



Core–periphery analysis of risk dependence among cryptocurrencies

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ABSTRACT

The paper aims at analyzing the dynamics of the core–periphery structure of tail risk dependence among 221 cryptocurrencies in the period Jan. 1st, 2022–Nov. 21st, 2025. From a methodological perspective, the paper proposes an integrated framework that combines breakpoint detection, CoVaR estimation, dynamic network construction, and spectral core periphery analysis to study the transmission of systemic tail risk in cryptocurrency markets. While most existing studies focus on static dependence structures, pairwise spillovers, or traditional centrality measures, our approach allows us to track how the core periphery structure changes over time and across different market regimes. From a theoretical point of view, the paper contributes to a better understanding of how systemic importance evolves in cryptocurrency markets. Our findings show that the market does not change gradually, but rather moves through distinct structural phases, each characterized by a different configuration of core and peripheral assets. The results point out that, across all periods, the core tends to follow a recurring pattern of expansion, consolidation, peak, and divergence. This highlights how the role of cryptocurrencies within the overall risk structure changes over time, with some assets becoming more central during periods of market stress and others moving back to the periphery. Identifying the cryptocurrencies that consistently belong to the core can be useful for risk management, since these assets are more likely to spread shocks during periods of market stress. Distinguishing between core and peripheral assets may also help investors identify better diversification opportunities, while from a regulatory perspective it may support the monitoring of cryptocurrencies that are becoming increasingly important for overall market stability.

1. Introduction

In recent years, cryptocurrencies have become an increasingly important part of global financial markets, attracting the attention of investors, regulators, and researchers alike Bejaoui et al. [1] and Levantesi et al. [2]. Despite their growing relevance, these assets remain highly volatile and subject to sudden shifts in market conditions. Cryptocurrency returns are often characterized by volatility clustering, heavy tails, and strong co-movements, especially during periods of market stress. In such situations, shocks can spread rapidly from one cryptocurrency to another, increasing instability across the entire market (Diebold and Yilmaz, [3]). This makes it difficult for traditional risk models, which usually focus on individual assets, to capture the broader dynamics of systemic risk.

For this reason, an increasing number of studies have moved away from the analysis of single cryptocurrencies and have started to examine the market as a system of interconnected assets. One of the most widely used measures in this context is the Conditional

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Value at Risk (CoVaR) introduced by Adrian and Brunnermeier [4]. CoVaR measures the risk of the system conditional on a specific asset being under distress and is therefore particularly suitable for capturing tail dependence in cryptocurrency markets. For example, Borri [5] analyzes conditional tail risk interdependence among major cryptocurrencies, while Waltz et al. [6] estimate CoVaR measures under different stress scenarios. In the same direction, Kumar et al. [7] show that connections among cryptocurrencies and trading venues become stronger during periods of market stress, reducing the opportunities for diversification.

Approaches based on network analysis are especially useful in this framework because they make it possible to identify not only which cryptocurrencies are more exposed to risk, but also which ones are responsible for transmitting it (Bartesaghi et al. [8]). In this respect, Ahelegbey et al. [9] propose tail dependence networks for cryptocurrency markets and show that extreme co-movements follow a time-varying and structured pattern. More recently, Zhang et al. [10] study the cryptocurrency market during the war between Russia and Ukraine, and between Israel and Hamas, highlighting the role of central nodes in transmitting geopolitical risk. However, their analysis mainly focuses on the most central cryptocurrencies and does not explicitly investigate the role of peripheral assets or how the boundary between the core and the periphery changes over time.

This issue can be better understood through core periphery (CP) models, which distinguish between a small group of highly interconnected assets and a larger group of more marginal cryptocurrencies (Borgatti and Everett [11]). CP structures have already been successfully applied in several financial contexts. For instance, Craig and Von Peter [12] analyze the tiered structure of the German interbank market, while Fricke and Lux [13] identify a stable core and high persistence over time of banks' identified positions as members of the core or periphery in the overnight money market. More generally, network methods are widely used to study systemic risk and resilience in financial systems. Battiston et al. [14] show that the most interconnected financial institutions are often "too central to fail", whereas Sui et al. [15] examine the 'robust-yet-fragile' structure of CP network. In addition, Minoiu and Reyes [16] examine the evolution and stability of CP structures in banking networks, and Cinelli et al. [17] address the methodological issue of missing data in the analysis of network resilience.

Although the literature on cryptocurrency interconnectedness has grown considerably in recent years (Ji et al. [18]), there is still limited evidence on how the CP structure of cryptocurrency markets evolves across different market regimes. Most existing studies focus either on pairwise dependence, on centrality measures, or on static network representations. As a consequence, we still know relatively little about which cryptocurrencies consistently play a systemic role, how the composition of the core changes over time, and how these changes influence the propagation of tail risk.

Starting from this gap, the aim of this paper is to investigate how the CP structure of cryptocurrency markets changes across different market conditions and what this implies for systemic risk transmission. To do so, we first identify structural breaks in the market in order to distinguish different regimes. We then estimate Value at Risk (VaR), CoVaR, and Δ CoVaR measures and use them to build dynamic networks of risk spillovers among cryptocurrencies. Finally, we apply a CP model to identify the cryptocurrencies that are persistently central in transmitting systemic risk and those that remain at the periphery.

The CoVaR framework introduced by Adrian and Brunnermeier [4] has been extensively utilized in the systemic risk literature and adapted to network contexts, where pairwise CoVaR measures are interpreted as directed weighted links that capture tail-risk spillovers among financial institutions. This viewpoint has been further elaborated in the tail-risk network literature. In particular, Hautsch et al. [19] simulate time-varying network structures utilizing high-frequency financial data, and Härdle et al. [20] develop networks grounded in tail-event dependencies through quantile regression methodologies. These contributions demonstrate the utility of CoVaR-based adjacency matrices in examining contagion and systemic significance within financial systems.

Focusing on the Δ CoVaR, we note the use of Δ CoVaR for evaluating the systemic risk. For instance, Carvalho and Kruly [21] analyze 40 cryptocurrencies from 2020 to 2026. Their findings distinguish between digital assets that are highly vulnerable to market-wide contagion and those that actively drive systemic sell-offs. In [22], Mba relies on the Δ CoVaR for ranking the top 10 cryptocurrencies by market capitalization according to their systemic importance. In [23], Abubakar et al. map the tail dependence and risk spillovers using a Copula- Δ CoVaR approach. This paper contributes to the literature in three main ways. First, it provides a regime analysis of systemic risk in cryptocurrency markets. Second, it combines CoVaR estimation with dynamic network analysis in order to capture both the intensity and the direction of tail risk spillovers. Third, it introduces a CP perspective into the study of cryptocurrency markets, making it possible to identify the assets that form the systemic core and to monitor how the boundary between the core and the periphery evolves over time.

The remainder of the paper is organized as follows. Section 2 describes the dataset and presents the main statistical properties of cryptocurrency returns. Section 3 introduces the methodology, including breakpoint detection, VaR and CoVaR estimation, dynamic network construction, and CP analysis. Section 4 discusses the empirical findings, with particular attention to the evolution of systemic risk and the CP structure across different market regimes. Finally, Section 5 concludes.

2. Data description

Data are obtained from the Yahoo Finance website. The period spans from January 1st, 2022 to November 21st, 2025, comprising 1420 trading days. Due to missing data, our final database contains 221 cryptocurrencies. Fig. 1 shows the time series of the closing price and trading volume of the first three cryptocurrencies by trading volume (BTC, ETH, XRP).

Let $r_{i,t} = 100 * \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$ denote the percentage daily returns of the i -th cryptocurrency observed at time t , for $t = 2, \dots, T$, where $P_{i,t}$ is the closing price at time t of the i th cryptocurrency.

We test the normality of the cryptocurrencies' returns. Both the Shapiro–Wilk and Jarque–Bera tests strongly reject the null hypothesis of normality, with approximately null p-values for all the time series considered, clearly indicating strong deviations from a Gaussian distribution. Overall, these results confirm that the time series of the cryptocurrencies' returns exhibit the typical

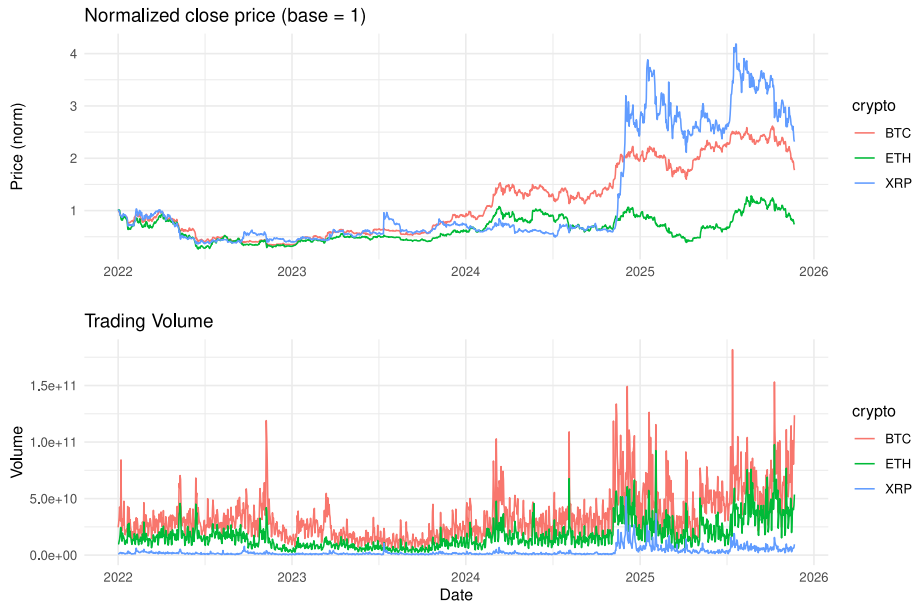


Fig. 1. Time series of selected cryptocurrencies (BTC, ETH, XRP): closing price on the top and trading volume on the bottom. Sample period: January 1st, 2022–November 21st, 2025.

Table 1

Descriptive statistics and results of the Shapiro–Wilk (SW stat, SW p) and Jarque–Bera (JB stat, JB p) normality tests for daily returns of the first ten cryptocurrencies by trading volume in 2025. “stat” denotes the test statistic, while “p” reports the associated *p*-value.

Crypto (<i>i</i>)	Mean	S.D.	Skew.	Kurt.	Min	Max	SW stat	SW p	JB stat	JB p
BTC	0.0403	2.7172	−0.1558	4.4315	−17.4053	13.5764	0.9399	0.0000	1167.6866	0.0000
ETH	−0.0216	3.6730	−0.0554	4.0769	−19.1844	19.7200	0.9440	0.0000	984.1517	0.0000
XRP	0.0592	4.3324	1.8515	22.9108	−21.7138	54.8555	0.8503	0.0000	31868.1996	0.0000
SOL	−0.0226	5.1950	−0.7090	10.9209	−54.9582	28.2125	0.9346	0.0000	7175.5270	0.0000
DOGE	−0.0143	4.8531	0.2998	5.7342	−25.2203	37.1172	0.9364	0.0000	1966.7212	0.0000
BNB	0.0318	3.0595	−0.3837	5.1537	−20.5370	15.9001	0.9360	0.0000	1606.3736	0.0000
ADA	−0.0847	4.5599	0.9849	16.7386	−27.8123	53.8407	0.9035	0.0000	16806.9710	0.0000
TRX	0.0904	3.2454	5.2677	124.6477	−24.8085	65.9226	0.6821	0.0000	925842.1172	0.0000
LINK	−0.0368	4.6779	−0.0525	2.9422	−23.7734	28.3915	0.9710	0.0000	512.8190	0.0000
LTC	−0.0416	4.0535	−0.2923	4.7452	−26.4897	24.3650	0.9414	0.0000	1352.4617	0.0000

features of volatility-related financial time series, such as asymmetry and heavy tails. Table 1 reports the summary statistics of the daily returns for the ten cryptocurrencies with the highest trading volume in 2025, together with the results of the Shapiro–Wilk and Jarque–Bera normality tests.

Stationarity test results. To assess the time-series properties of cryptocurrency returns, stationarity tests are performed on percentage daily returns $r_{i,t}$. In particular, the Augmented Dickey–Fuller (ADF) test is employed to investigate the presence of a unit root. The ADF test strongly rejects the null hypothesis of a unit root for all cryptocurrency returns. The test statistics are consistently large in absolute value and highly significant (*p*-values equal to 0.01 across all series), as shown in Table A.6 in Appendix. These results provide robust evidence that returns are stationary processes, in line with standard findings in financial time series analysis. Therefore, no further differencing is required before modeling.

3. Methodology

This section shows the analytical framework used to examine systemic risk in the bitcoin market. It explains how the authors first identify structural regimes in the return series using multivariate breakpoint detection, then estimate tail risk using Value-at-Risk (VaR) models and confirm them using backtesting procedures. The estimated VaR is then used to compute conditional risk spillovers (CoVaR) and build a time-varying network of interdependencies among cryptocurrencies. Finally, a CP model is applied to this network to distinguish the most systemically relevant assets from peripheral ones and analyze how their roles alter under different market conditions.

3.1. Breakpoints detection

The first step of our preliminary analysis consists in determining breakpoints or change points. In economics and finance, multivariate breakpoint analysis is widely used to detect when the joint behavior of time series undergoes structural changes, potentially due to events such as economic cycles, market disruptions, or policy interventions. Such changes may affect the mean, variance, covariance structure, resulting in different regimes and co-dependence relationships. We apply two complementary breakpoints detection methods, widely used for detecting structural breakpoints, particularly in long and noisy time series, such as those observed in cryptocurrency markets: the variance based change point test, and the Binary Segmentation (Bai and Perron [24,25], and Cho and Fryzlewicz [26]). The variance-based change-point (CPT_var) approach (Killick et al. [27]) estimates breakpoints solely based on shifts in variance using the Pruned Exact Linear Time (PELT) algorithm. To maintain consistency across analyzes, if more than two breakpoints are detected, only the first two are retained, and the start and end points of the series are added to define periods for subsequent analysis. The Binary Segmentation (BISEG) (Scott et al. [28]), is a recursive procedure for detecting multiple structural breakpoints in a time series. BISEG iteratively splits the series at the point that maximizes a chosen test statistic (e.g., the partition which leads to the minimal changes of mean and variance in each set of the partition), then applies the same procedure to the resulting sub-segments until a stopping criterion is met. This method is particularly suitable for relatively long and noisy time series, as it tends to produce stable and chronologically ordered breakpoints.

