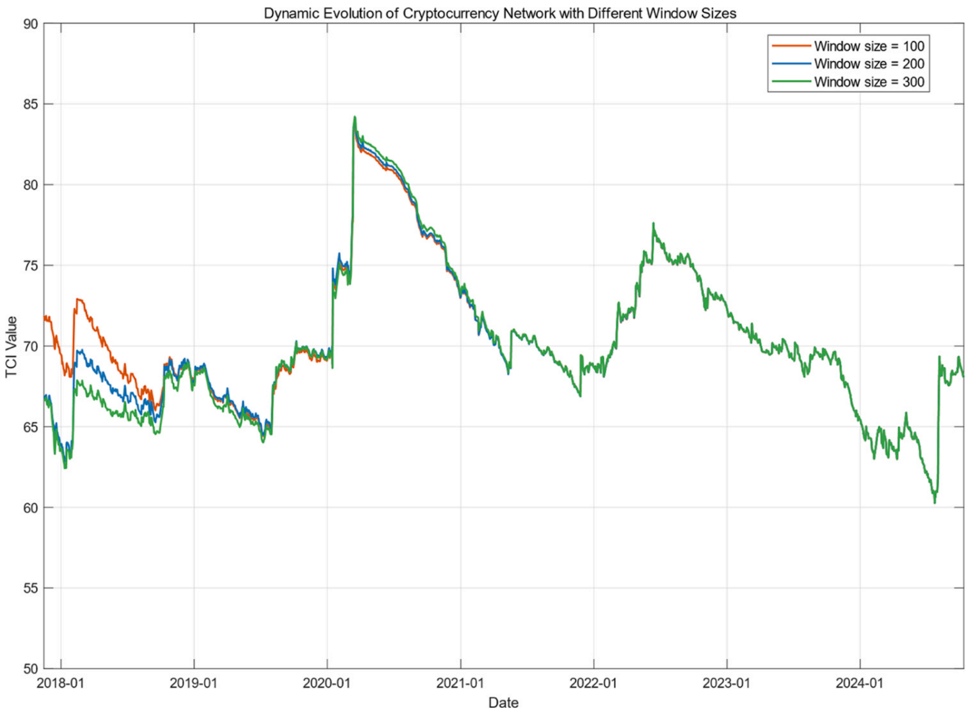

Fig. 5. Dynamic Spillovers in the Cryptocurrency Network Across Different Windows. The red, blue, and green lines represent the dynamic spillovers in the cryptocurrency risk network for window lengths of 100, 200, and 300, respectively.

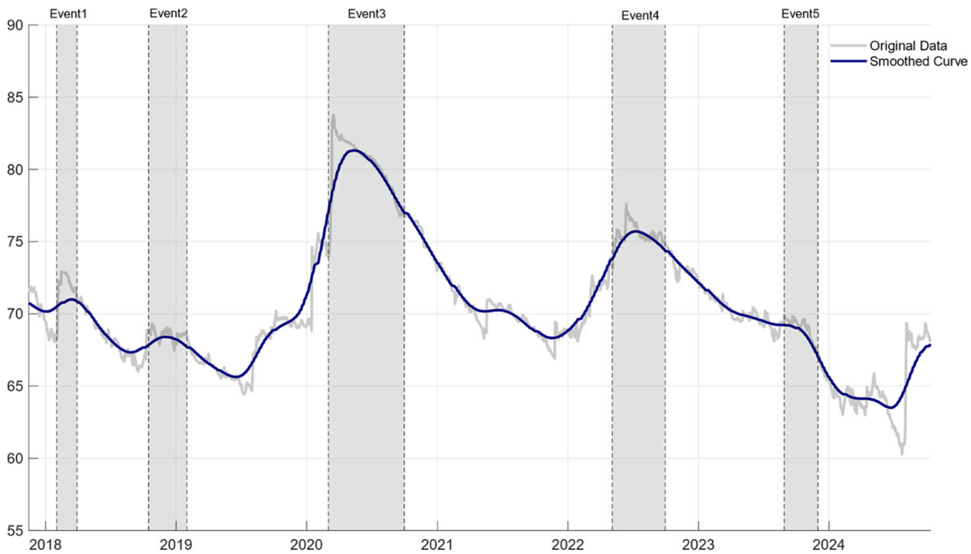

Fig. 6. Comparison of Smoothed Dynamic Spillover Curves and Extreme Events in the Cryptocurrency Network.