3.2. VaR: modeling and backtesting

Given the return $r_{i,t}$ and a confidence level $\alpha \in (0, 1)$, the Value-at-Risk (VaR) is defined as:

$$\Pr(r_{i,t} \leq \text{VaR}_{i,t}(\alpha)) = \alpha. \quad (1)$$

For the application on our empirical dataset, we estimate the probability basing on a rolling window of size W using alternative methodologies. We compare four approaches: the Historical Simulation model, the parametric Normal model, and the standard Gaussian Exponentially Weighted Moving Average (EWMA) model, and the Asymmetric Exponentially Weighted Moving Average (AEWMA) model. For the details we refer to Pilar et al. [29].

The backtesting procedure is designed to evaluate the out-of-sample predictive accuracy of the competing one-day-ahead VaR models within each regime identified by the breakpoint analysis. For each period defined by the global breakpoints, the corresponding subsample is further split into two non-overlapping segments. The first segment is used as an estimation window to initialize model parameters and to generate rolling VaR forecasts, while the second segment constitutes the genuine backtesting window: VaR is estimated on each cryptocurrency, for each time t in each second segment of each regime. Three adequacy tests are applied to assess model performance, the Kupiec unconditional coverage test (Kupiec [30]), that evaluates whether the total number of violations is consistent with the nominal probability, the Christoffersen independence test (Christoffersen [31]), that checks whether violations occur independently over time, and their joint conditional coverage test. This procedure allows for a robust comparison of risk forecasting performance across different volatility regimes.

VaR violation indicator. A VaR violation at time t is defined by the indicator $I_{i,t}^{VaR(\alpha)} = \mathbb{I}_{\{r_{i,t} < \text{VaR}_{i,t}(\alpha)\}}$. Over a backtesting window of length n , the total number of violations is $X_i^{VaR(\alpha)} = \sum_{t=1}^n I_{i,t}^{VaR(\alpha)}$.

Kupiec unconditional coverage test. The null hypothesis $H_0 : p = \alpha$ states that violations occur with the nominal probability α . The likelihood ratio statistic is $LR_{UC} = -2(\ell_0 - \ell_1) \sim \chi_1^2$, where the log-likelihood under the null is $\ell_0 = (n - x) \ln(1 - \alpha) + x \ln \alpha$, while under the alternative it is $\ell_1 = (n - x) \ln(1 - \hat{p}) + x \ln \hat{p}$, with $\hat{p} = x/n$, and $x = X_{VaR(\alpha)}$.

Christoffersen independence test. Let n_{ij} denote the number of transitions ($I_{t-1} = i, I_t = j$), $i, j \in \{0, 1\}$. Define the transition probabilities $\pi_{01} = n_{01}/(n_{00} + n_{01})$, $\pi_{11} = n_{11}/(n_{10} + n_{11})$, and the unconditional violation probability $\pi_1 = (n_{01} + n_{11})/n$. Independence is tested using $LR_{Ind} = -2(\ell_{ind} - \ell_{Markov}) \sim \chi_1^2$, where $\ell_{ind} = (n_{00} + n_{10}) \ln(1 - \pi_1) + (n_{01} + n_{11}) \ln \pi_1$ and $\ell_{Markov} = n_{00} \ln(1 - \pi_{01}) + n_{01} \ln \pi_{01} + n_{10} \ln(1 - \pi_{11}) + n_{11} \ln \pi_{11}$.

Conditional coverage test. The conditional coverage test jointly assesses unconditional coverage and independence by combining the two statistics as $LR_{CC} = LR_{UC} + LR_{Ind} \sim \chi_2^2$. The null hypothesis is $H_0 : p = \alpha$ and violations are independent, and the corresponding p -value is $1 - F_{\chi_2^2}(LR_{CC})$.

3.3. Network construction

For each day t in which the VaR forecast is estimated, we define the network set as $G_t = (V, E_t)$, where each element in V represents a cryptocurrency, and each couple $(i, j) \in E_t$ is an edge. For each time t , to define the network weights $w_{ij,t}$, we rely on CoVaR. It is a measure of systemic risk that captures the risk of a financial asset conditional on another asset being under financial distress. CoVaR represents the VaR of the asset i given that asset j is experiencing an extreme adverse event identified by its VaR. Unlike the traditional VaR, which only measures the standalone risk of a single asset, CoVaR takes into account the dependence structure among cryptocurrencies and therefore allows the analysis of contagion effects and systemic spillovers within the financial system. More negative values of CoVaR indicate stronger downside spillovers and a higher contribution to systemic risk. We base on Adrian and Brunnermeier [4] and on Das and Fasen-Hartmann [32] for calculating the CoVaR. We recall that the CoVaR measure is

defined as the Value-at-Risk of cryptocurrency i conditional on cryptocurrency j being under distress. Formally, for given confidence levels α and β , CoVaR is defined as

$$\Pr \left(r_{i,t} \leq \text{CoVaR}_{i|j,t}(\alpha | \beta) \mid r_{j,t} = \text{VaR}_{j,t}(\beta) \right) = \alpha,$$

where $r_{i,t}$ and $r_{j,t}$ denote the returns of cryptocurrencies i and j at time t , respectively. Assuming that the vector of returns follows a bivariate normal distribution with zero mean,

$$\begin{pmatrix} r_{i,t} \\ r_{j,t} \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{i,t}^2 & \rho_{ij,t} \sigma_{i,t} \sigma_{j,t} \\ \rho_{ij,t} \sigma_{i,t} \sigma_{j,t} & \sigma_{j,t}^2 \end{pmatrix} \right), \quad (2)$$

the conditional distribution of $r_{i,t}$ given $r_{j,t} = \text{VaR}_{j,t}(\beta)$ is Gaussian with conditional mean and variance equal to

$$\mathbb{E} (r_{i,t} \mid r_{j,t} = \text{VaR}_{j,t}(\beta)) = \rho_{ij,t} \frac{\sigma_{i,t}}{\sigma_{j,t}} \text{VaR}_{j,t}(\beta),$$

and

$$\text{Var} (r_{i,t} \mid r_{j,t} = \text{VaR}_{j,t}(\beta)) = (1 - \rho_{ij,t}^2) \sigma_{i,t}^2.$$

Therefore, the conditional distribution can be written as

$$r_{i,t} \mid (r_{j,t} = \text{VaR}_{j,t}(\beta)) \sim \mathcal{N} \left(\rho_{ij,t} \frac{\sigma_{i,t}}{\sigma_{j,t}} \text{VaR}_{j,t}(\beta), (1 - \rho_{ij,t}^2) \sigma_{i,t}^2 \right).$$

Accordingly, the CoVaR admits the following closed form expression:

$$\text{CoVaR}_{i|j,t}(\alpha | \beta) = \rho_{ij,t} \frac{\sigma_{i,t}}{\sigma_{j,t}} \text{VaR}_{j,t}(\beta) + \sqrt{1 - \rho_{ij,t}^2} \text{VaR}_{i,t}(\alpha).$$

Following Adrian and Brunnermeier [4], we consider the marginal contribution to systemic risk measured by ΔCoVaR , defined as

$$\Delta \text{CoVaR}_{i|j,t}(\alpha | \beta) = \text{CoVaR}_{i|j,t}(\alpha | \beta) - \text{CoVaR}_{i|j,t}(\alpha | 50\%).$$

Under the Gaussian assumption, this simplifies to

$$\Delta \text{CoVaR}_{i|j,t}(\alpha | \beta) = \rho_{ij,t} \frac{\sigma_{i,t}}{\sigma_{j,t}} \text{VaR}_{j,t}(\beta).$$

In the empirical analysis, we set $\alpha = \beta$, so that

$$\Delta \text{CoVaR}_{i|j,t}(\alpha) = \rho_{ij,t} \frac{\sigma_{i,t}}{\sigma_{j,t}} \text{VaR}_{j,t}(\alpha) \quad (3)$$

Literature is rich of contributions that examine networks based on the ΔCoVaR measures (Adrian and Brunnermeier [4], Cornaro et al. [33], Torri et al. [34], Chen et al. [35], Deng et al. [36], Salman et al. [37], Yin et al. [38]). We start from Eq. (3) to construct the weights $w_{i,j}$ of the network that, as it is well known in the literature, have to be non negative. Instead, the estimated ΔCoVaR measures may exhibit both positive and negative values and cannot be used as it is in the network but a transformation is necessary. Common approaches include taking absolute values, mapping correlations into the unit interval via affine transformations, or converting correlations into distances (Xu et al. [39], Mantegna and Stanley [40], Tumminello et al. [41], Costantini and Perugini [42]). Since the sign of ΔCoVaR carries an important economic interpretation, the direct use of absolute values is generally not recommended. Negative values of ΔCoVaR indicate that the distress of cryptocurrency i increases systemic downside risk, whereas positive values may reflect hedging effects, diversification benefits, or stabilizing relationships. For this reason, the literature generally interprets adverse systemic spillovers through the negative component of ΔCoVaR . To construct the weighted network, we retain only the adverse component of ΔCoVaR , consistently with the systemic risk literature where negative ΔCoVaR values are interpreted as destabilizing spillovers. For each time t , we propose to define the weight of the edge from cryptocurrency j to the cryptocurrency i as

$$w_{ji,t} = \max(0, -\Delta \text{CoVaR}_{i|j,t}) \quad (4)$$

Under this specification, a negative value of $\Delta \text{CoVaR}_{i|j,t}$ implies that the edge weight is positive, meaning that the cryptocurrency j contributes to the risk of cryptocurrency i ; a negative value of $\Delta \text{CoVaR}_{i|j,t}$ implies that the edge weight is 0, so positive ΔCoVaR values are not interpreted as adverse systemic spillovers.

The selection of the network weights preserves both the sign and the magnitude of extreme losses and allows us to study how the network structure changes across different market regimes. Within this setting, the rows correspond to transmitting cryptocurrencies and the columns to receiving cryptocurrencies (Diebold and Yilmaz [3]). The total number of networks examined is equal to half of the total time length, because each network is built up on each time t of each second half of the time frame corresponding to each regime.

3.4. Core-periphery networks model

As the name suggests, the CP model of a network classifies the nodes into two groups: the *core* and the *periphery*. Nodes in the core are mostly interconnected with each other and typically have high rank in accord with the most common centrality measures. The density of the connections is quite high. As opposed to that, peripheral nodes have few connections and are typically linked mainly to core nodes rather than among themselves. The infra-group density is quite low (Cinelli et al. [17]). Therefore, the two groups show quite different structures.

CP models take detect network configurations which are neither fully centralized nor completely decentralized.

Spectral CP detection. Literature offers various approaches for identifying the core and the peripheral nodes a network (Cucuringu et al. [43], Rombach et al. [44]). Spectral methods have been shown to be more robust to local fluctuations compared to degree based methods (Stephan and Laurent Massoulié [45], and Tudisco and Higham [46]). The function reported in the *Algorithm 1* pseudo-code belongs to the class of models based on spectral methods. First, the rank-1 singular value decomposition of the weighted adjacency matrix is calculated. The method applies to directed networks. The leading left and right singular vectors are extracted. They are interpreted as outgoing and incoming coreness. Next, a convex combination of these two components is calculated. The output provides the values for the core score for each node. Nodes whose score exceeds a threshold based on the mean and standard deviation of the distribution are classified as core (line 4 of Algorithm 1, with $\tau = 1$), while the remaining nodes are assigned to the periphery. Isolated nodes are retained in the graph and assigned a zero core score.

Algorithm 1 Spectral Core-Periphery Detection

Require: Adjacency matrix A (weighted), mixing parameter $\alpha \in [0, 1]$, threshold parameter $\tau \geq 0$

Ensure: Core score and CP classification for each node

- 1: Compute the rank-1 SVD of A : $A \approx \sigma_1 \mathbf{u}_1 \mathbf{v}_1^T$ on the subset of connected nodes
 - 2: Define outgoing coreness $c^{out} = |\mathbf{u}_1|$ and incoming coreness $c^{in} = |\mathbf{v}_1|$
 - 3: Compute the combined core score: $c = \alpha c^{out} + (1 - \alpha) c^{in}$
 - 4: Compute the threshold: $\theta = \mathbb{E}(c) + \tau \cdot \text{std}(c)$
 - 5: Classify each node: $\text{class}(i) = \begin{cases} \text{core}, & c_i \geq \theta, \\ \text{periphery}, & c_i < \theta \end{cases}$
 - 6: Assign core score 0 and class *periphery* to isolated nodes
 - 7: Attach core scores and classes as node attributes
 - 8: **return** Graph with core-periphery labels and a summary table
-

The analytical core, the global core, and the visual core. In large networks, the identification of relevant subsets points out the most meaningful information. We differ from the techniques which select a subset of links, just setting a threshold like as in the Minimum Spanning Tree or a Planar Maximally Filtered Graph (Mantegna [47], Di Matteo et al. [48], D’Arcangelis et al. [49], D’Arcangelis and Rotundo [50], Pozzi et al. [51], Tumminello et al. [52]). Rather, we focus on the most relevant cryptocurrencies. For each time t , each node in the $\Delta CoVaR$ based network represents a cryptocurrency and each directed weighted edge from node j to node i captures the conditional level of risk transmitted from cryptocurrency j to cryptocurrency i , as measured by $\Delta CoVaR_{i|j,t}$. Within this setting, we identify the analytical core and the global core. The *analytical core* is defined as the sub-network composed of cryptocurrencies that are systemically relevant according to local (pairwise) risk transmission measures. Formally, a cryptocurrency j belongs to the analytical core if it generates significant spillovers to other cryptocurrencies, i.e.

$$\sum_{i \neq j} |\Delta CoVaR_{i|j,t}(\alpha) - VaR_{i,t}(\alpha)|$$

exceeds a given threshold or ranks in the upper tail of the empirical distribution. Hence, the analytical core identifies cryptocurrencies that are important *risk transmitters* at the bilateral level, capturing direct contagion effects embedded in the $\Delta CoVaR$ network. While the analytical core focuses on local spillover effects, the *global core* accounts for the overall position of institutions within the entire $\Delta CoVaR$ network. In our analysis the global core is the output of Algorithm 1, witnessing high levels of co-dependencies. Empirical papers show that the nodes in the core are very likely to be relevant in accord to centrality measures (Barucca et al. [53], [54]), further validating the relevance of the nodes in the core. Cryptocurrencies in the global core are those whose distress has the potential to affect the system not only directly, but also indirectly through chains of interconnected exposures. Therefore, the global core captures system-wide systemic importance, reflecting higher-order contagion and amplification mechanisms.

The visual core reports the global core together with edge filtering, to the purpose to improve the readability of the plot. The filtering keeps the edges involving at least one core node, and a top fraction of edges by weight. The filtering happens only inside the plotting function, and does not affect the numerical estimates.

We apply several measures to check the stability of the core, starting from the simple counting of the permanence of each cryptocurrency in the core, to the heatmap, to the Jaccard similarity matrices (Jaccard [55]), and dendrograms. As further comparison on the tendency of the cryptocurrencies in the core to group together in terms of tail risk, we apply the Louvain method (Blondel et al. [56]) for detecting temporal communities, and observe the persistency of the partitions of nodes.

Table 2

Regime segmentation with descriptive statistics of cryptocurrency returns. Regimes are identified using the BISEG structural break detection method.

	Period 1	Period 2	Period 3	Period 4
Initial–final date	02/01/22–09/11/22	10/11/22–01/01/24	02/01/24–08/01/25	09/01/25–21/11/25
Nr. obs.	312	418	373	317
Mean return	−0.5432	0.1385	0.0150	−0.2870
Volatility	7.5600	9.8460	8.5850	11.3846
Skewness	−8.6622	3.7773	−0.0773	−2.2024
Kurtosis	702.0504	2635.9138	224.8364	1063.8594

Table 3

Number of observations and the corresponding initial and final dates for each backtesting period.

	Period 1	Period 2	Period 3	Period 4
Initial–final date	06/06/22–09/11/22	06/06/23–01/01/24	07/05/24–08/01/25	06/15/25–21/11/25
Nr. obs.	157	210	188	160

4. Results

The section sums up the results on the breakpoint detection, on the estimate of the best VaR (hence, CoVaR) model, and proceeds with the analysis of the networks.

4.1. Breakpoints detection

Breakpoints are first detected separately for each cryptocurrency using both CPT_var and BISEG, and then aggregated across assets by taking the cross-sectional median for each breakpoint position. This approach provides a robust estimate of global structural changes and mitigates the influence of idiosyncratic noise. The BISEG method delivers more stable (lower variance) than the CPT_var and chronologically coherent breakpoints across series, and is therefore used to define the final four-regime partition. The four regimes exhibit markedly different statistical properties in terms of mean returns, volatility, skewness, and kurtosis (see Table 2). Periods 1 and 4 correspond to stress conditions, with negative skewness and extremely high kurtosis indicating pronounced tail risk. Period 2 reflects a rebound phase, characterized by positive average returns but still elevated tail asymmetry. Period 3 appears comparatively more stable, with near-symmetric returns and substantially lower kurtosis. These differences confirm that the detected breakpoints correspond to structurally distinct market environments rather than arbitrary time partitions. Taken together, the statistical evidence supports the interpretation of the four regimes as distinct phases of market dynamics, providing a meaningful framework for the subsequent analysis of tail-risk spillovers and core–periphery structures.

The economic interpretation of the breakpoints further reinforces their relevance. The first breakpoint, on November 10th, 2022 occurs in correspondence of the exogenous liquidity shock due to the collapse of the FTX exchange. In that moment, the market experienced an increase in volatility and changes in the dependence structures across cryptocurrencies. It is frequent that and exogenous shock can influence market confidence, trading volumes and correlations between assets. The second breakpoint, on January 2th, 2024, marks the beginning of a recovery phase, characterized by renewed institutional interest in crypto assets thanks to regulatory clarifications and the anticipation of spot Bitcoin ETF approvals. In this period, a gradual decline in volatility and a reorganization of network centralities occurs, consistent with a transition toward a more stable market environment. The third breakpoint, on January 9th, 2025, signals the onset of a high-activity regime marked by increased speculative trading and heightened sensitivity to global macro-financial conditions. This phase reflects a shift toward more aggressive risk-taking and stronger cross-market spillovers. Overall, these breakpoints can be interpreted as endogenous responses of the cryptocurrency market to major financial disruptions, regulatory and macroeconomic turning points, and innovation-driven cycles. They highlight the strong interaction between external events and the internal evolution of risk dependence structures.

4.2. VaR modeling and backtesting

For each time interval i identified by the BISEG method (Table 2), the first half is used for the first calculus of quantities which intervene in the formulas of Historical Simulation, Normal, EWMA, and AEWMA models; and we calculate the one-day-ahead VaR forecasts on each day of the second half of the series through a rolling window mechanism (i.e. the length of the time series used for the forecast at time is always equal to $T_i/2$, where T_i is the time length of the time interval i). Table 3 reports the exact dates. The Standard Gaussian EWMA model is the best performer on backtesting, sticking to the 95% selection, so we rely on it for the next step of our analysis.

Figs. 2–5 provide a visual comparison of the one-day-ahead VaR forecasts produced by the Historical Simulation, Normal, EWMA, and AEWMA models for BTC across the four regimes identified by the breakpoint analysis, and they highlight how model performance varies with changing market conditions.

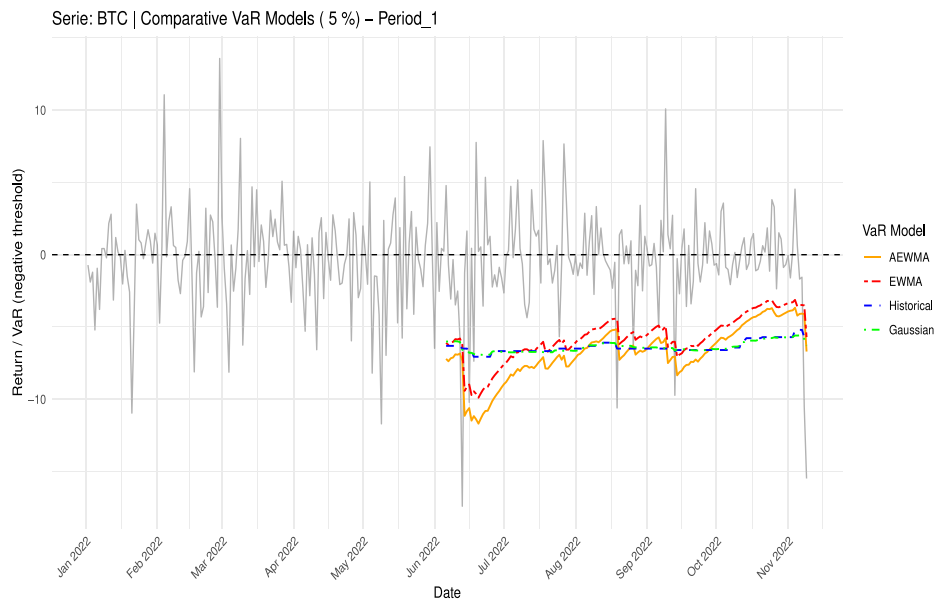


Fig. 2. Comparative analysis of VaR models ($\alpha = 5\%$), Period 1, BTC series.

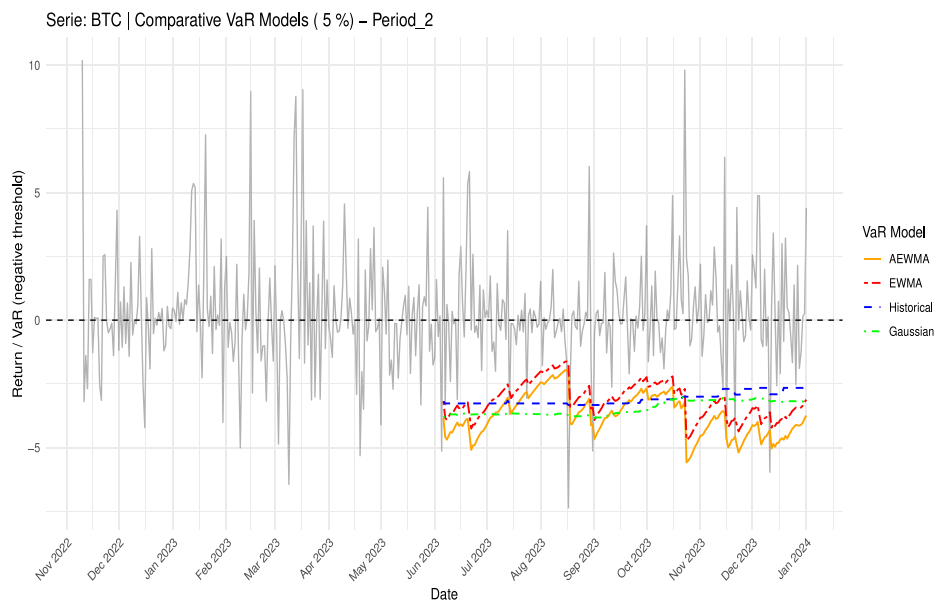


Fig. 3. Comparative analysis of VaR models ($\alpha = 5\%$), Period 2, BTC series.

In Period 1 (Fig. 2), which corresponds to the high-stress phase surrounding the 2022 market turmoil, returns exhibit pronounced volatility clustering and extreme negative spikes. In this regime, the Normal VaR clearly underestimates tail risk, frequently failing to adjust to sudden volatility increases, while the EWMA and especially the AEWMA models react more rapidly to large negative returns, producing wider and more adaptive risk bands. The Historical Simulation captures some extreme movements but appears sluggish when volatility shifts abruptly. In Period 2 (Fig. 3), associated with a more stable but still volatile market environment, overall fluctuations are less extreme and VaR exceedances become less frequent. Here, differences among models narrow: the Normal VaR improves but still tends to be optimistic in the presence of mild tail events, whereas EWMA-based models provide smoother and more consistent coverage. Period 3 (Fig. 4) reflects a recovery and normalization phase, characterized by lower volatility and fewer extreme returns. In this context, all models perform relatively well, with VaR forecasts closely tracking realized returns; however, the adaptive nature of EWMA and AEWMA results in tighter VaR bands that better reflect the reduced risk environment, while Historical Simulation remains influenced by past high-volatility observations. Finally, Period 4 (Fig. 5) shows renewed volatility

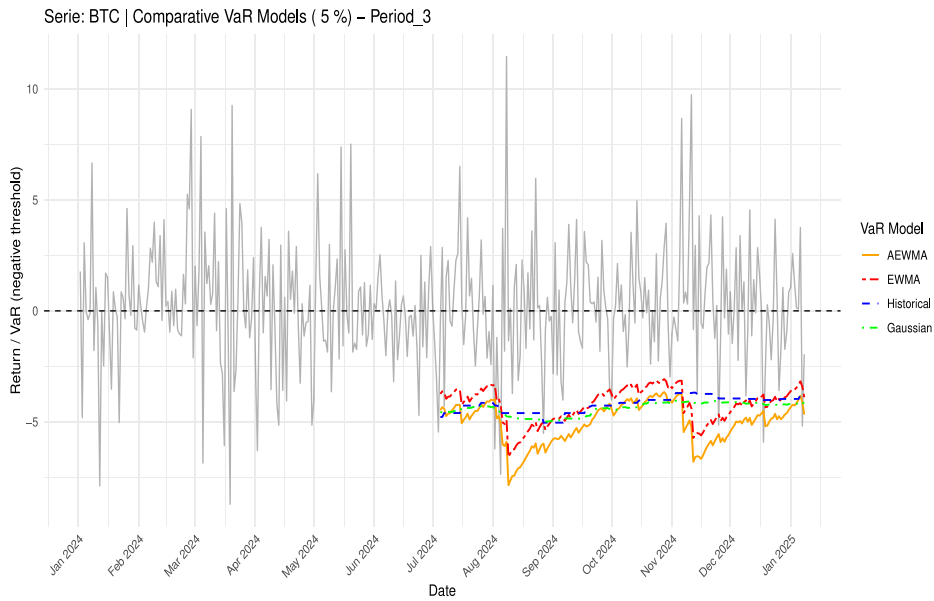


Fig. 4. Comparative analysis of VaR models ($\alpha = 5\%$), Period 3, BTC series.