fraudulent activities. Regulatory interventions, such as China's ban on fiat-to-cryptocurrency transactions in 2017 and emerging U.S.-China trade tensions in 2018, further pushed the risk spillover index higher (E1). Global expectations of tighter regulation undermined cryptocurrency legitimacy, prompting investors to offload Bitcoin. Frequent hacks and internal disputes further eroded confidence, driving Bitcoin's market cap below $100 billion and its price nearly one-third lower, to under $4000 by the end of 2018. This volatility exacerbated market turmoil and risk spillovers in the cryptocurrency sector (E2). In 2020, the onset of the COVID-19 pandemic triggered severe financial market disruptions. The U.S. stock market experienced four circuit breakers within two weeks, while 11 other markets also faced similar halts, causing the global tail risk spillover index to surge to unprecedented levels (E3). In 2022, the Russia-Ukraine conflict led to energy and food crises, with sanctions imposed by the U.S. and U.K. exacerbating instability and amplifying risk spillovers between cryptocurrencies and equities (E4). By 2023, persistent Federal Reserve rate hikes and escalating global inflation intensified cryptocurrency market volatility through pronounced risk contagion effects (E5). The dynamic evolution of the cryptocurrency risk spillover index reveals significant heterogeneity across market states. During periods of major shocks, the spillover index increases sharply, with the magnitude of disruptions amplifying the extent of risk contagion.

Until 2020, Europe maintained closer ties to cryptocurrencies, supported by its relaxed regulatory stance (see in Fig. 7). For instance, Switzerland fostered a favorable environment by establishing an ICO working group to enhance transaction legitimacy. In contrast, the U.S. enforced stricter measures, with the SEC rejecting Bitcoin ETF applications and Facebook's 2018 ban on cryptocurrency ads, which, despite targeting fraud, also hindered legitimate blockchain projects. From 2021, U.S. risk spillovers to the cryptocurrency market stabilized, with cryptocurrencies increasingly acting as "risk receivers". This shift resulted from the SEC's strengthened oversight, including exchange regulations and approval of Bitcoin futures ETFs. In 2023, Senator Cynthia Lummis proposed the U.S. Bitcoin Strategic Reserve Act to acquire 1,000,000 Bitcoins—5 % of total supply—to bolster financial security. The 2024 21st Century Financial Innovation and Technology Act further advanced fintech and strengthened consumer protections. These measures have fostered innovation in the cryptocurrency industry and reinforced the U.S.'s dominant role in the global financial system.

Between 2020 and 2021, risk spillovers between cryptocurrencies and Chinese mainland stock markets exhibited marked volatility. In early 2020, the COVID-19 pandemic induced severe fluctuations in Chinese equities, while Bitcoin surged as a perceived safe haven, peaking in its positive spillover on stocks (Fig. 8). As pandemic measures improved market sentiment and reduced safe-haven demand, spillover effects declined sharply. In 2021, stricter Chinese regulations—including bans on virtual currency activities, classification of cryptocurrency trading as illegal, and intensified mining crackdowns—disrupted the direct link between cryptocurrencies and equities, substantially diminishing risk spillovers.

In contrast, around 2022, cryptocurrency spillovers to Asian and Oceanian markets (such as Nikkei, TAIEX, KOSPI, and ASX) intensified. The Russia–Ukraine conflict, which triggered energy and food crises, along with the Fed's aggressive rate hikes and the Terra-LUNA collapse, bolstered Bitcoin's safe-haven role and increased capital flow volatility. Moreover, regional regulatory shifts, notably Hong Kong's supportive Policy Declaration on Virtual Assets, attracted international investors and strengthened ties with broader Asian markets. Combined with prevailing geopolitical tensions and supply chain disruptions, these factors amplified the risk spillover effects from cryptocurrencies to traditional financial markets.

Fig. 9 highlights the evolving influence of major market indices from 2017 to 2024, underscoring their central roles in the global financial system and market dynamics. The SPX stands out as the most influential index, particularly cementing its dominance after the COVID-19 pandemic in 2020, driven by economic stagnation and large-scale stimulus measures. The CAC's impact peaked from March to October 2020. In March, COVID-19 triggered market panic and a 40 % plunge from February's highs. A two-hour trading halt on October 19 due to technical issues further heightened volatility and underscored financial infrastructure vulnerabilities.

Similarly, the NASDAQ became a global benchmark from early 2022 to July 2022, amid the Fed's rate hikes, supply chain disruptions, and the Russia-Ukraine conflict. Between December 2022 and April 2023, ETH and BTC dominated. FTX's collapse in November 2022 sparked a prolonged crisis of confidence and volatility, with Binance's SEC probe intensifying market fears and causing sharp declines in February 2023. However, Ethereum's Shanghai upgrade in April 2023 enhanced network performance and spurred Layer-2 development, reaffirming its market influence. These shifting periods of dominance illustrate how global indices respond to economic shocks, policy interventions, and market uncertainties, shaping the interconnected financial landscape.

Fig. 10 depicts the dynamic evolution of major market indices from 2017 to 2024, capturing the complex interplay of global economic events, policy adjustments, and market volatility. Before July 2019, the China–US trade war notably impacted the global economy. The United States imposed three rounds of tariffs on 66.4 % of Chinese imports, raising the average rate from 3.2 % to 19.3 % and causing a permanent loss in exports for some products. During this period, the Nikkei and TAIEX indices alternated as the most affected. LTC emerged as a leading asset in the cryptocurrency market from May 2021 to February 2022. In May 2021, its price peaked at approximately €340, reaching a record high of $386.45 on May 9. During Q2 2021, the Litecoin network also experienced its largest-ever USD value transfer. Between February and August 2022, ETH became a leading crypto asset, propelled by significant network upgrades. Its shift to Proof of Stake in 2022 improved efficiency and security while reducing energy use, drawing notable investor interest. Its speculative nature and uncertainty surrounding these upgrades heightened its price volatility and market risk. From late 2022, the ASX faced challenges from a global economic slowdown, liquidity contraction, the Russia–Ukraine conflict, domestic policy shifts, and volatile energy and commodity prices. Nonetheless, it showed resilience by leading global subordinated capital raisings in 2022—exemplified by BHP's success—while growth in trading and technology sectors renewed market momentum, underscoring its adaptability and long-term potential.

In summary, these episodes of market volatility highlight the dynamic nature of global financial influence, shaped not by a single factor but through the interplay of economic fundamentals, technological innovation, policy changes, and market sentiment. Understanding these interconnected drivers is crucial for comprehensively assessing risks and opportunities in the global financial system.

5. Conclusions and discussion

Cryptocurrencies, as highly speculative financial instruments beyond traditional regulatory controls, pose significant systemic risks. Managing tail risk contagion between cryptocurrencies and global stock markets remains a critical challenge for regulators. Existing research lacks a global perspective on cryptocurrency-induced risk shocks and rarely applies robust denoising techniques to multi-dimensional time series data. Moreover, studies often overlook network community structures and fail to dynamically track the most influential indices, limiting the precision of risk regulation policies.