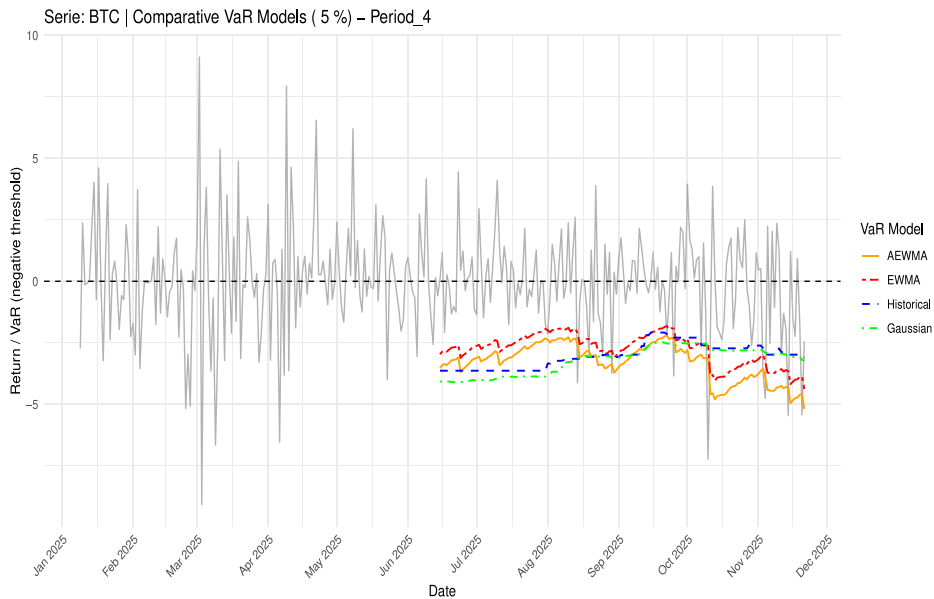


Fig. 5. Comparative analysis of VaR models ($\alpha = 5\%$), Period 4, BTC series.

and sporadic extreme movements. The Normal model again appears insufficiently responsive, whereas EWMA and AEWMA adjust more effectively to changing risk conditions, with AEWMA displaying a particularly strong ability to accommodate asymmetric downside risk. Overall, these figures visually confirm that model performance is regime-dependent and that volatility-adaptive and asymmetric specifications are better suited to capturing tail risk in cryptocurrencies, especially during periods of market stress and transition.

In order to provide a further validation of the selection of EWMA, we report the observed VaR violations compared to their expected number under each model. Fig. 6 shows the total violations versus the expected counts. The EWMA and AEWMA models display violation counts that are more closely aligned with theoretical expectations, indicating a better calibration of tail risk across regimes. In contrast, the Normal VaR systematically underestimates risk, especially in periods characterized by higher volatility, while the Historical Simulation model shows greater dispersion.

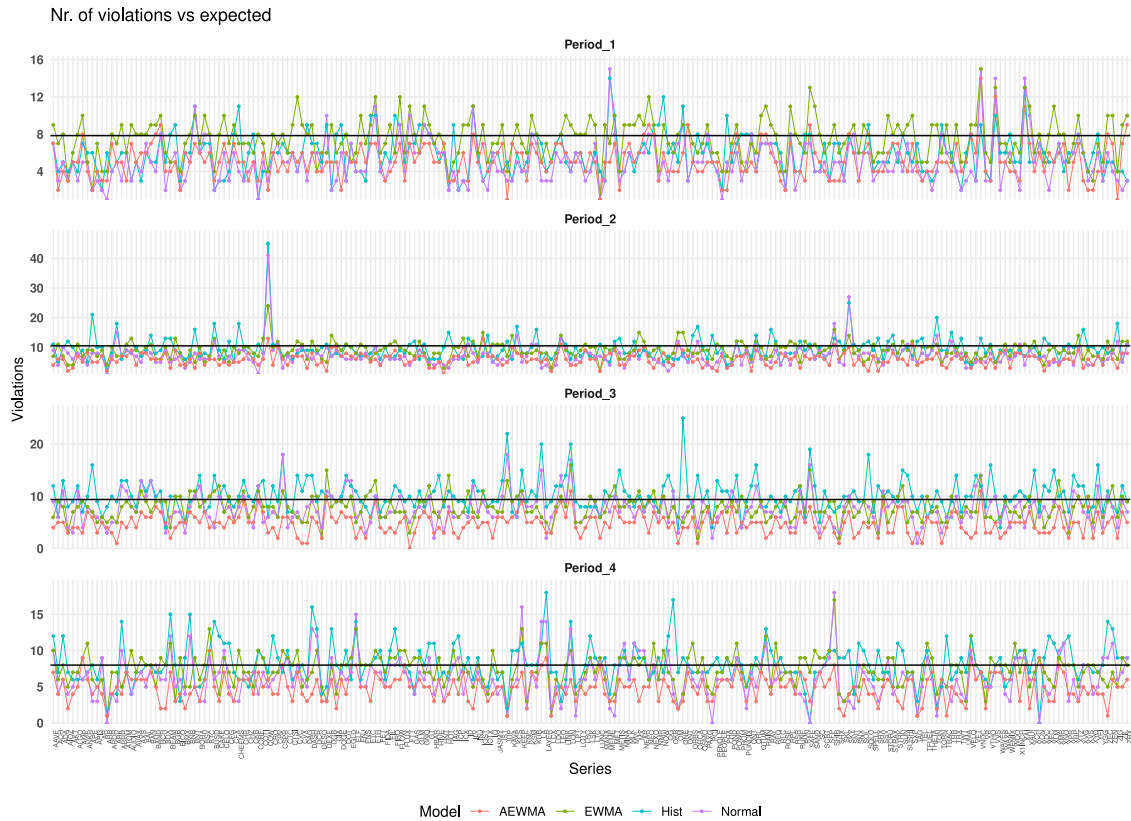


Fig. 6. Violations vs expected.

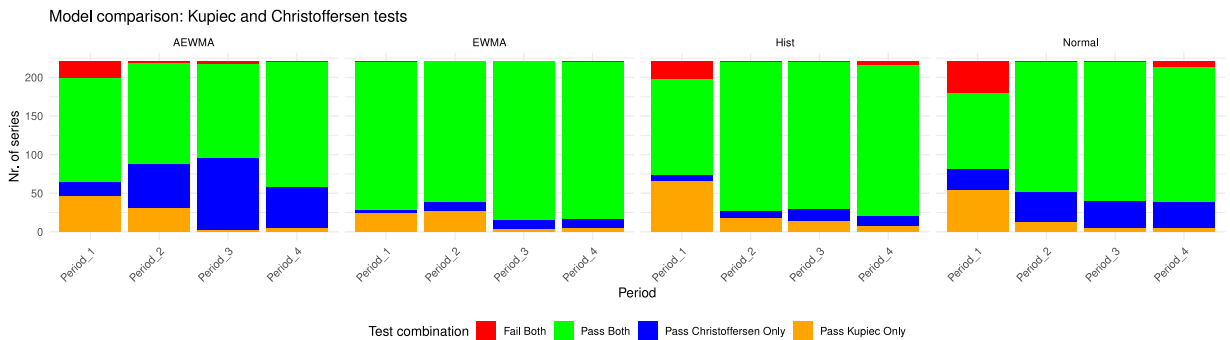


Fig. 7. Stacked bar plot showing the number of series for each model and period according to the combination of test outcomes. Colors indicate the result combination: green for passing both the Kupiec and Christoffersen tests, red for failing both, orange for passing only the Kupiec test, and blue for passing only the Christoffersen test.

Figs. 7–9 summarize the statistical tests (Kupiec Unconditional Coverage Test, Christoffersen Independence Test, and Conditional Coverage Test) results across different models, series, and analysis periods, using both scatter plots and heatmaps to highlight patterns in test outcomes and significance levels. Fig. 7 displays the number of series per model and period across all combinations of test outcomes, illustrating the distribution of results. The figure reveals a clear dominance of EWMA models, particularly AEWMA, in terms of the proportion of cryptocurrencies that simultaneously satisfy both correct coverage and independence of violations. The Normal model shows a substantially higher share of series failing both tests, especially in stress regimes. The Historical Simulation model often passes the unconditional coverage test but fails the independence test. These patterns highlight that correct VaR calibration in cryptocurrency markets requires not only matching the expected number of exceedances but also accurately modeling their temporal dependence, a feature more effectively captured by adaptive volatility-based approaches.

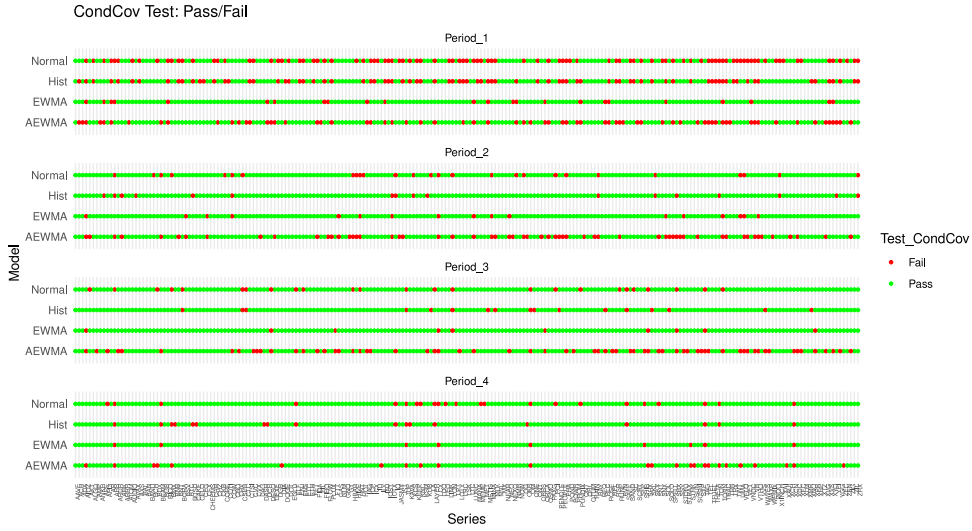


Fig. 8. Scatter plot showing the results of the Conditional Coverage test for each model and series across different periods. Green points indicate series that pass the test ($p\text{-value} \geq 0.05$), while red points indicate series that fail the test ($p\text{-value} < 0.05$).



Fig. 9. Heatmaps of p-values from backtesting procedures across different series and models, grouped by analysis periods. The left panel reports results from the Kupiec unconditional coverage test, while the right panel shows results from the Christoffersen independence test. Colors indicate significance levels: red for p-values < 0.05 (statistically significant violations), yellow for values around 0.05, and green for p-values > 0.05 (no evidence of violations).

4.3. Network analysis

This section presents the results of the core periphery (CP) analysis of the cryptocurrency networks based on $\Delta CoVaR$. For each one day ahead VaR forecast, we construct a directed weighted network according to Eq. (4). The analysis is divided into three parts. First, we show some representative snapshots of the networks for each market regime identified through the breakpoint analysis. Then, we study how the size of the core changes over time. Finally, we analyze how stable the core composition is by using persistence measures, heatmaps, similarity matrices, dendrograms, and temporal communities. Overall, the results provide a dynamic picture of how systemic risk spreads across the cryptocurrency market. The correlations $\rho_{ij,t}$ used in Eq. (3) are estimated through the EWMA covariance structure:

$$\rho_{ij,t}^{EWMA} = \frac{Cov_{ij,t}^{EWMA}}{\sigma_{i,t}\sigma_{j,t}}.$$

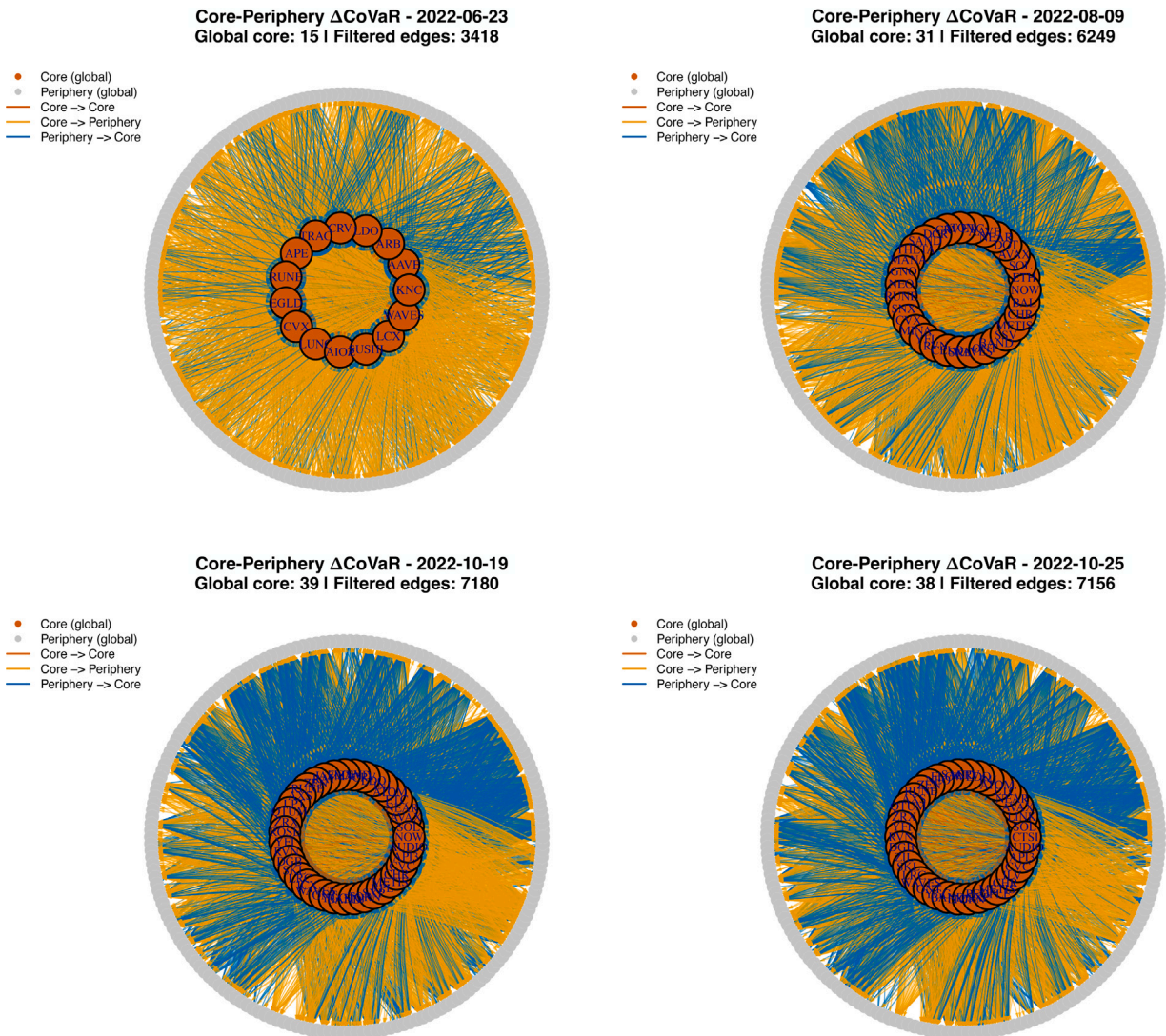


Fig. 10. Static Core-Periphery Structure of the Network - Period 1. Core nodes are highlighted in orange and peripheral nodes in gray. Core-core interactions are shown in dark orange, core-periphery interactions in light orange, and periphery-core interactions in blue. The list of cryptocurrencies belonging to the global core is reported in the Appendix (Table B.7).