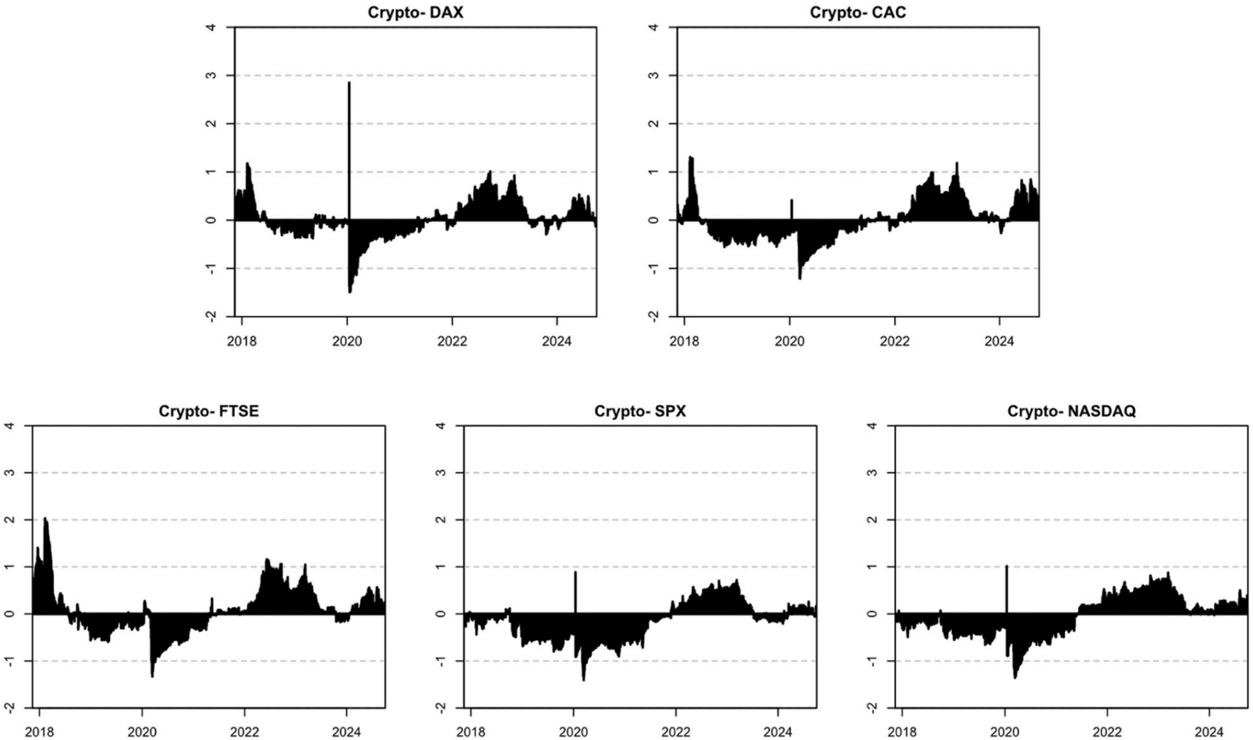

Fig. 7. Dynamic Spillovers Between Cryptocurrencies and Western Stock Indices. Given the consistent spillover trends across the seven cryptocurrencies and stock markets, the average pairwise spillover effect is presented to illustrate the dynamic evolution. By calculating the directional connection (i.e., the spillover from cryptocurrencies to stock indices minus that from stock indices to cryptocurrencies), regions where values exceed zero indicate stronger risk spillovers from cryptocurrencies to stock markets, while negative values highlight more pronounced risk transmission from stock markets to cryptocurrencies.

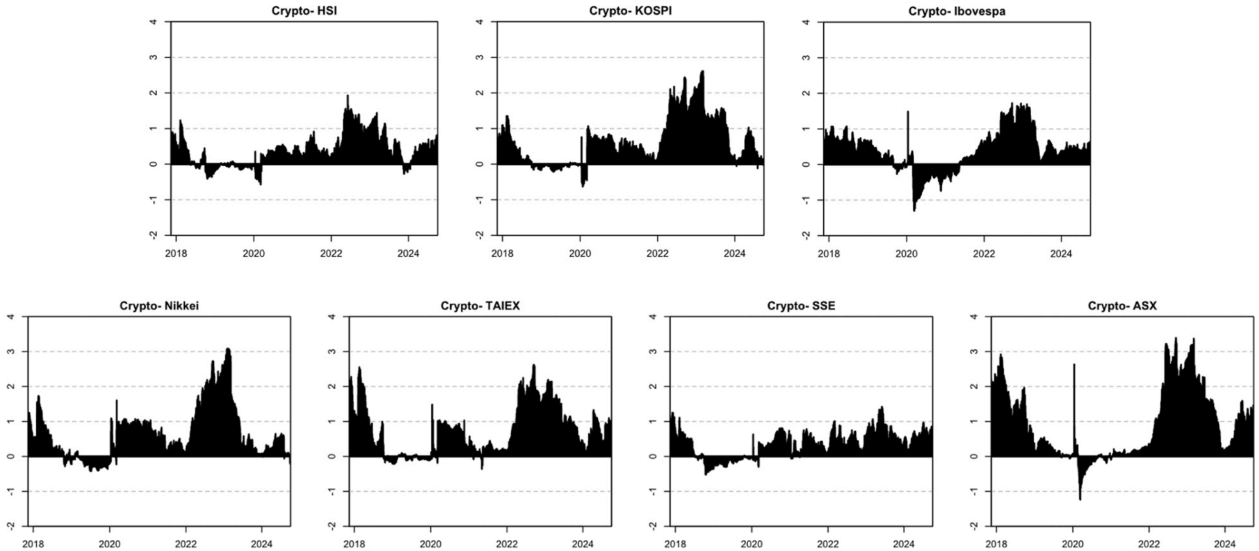

Fig. 8. Dynamic spillover between cryptocurrencies and Asian and other stock indices.