Core-periphery snapshots. The CP structure clearly appears in all periods. A small group of cryptocurrencies forms the core of the network and acts as the main transmitter of tail risk, while most cryptocurrencies remain in the periphery and play a less important systemic role. Even if the CP structure is always present, the size and composition of the core change considerably over time. For each regime, we identify four representative phases: minimum, expansion, peak, and divergence. The minimum phase corresponds to the smallest core configuration, while the expansion phase captures the rapid growth of interconnected cryptocurrencies. The peak phase identifies the moment in which the core reaches its maximum size and connectivity. Finally, the divergence phase corresponds to the point where the visual and analytical measures of the core begin to differ, usually signaling a structural change in the network. The selected dates are reported in Table 4. Figs. 10–13 show the CP network structures for the four periods. Nodes represent cryptocurrencies, while directed weighted edges represent adverse systemic spillovers measured through the affine transformation of ΔCoVaR . Core nodes are highlighted in orange, peripheral nodes in gray, core-core links in dark orange, core-periphery links in light orange, and periphery-core links in blue. The filtered edges reported in the figures correspond to the edges retained after the filtering procedure described in Section 3.4. Fig. 10 refers to Period 1, which includes the collapse of the FTX exchange in November 2022. This event generated panic in the cryptocurrency market and caused a strong increase in volatility. As a consequence, the network becomes denser and the core grows rapidly, moving from 15 core cryptocurrencies in the minimum phase to 39 in the peak phase. This suggests that contagion effects became stronger and that many cryptocurrencies started moving together during the crisis. Fig. 11 corresponds to the recovery phase observed during 2023. After the instability of 2022, markets gradually became

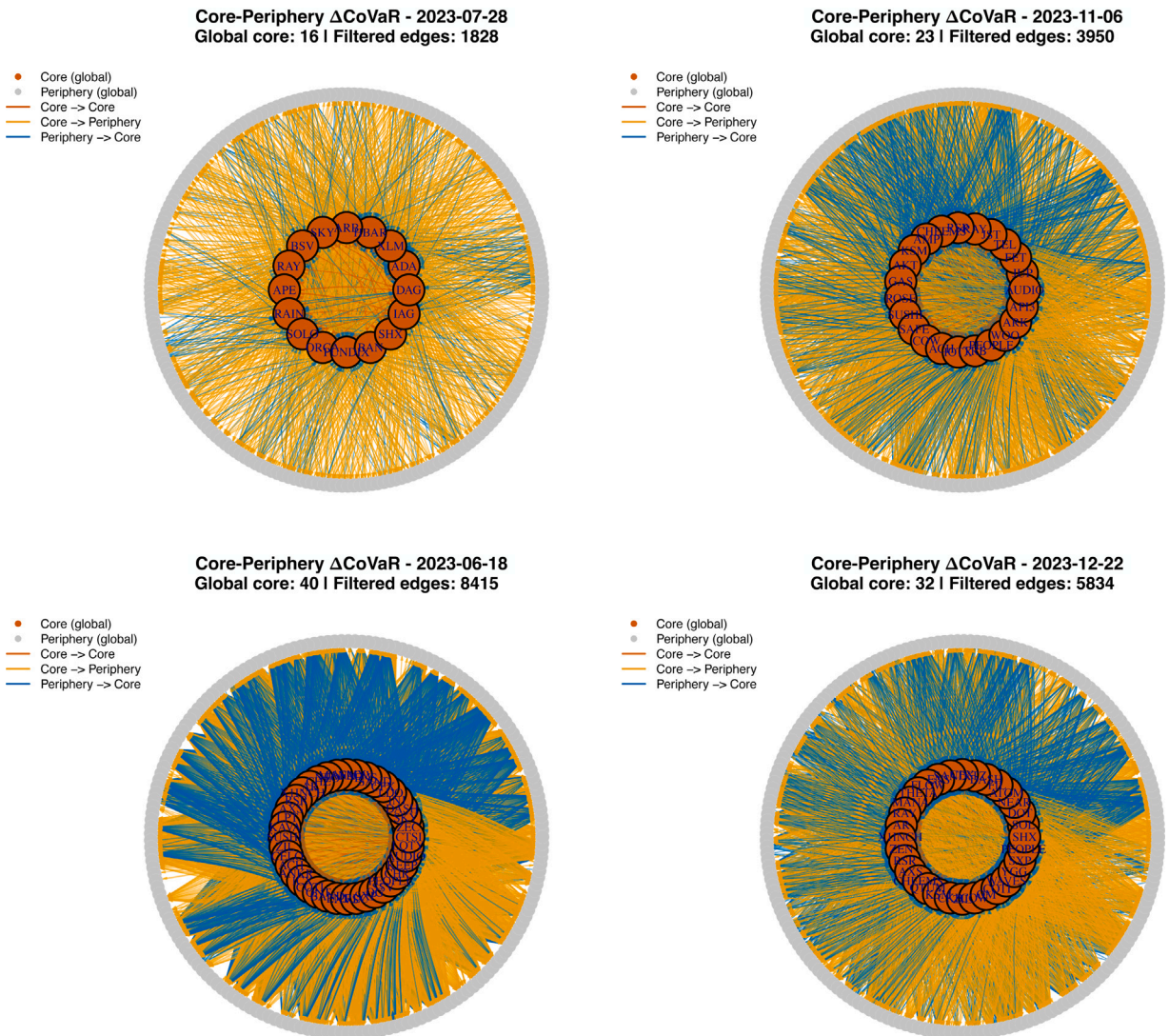


Fig. 11. Static Core-Periphery Structure of the Network - Period 2. Core nodes are highlighted in orange and peripheral nodes in gray. Core-core interactions are shown in dark orange, core-periphery interactions in light orange, and periphery-core interactions in blue. The list of cryptocurrencies belonging to the global core is reported in the Appendix (Table B.8).

more optimistic thanks to improving macroeconomic conditions and increasing expectations about the approval of Bitcoin ETFs in the United States. The network remains highly interconnected and reaches the highest number of core nodes and filtered edges observed in the sample, indicating that systemic importance temporarily spreads across a broader set of cryptocurrencies. Fig. 12 refers to a more unstable and fragmented phase. This period includes the approval of Bitcoin ETFs in early 2024 together with increasing participation of institutional investors. At the same time, markets were still affected by uncertainty related to interest rates and geopolitical tensions. Compared with the previous periods, the network appears less compact and more heterogeneous, suggesting that the role of the most systemically important cryptocurrencies changes more rapidly over time. Finally, Fig. 13 reflects market conditions during 2025. Compared with the previous periods, the network appears more regular and stable, with stronger coherence between the analytical and visual core measures. The same cryptocurrencies tend to remain in the core for longer periods, suggesting the emergence of a more mature and consolidated market structure. Overall, Figs. 10–13 show that cryptocurrency networks react strongly to major global and financial events. Periods of crisis generate larger and denser cores, reflecting stronger contagion effects and higher synchronization among cryptocurrencies, while more stable periods are associated with smaller and less connected cores.

Comparison of analytical and visual core dynamics. Fig. 14 compares the evolution of the analytical and visual core sizes across the four market regimes. The results show that the size of the systemic core changes considerably over time and follows different patterns depending on market conditions. In Period 1, both measures show a clear expansion followed by a pronounced peak,

Table 4
Representative dates selected from the evolution of the core size through the backtesting periods: minimum size of the core, expansion, peak (maximum), and divergence.

Period	Minimum	Expansion	Peak	Divergence
Period 1	2022-06-23	2022-08-09	2022-10-19	2022-10-25
Period 2	2023-07-28	2023-11-06	2023-06-18	2023-12-22
Period 3	2024-09-25	2024-11-14	2024-11-29	2025-01-03
Period 4	2025-06-27	2025-07-17	2025-11-11	2025-11-16

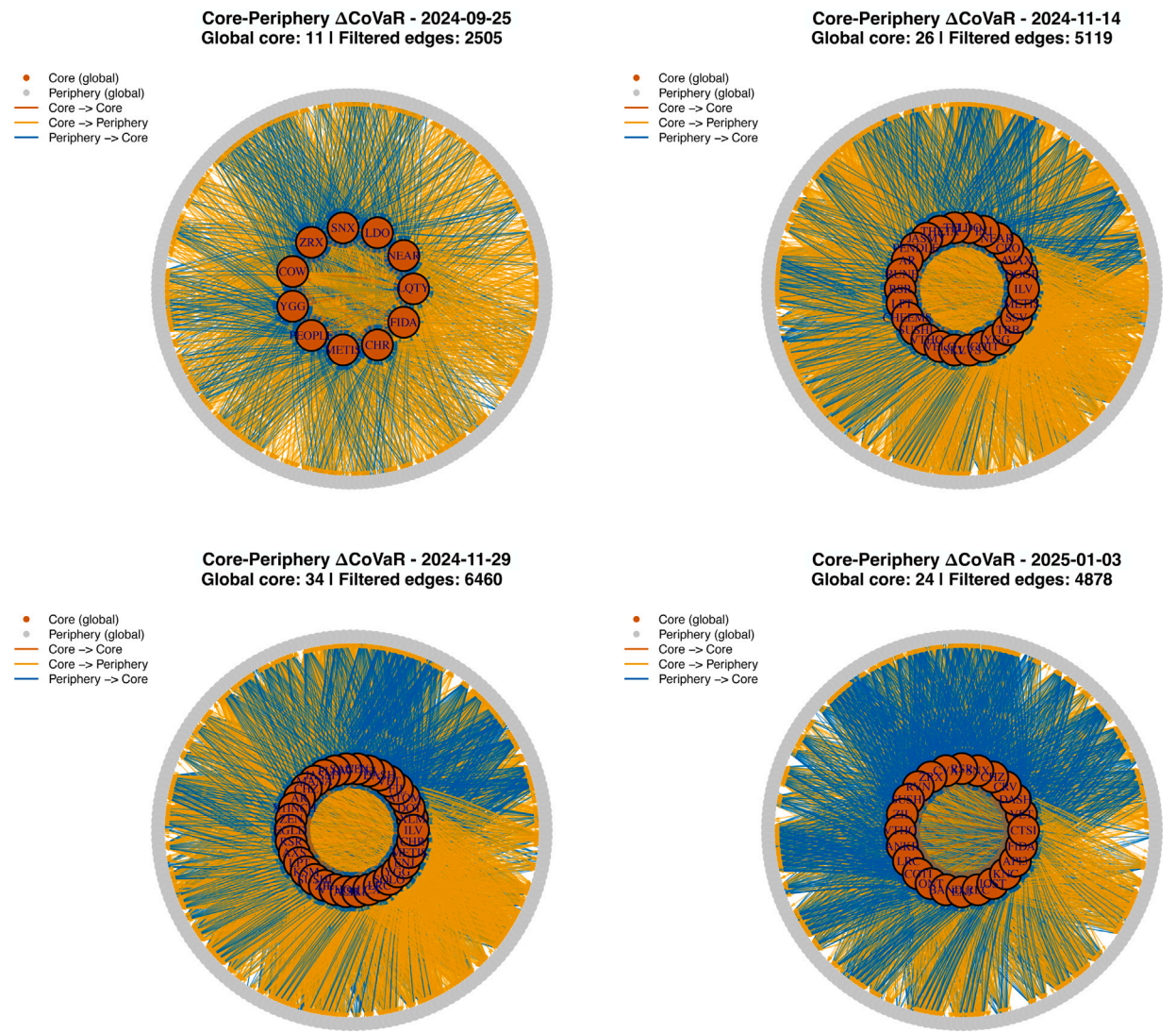


Fig. 12. Static Core-Periphery Structure of the Network - Period 3. Core nodes are highlighted in orange and peripheral nodes in gray. Core-core interactions are shown in dark orange, core-periphery interactions in light orange, and periphery-core interactions in blue. The list of cryptocurrencies belonging to the global core is reported in the Appendix (Table B.9).

consistently with the increase in interconnectedness observed after the FTX crisis. The analytical core evolves more smoothly, while the visual core reacts more quickly to local changes in the network structure. Period 2 shows stronger fluctuations and a larger discrepancy between the two measures, especially around the peak phase. This suggests that the network experiences several short-term reorganizations, leading to temporary concentrations of systemic importance. In Period 3, the divergence between the analytical and visual measures becomes even more evident. The visual core shows larger oscillations and reacts more strongly to local connectivity changes, while the analytical core remains comparatively smoother and more stable. This behavior suggests the presence of an unstable transition phase characterized by frequent changes in the network structure. Finally, Period 4 displays a more

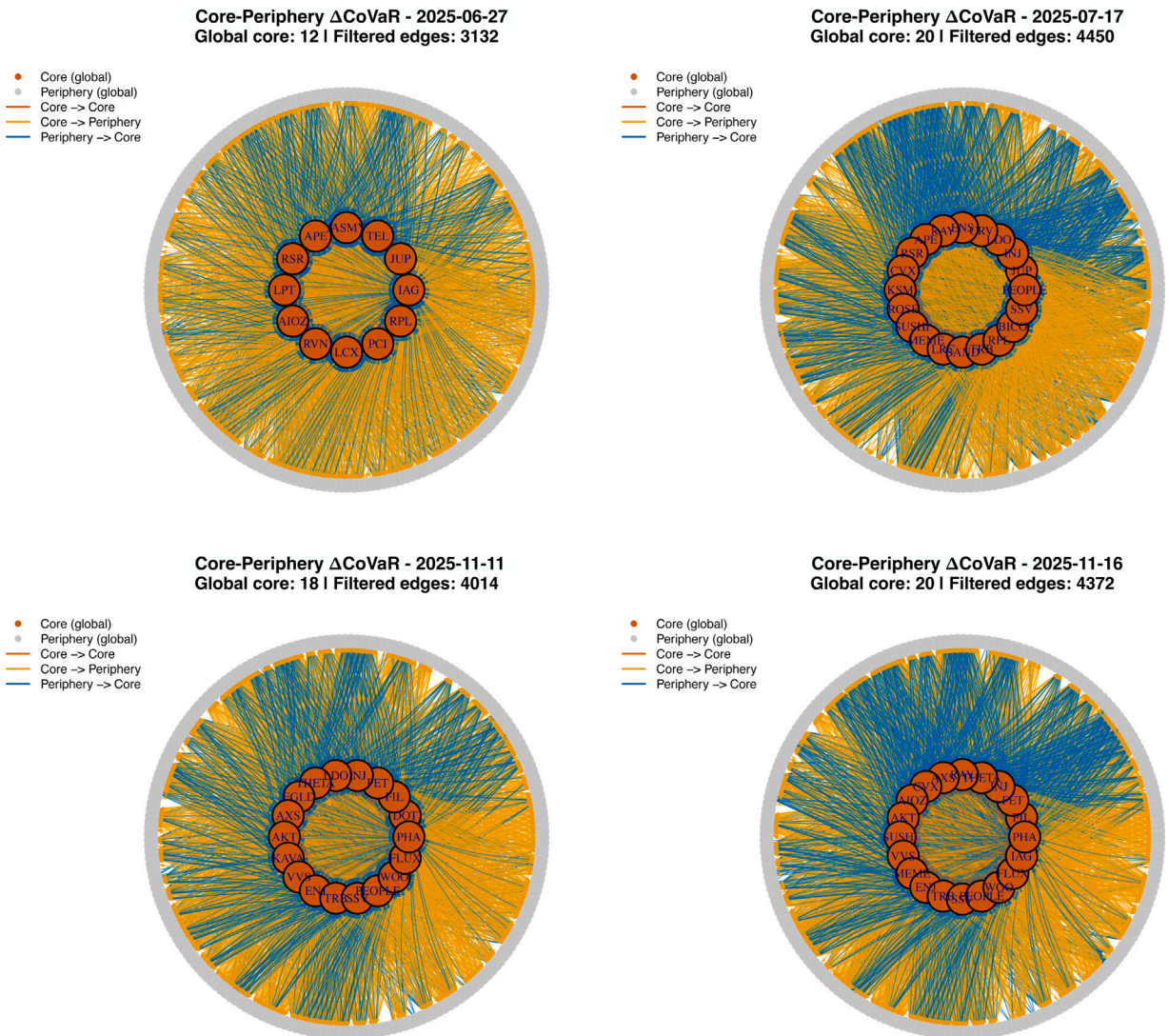


Fig. 13. Static Core-Periphery Structure of the Network - Period 4. Core nodes are highlighted in orange and peripheral nodes in gray. Core-core interactions are shown in dark orange, core-periphery interactions in light orange, and periphery-core interactions in blue. The list of cryptocurrencies belonging to the global core is reported in the Appendix (Table B.10).

regular and persistent evolution of the core size. The analytical and visual measures remain relatively close over time, indicating a more coherent and stable CP structure. The lower divergence between the two measures suggests that systemic importance becomes less sensitive to short-term fluctuations and more structurally embedded within the network. Overall, the analytical core provides a smoother and more conservative estimate of systemic relevance, whereas the visual core reacts more strongly to temporary structural changes. Periods characterized by strong divergence between the two measures usually correspond to phases of structural transition and market reorganization.

Core stability: persistence and instability. Fig. 15 summarizes the persistence of core membership across periods by showing how often each cryptocurrency belongs to the global core. Only a limited number of cryptocurrencies remain persistently in the core, confirming their structurally central role in transmitting systemic risk. Most cryptocurrencies instead show unstable or intermittent participation in the core, meaning that their systemic importance strongly depends on market conditions.

Core membership heatmap. Fig. 16 reports the heatmap of core membership across all periods. Rows correspond to cryptocurrencies and columns to time periods. Red cells indicate that a cryptocurrency belongs to the core during the corresponding period, while lighter colors indicate peripheral status. The heatmap highlights the coexistence of highly persistent cryptocurrencies and assets whose systemic importance emerges only temporarily during specific market phases.

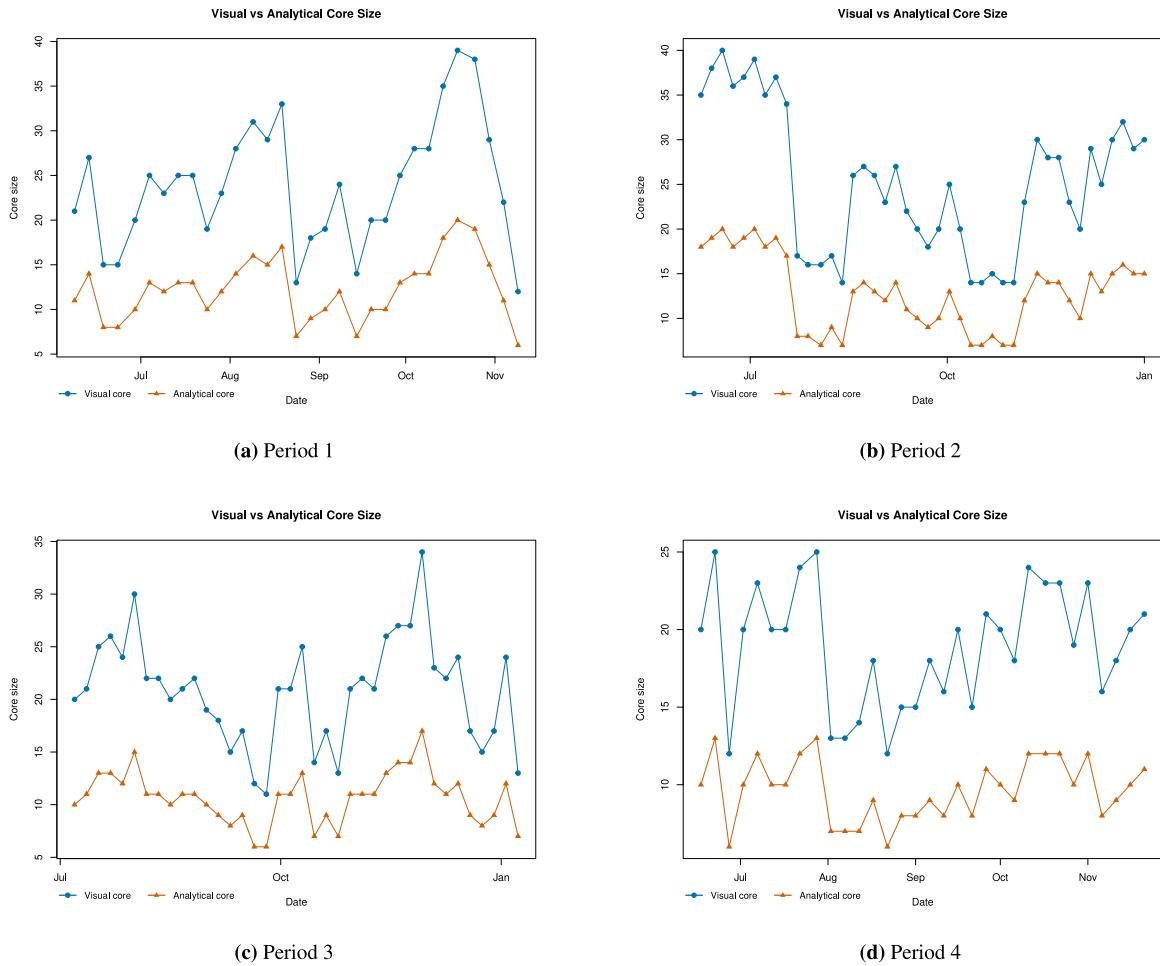


Fig. 14. Comparison of analytical and visual core dynamics across the four periods.

Jaccard similarity matrices. Fig. 17 displays the Jaccard similarity matrices comparing core sets across all pairs of periods. Each cell measures the overlap between two core configurations, ranging from 0 (no common members) to 1 (identical cores). The matrices reveal moderate similarity between adjacent periods and lower similarity across distant regimes. This indicates that structural changes in market conditions significantly reshape the composition of the systemic core.

Dendrogram of core similarity. Fig. 18 shows a hierarchical clustering dendrogram based on the Jaccard distances between core sets. The dendrogram groups periods according to the similarity of their core structures. The clustering confirms that periods with comparable volatility regimes tend to share similar core configurations. The largest separation occurs between the early 2022 stress regime and the late 2025 high-activity phase, reflecting substantial structural reorganization.

Temporal clusters (Louvain). Fig. 19 reports the temporal clusters obtained by applying the Louvain community detection algorithm to the sequence of core sets. Each cluster groups periods with similar systemic structures. The Louvain clustering identifies a small number of coherent temporal blocks, suggesting that the evolution of systemic risk is not continuous but characterized by distinct structural phases. These clusters align closely with the breakpoints detected earlier.

Jaccard similarity over time. Fig. 20 plots the Jaccard similarity between consecutive periods, providing a dynamic measure of how rapidly the core structure changes over time. Sharp drops in similarity correspond to major period transitions, while smoother segments indicate periods of structural stability. This reinforces the interpretation of breakpoints as genuine shifts in systemic risk architecture. Fig. 20 shows how stable the core is. When the Jaccard similarity is high, roughly the same cryptocurrencies remain at the center of the network. When similarity drops during period of uncertainty, the composition of the core changes rapidly, showing that assets move in and out of systemic relevance. This suggests that cryptocurrency markets are subject to changes in who carries the systematic risk.

Cluster timeline. Fig. 21 presents a timeline of the temporal clusters, showing how the market changes as function of the time. Each segment corresponds to a Louvain-identified cluster. The timeline reveals long stretches of structural coherence punctuated by

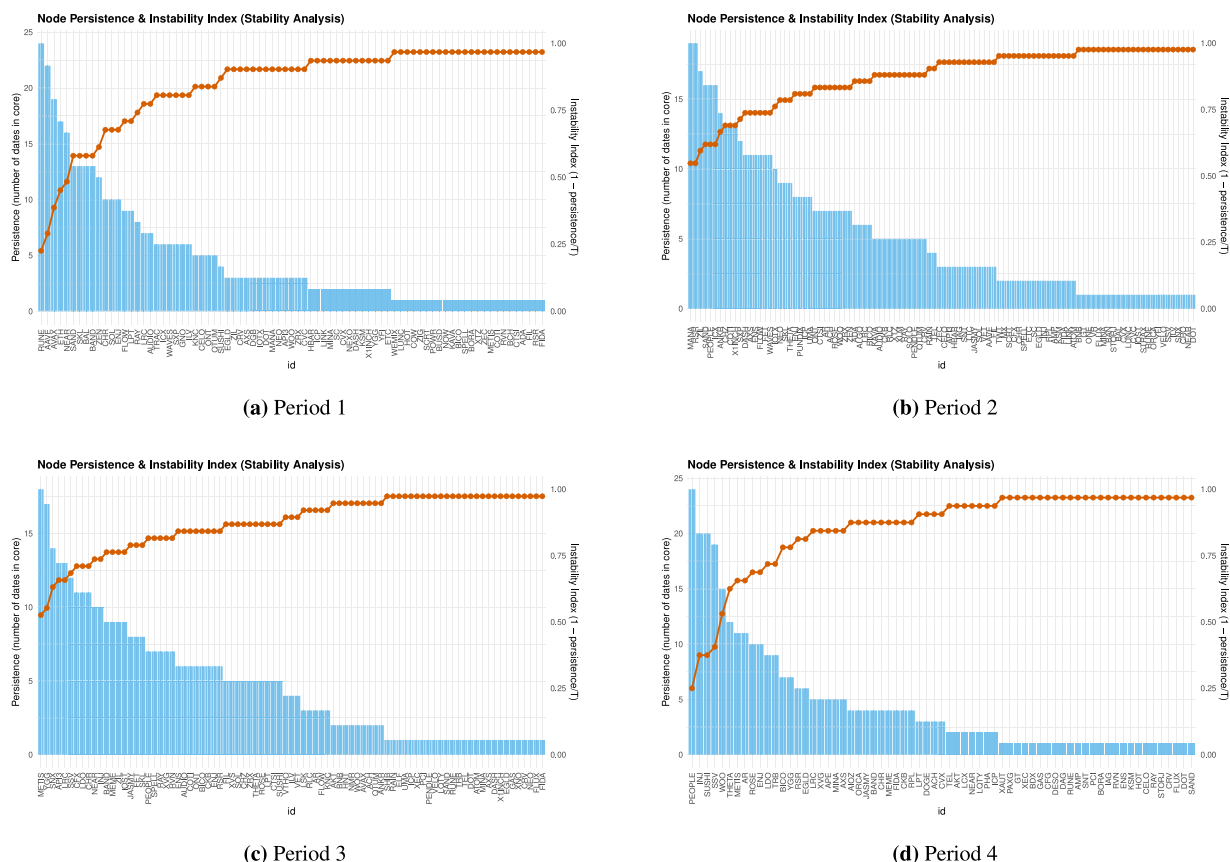


Fig. 15. Core persistence and instability across the four periods. The blue bars report the number of times in which the cryptocurrency reported on the x-axis is in the core. The red curve is the complementary measure.