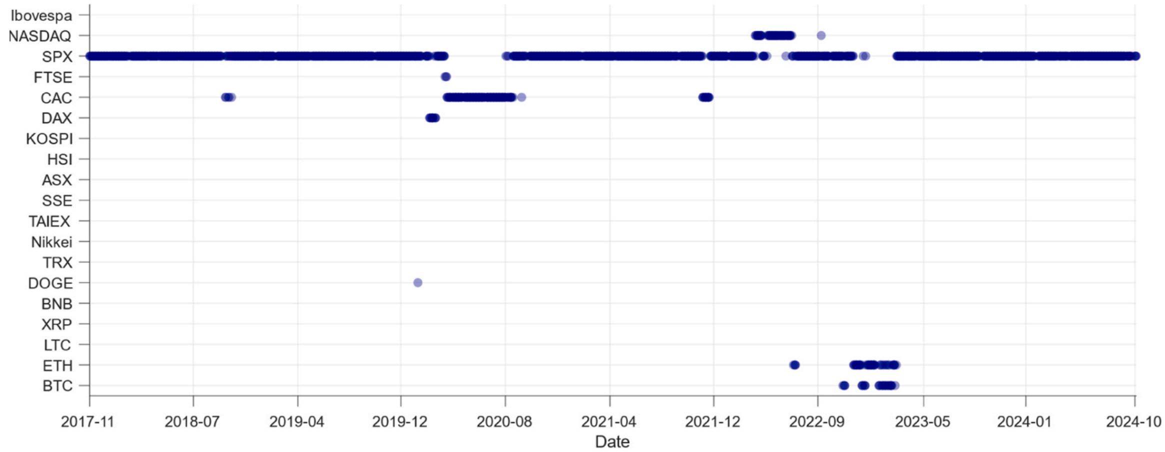

Fig. 9. Dynamic evolution of the most influential nodes in the cryptocurrency network.

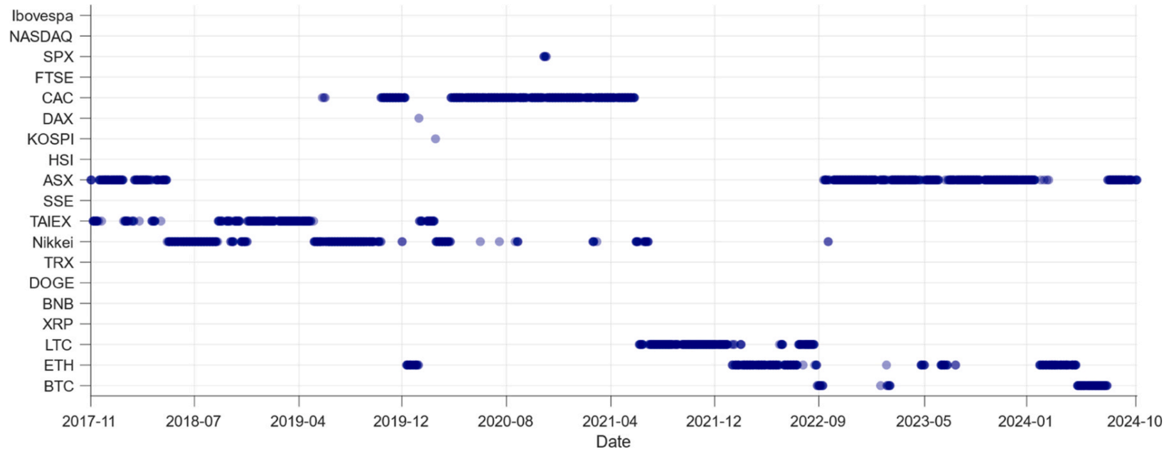

Fig. 10. Dynamic evolution of the most affected indicators in the cryptocurrency network.