Table 5
Maximum $\Delta CoVaR$ values by period and date.

Periods 1-2			Periods 3-4		
Period	Date	Max $\Delta CoVaR$	Period	Date	Max $\Delta CoVaR$
1	2022-09-03	0.9785	3	2024-10-25	1.0220
1	2022-08-24	0.8925	3	2024-12-04	0.8598
1	2022-09-08	0.8222	3	2024-10-30	0.8375
1	2022-09-14	0.7989	3	2024-10-20	0.8295
2	2023-12-12	2.0570	4	2025-08-17	1.8623
2	2023-12-17	1.6871	4	2025-08-22	1.3064
2	2023-10-07	1.3143	4	2025-08-27	1.0715
2	2023-12-22	1.2781	4	2025-11-11	1.0452

abrupt transitions. These transitions coincide with major market events and volatility shifts, underscoring the responsiveness of the CP network structure to external shocks.

$\Delta CoVaR$ maximum values. Table 5 reports the $\Delta CoVaR$ maximum values observed for each period, together with the corresponding dates.

To conclude this section, we highlight that our findings are broadly consistent with the existing literature on cryptocurrency interconnectedness and systemic risk, which shows that periods of market stress are typically associated with stronger contagion effects, higher synchronization among assets, and increased tail risk spillovers. In line with previous studies based on $\Delta CoVaR$ and tail dependence networks, we find that the cryptocurrency market becomes more interconnected during turbulent phases such as the collapse of FTX, while more stable periods are characterized by smaller and less cohesive systemic structures. At the same time, our analysis extends the existing literature by adopting a dynamic core periphery perspective, showing that the systemic core does

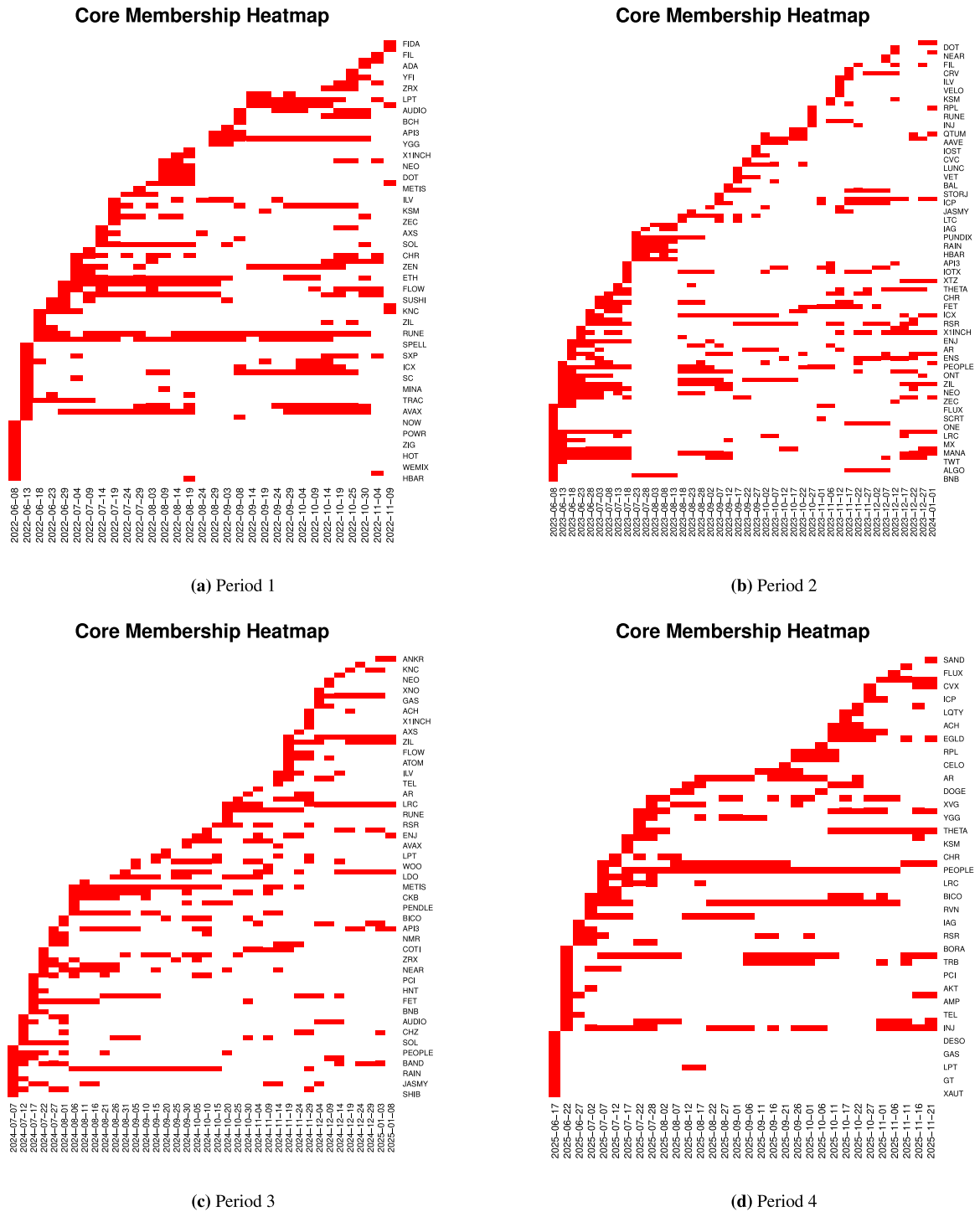


Fig. 16. Core membership heatmap across the four periods.

not evolve over time but rather through recurrent phases of expansion, peak, and reorganization. Unlike approaches based only on static networks or standard centrality measures, our framework highlights how the composition of the systemic core changes across different market regimes, with some cryptocurrencies becoming temporarily central only during specific phases of market stress. Overall, the results suggest that systemic importance in cryptocurrency markets is highly dynamic and strongly influenced by external financial and geopolitical events.

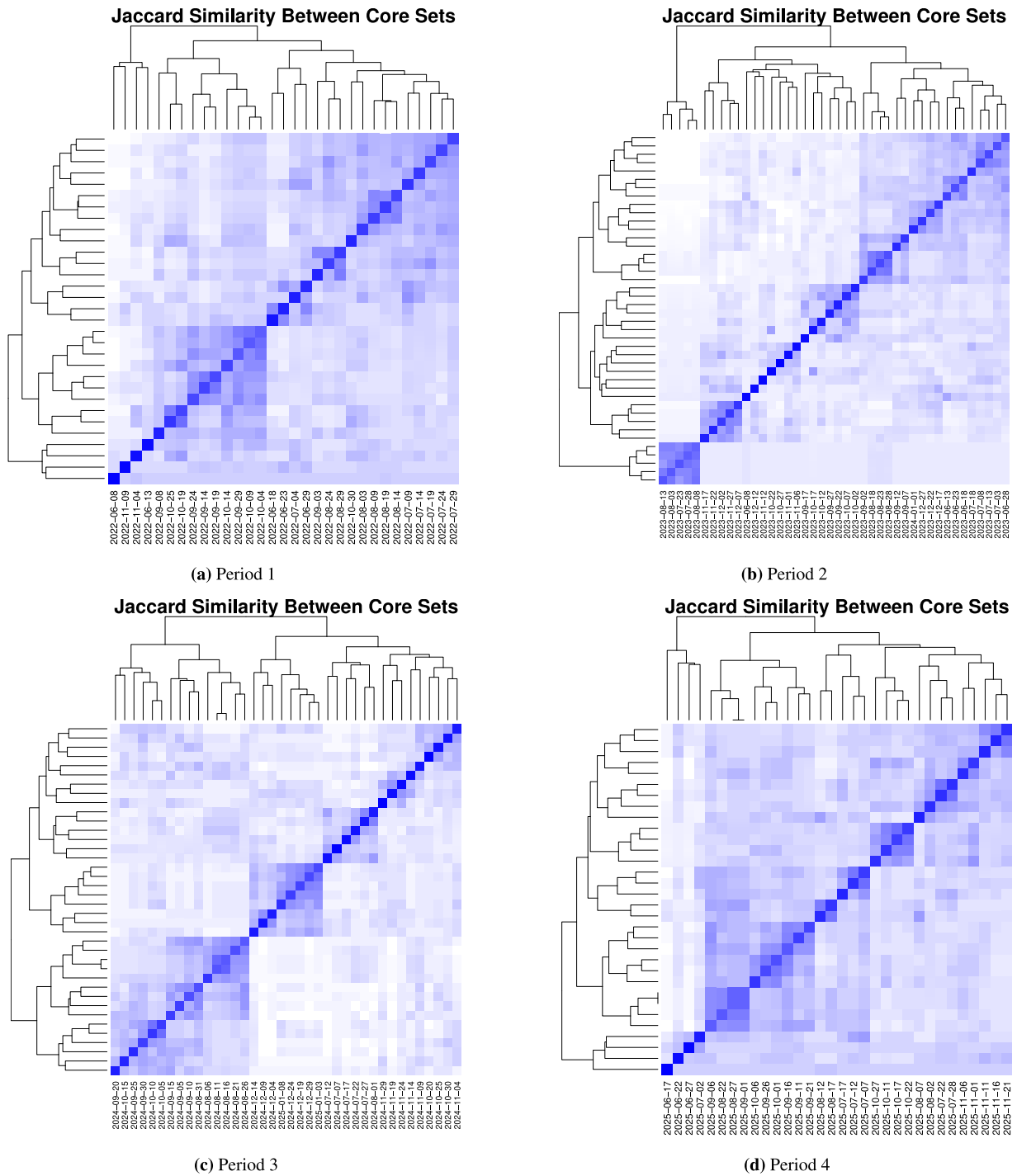


Fig. 17. Heatmap of Jaccard similarity matrices across the four periods.

5. Conclusions

This paper studies the evolution of systemic risk in cryptocurrency markets through a dynamic core-periphery framework based on VaR, $\Delta CoVaR$, and network analysis. Using a sample of 221 cryptocurrencies from January 2022 to November 2025, we first identify structural breaks in market dynamics and then construct time-varying networks of tail-risk spillovers. The results show that the cryptocurrency market has a clear core-periphery structure, where a relatively small group of cryptocurrencies plays a

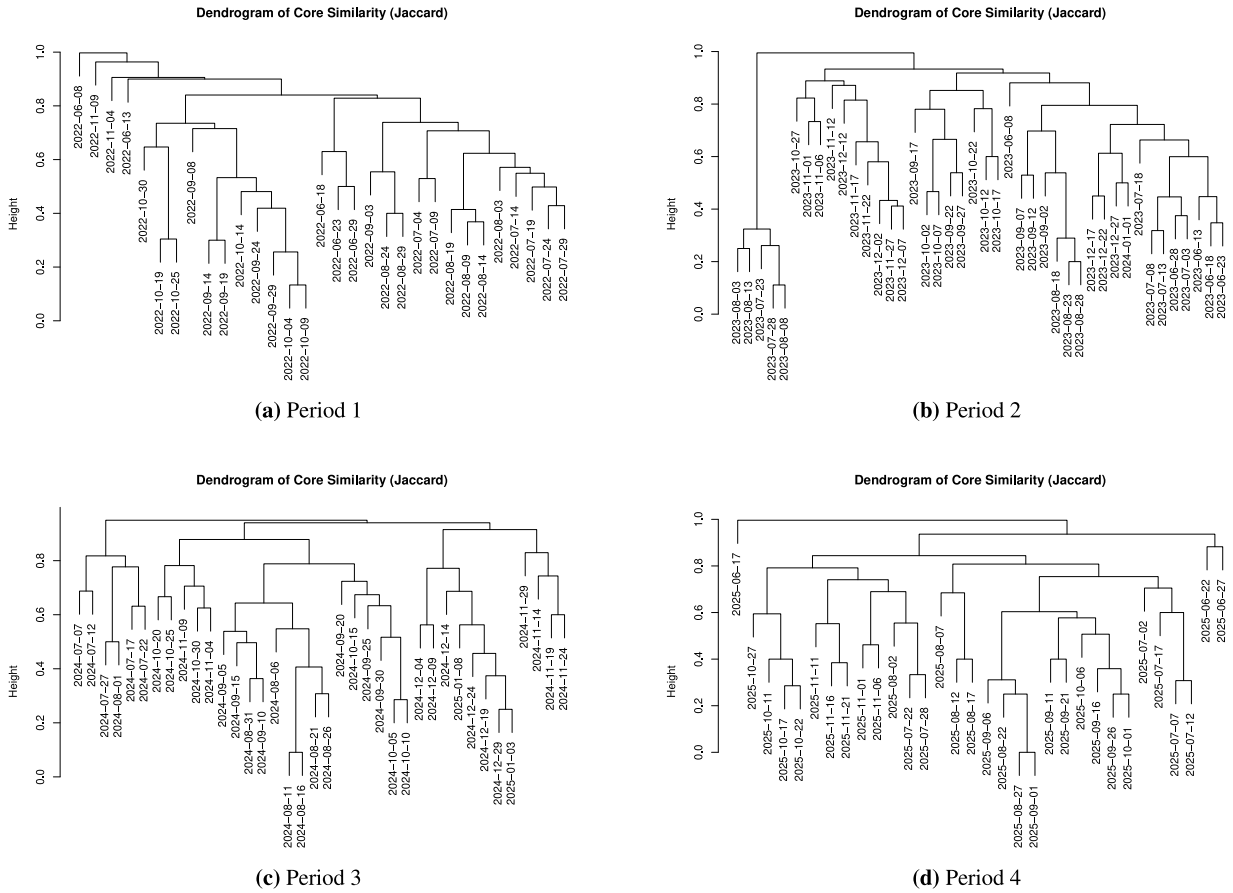


Fig. 18. Dendrogram of core similarity across the four periods.