We construct a risk spillover matrix between cryptocurrency market and global stock markets using the Elastic-Net-GFEVD model. Applying DMST and DPMFG methods, we denoise multi-dimensional time series data and build static directed networks to identify risk transmission pathways and critical nodes. To analyze network community structures, the INFOMAP algorithm is employed and integrated with DMST and DPMFG results, offering a comprehensive view of risk contagion. Additionally, dynamic spillover networks and connectivity are evaluated through TVP-VAR and smoothing techniques.

The findings indicate that, before the COVID-19 outbreak, the network between stock and cryptocurrency markets exhibited a relatively loose structure. In contrast, stock markets showed strong internal connections, while cryptocurrency markets were relatively independent and exerted limited influence on other stock markets. During the pandemic, heightened economic uncertainty amplified spillovers, particularly from Ibovespa and HSI, while risk transmission pathways evolved from a tree-like to a chain-like structure. Post-pandemic, economic recovery intensified connections between cryptocurrencies and stock markets, with Bitcoin emerging as the central bridging node linking cryptocurrencies to traditional capital markets via NASDAQ. The U.S. stock market replaced European indices as the dominant hub in the spillover network. In addition, TVP-VAR analysis reveals the time-varying nature of tail risk spillovers between cryptocurrency markets and global stock markets. Testing different window lengths (100, 200, and 300 days) demonstrates the model's robustness across time scales. Regional differences are evident: in Europe and the U.S., cryptocurrencies largely act as risk "receivers," while in Asia, they serve as significant risk "transmitters." Major global events, such as the 2020 COVID-19 pandemic and the 2022 Russia-Ukraine conflict, amplified stock market volatility and strengthened spillover effects to cryptocurrencies. These findings highlight how the evolving global economic environment and major shocks have reshaped risk transmission dynamics, with cryptocurrencies transitioning from passive receivers to active transmitters, underscoring their growing importance in the global financial network.

Based on the above findings, we propose the following policy recommendations. First, governments should establish rigorous regulatory frameworks to assess systemic risk transmission within interconnected networks, preventing cross-market contagion and further risk amplification. Given the decentralized and cross-border nature of cryptocurrency markets, international cooperation is essential. Governments should actively participate in global organizations to develop comprehensive cross-border regulatory mechanisms. Second, policymakers should implement dynamic risk prevention and early warning systems to promptly identify and address risks in cryptocurrency markets, mitigating short-term volatility and preventing larger crises. Tailored national policies that align cryptocurrency development with strategic planning are also crucial. Finally, regulators must remain vigilant to cryptocurrency price fluctuations, enhancing their ability to detect and anticipate risk spillovers. A comprehensive assessment of external shocks and their impact on cryptocurrency and global stock market risks is necessary, alongside clear, situation-specific control measures.

In this study, despite employing multiple methods to verify the robustness of the extracted correlations between cryptocurrency and financial markets, there remains a gap in the supervision and comparison of various correlation approaches. For future research, we plan to generate dynamic risk curves for cryptocurrency and financial markets using the time-varying parameter vector autoregressive (TVP-VAR) model as risk assessment indicators. Additionally, we aim to characterize diverse financial relationships and interactions within cryptocurrency-financial networks via methods such as QVAR, elastic networks, and transfer entropy, and construct multi-layer dynamic networks, which will be converted into graph data formats for graph neural network (GNN) models. Leveraging the supervisory properties of models like graph convolutional networks (GCNs) or graph attention networks (GATs), we will compare network construction results from different correlation methods to reveal the topological structure of cryptocurrency networks, thereby enabling risk early warning in cryptocurrency-financial markets. Such analyses will help identify key nodes and edges in the networks, evaluate their impacts on market risks, and enhance our understanding of risk transmission mechanisms, providing practical insights for financial regulation and risk management. This approach is expected to facilitate a more comprehensive understanding of inter-layer interactions and risk transmission paths, offering new perspectives for studying systemic risks in cryptocurrency markets and supporting the formulation of regulatory and risk management strategies.

CRediT authorship contribution statement

Lu Qiu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yueyi Huang:** Writing – review & editing, Writing – original draft, Software. **Dong Ge ge:** Data curation.

Declaration of Competing Interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.physa.2025.131111.

Data availability

Data will be made available on request.

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