central role in the transmission of systemic risk. At the same time, the size and composition of the core change considerably over time, following recurring phases of expansion, peak, and reorganization. Our findings are consistent with the existing literature on cryptocurrency interconnectedness and systemic risk. Similarly to previous studies based on CoVaR and tail-dependence networks, we find that periods of market stress are associated with denser and more interconnected networks, stronger contagion effects, and higher synchronization among cryptocurrencies. For example, the collapse of FTX is associated with a rapid expansion of the systemic core and with a stronger concentration of risk transmission. At the same time, our analysis adds a dynamic perspective to the literature by showing that systemic importance is not stable over time but changes across different market regimes. Some cryptocurrencies remain persistently central, while others become important only during specific phases of market stress. The paper also presents some limitations. First, the analysis is based on the Gaussian assumption in the estimation of $\Delta CoVaR$, which may not fully capture the heavy tails and nonlinear relationships that characterize cryptocurrency returns. Second, the results may depend on the selected filtering procedure and on the specific core-periphery algorithm used in the analysis. Finally, cryptocurrency markets evolve very rapidly, with new assets continuously entering the market, and this may affect the stability of the network structure over time. Future research could extend the analysis in different directions. For example, alternative dependence measures such as copula-based CoVaR or quantile regression approaches could be used to better capture nonlinear tail dependence. Another possible extension would be the inclusion of macroeconomic and geopolitical variables in order to study how external shocks influence the evolution of the systemic core. Future studies could also compare different community detection and core-periphery algorithms or investigate the connections between cryptocurrency markets and traditional financial systems. To conclude we highlight that assets that are in the periphery in one phase can become relevant in another. This means that the risk management of cryptocurrency portfolio must be dynamic and not only based on a fixed list of tokens. From a practical perspective, this implies that regulators and market participants should pay attention not only to individual cryptocurrencies, but also to how their relationships evolve over time. The framework developed in this paper provides a useful way to understand these dynamics in an increasingly complex and interconnected digital asset ecosystem.

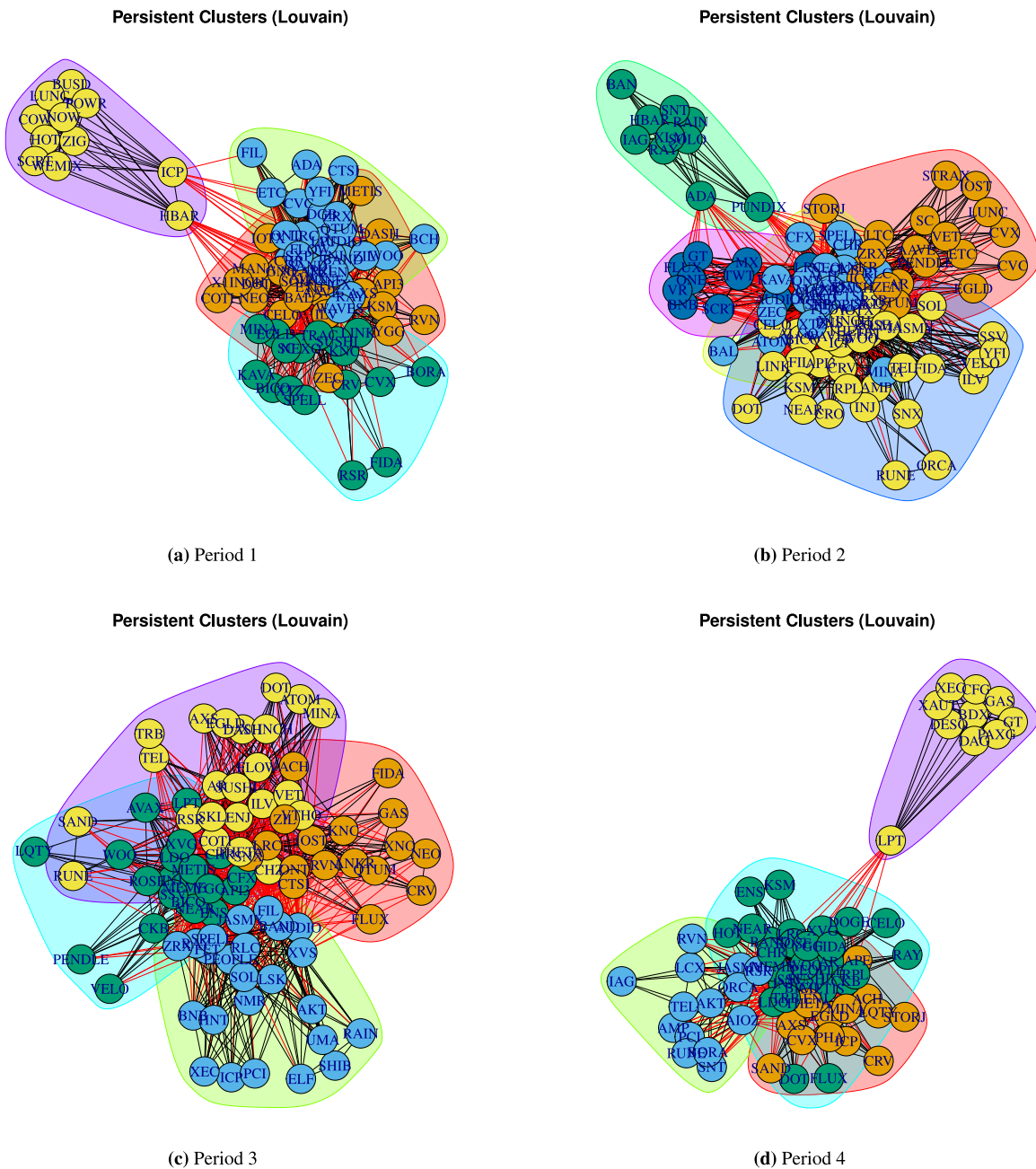


Fig. 19. Persistent core groupings over time across the four periods.

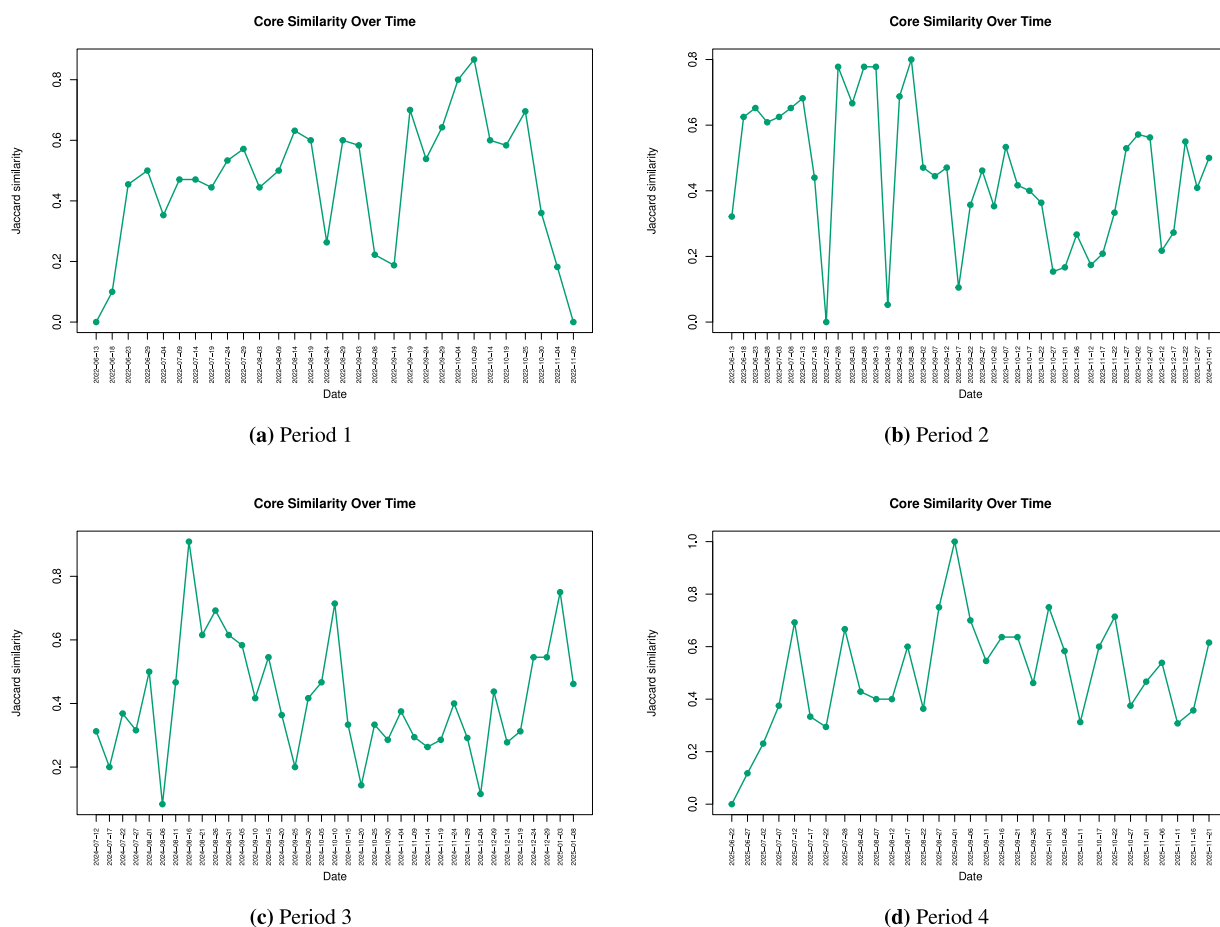


Fig. 20. Jaccard similarity over time across the four periods.

CRediT authorship contribution statement

Susanna Levantesi: Writing – original draft, Validation, Supervision, Software, Investigation, Data curation, Conceptualization. **Gabriella Piscopo:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Giulia Rotundo:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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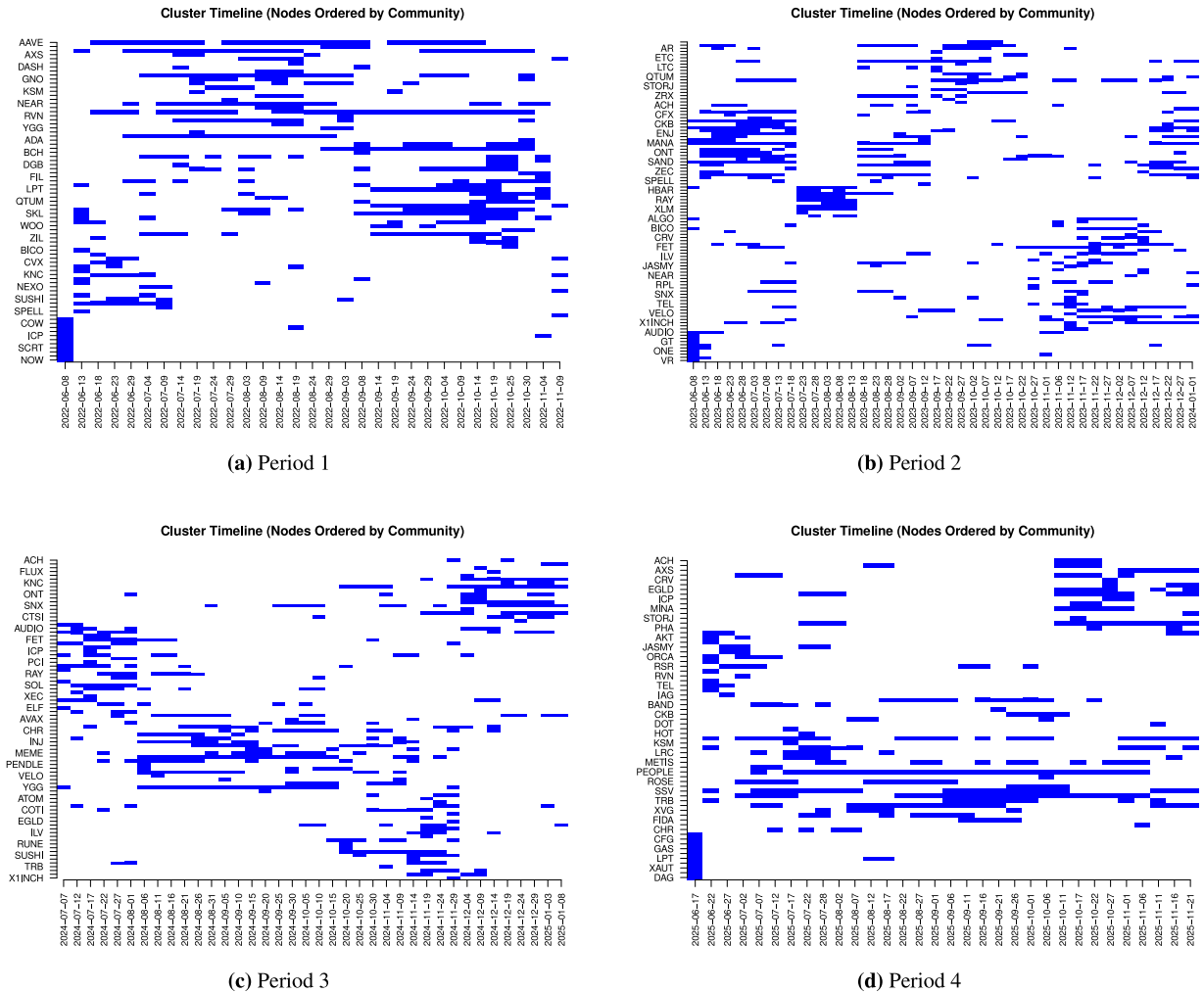


Fig. 21. Clusters' timeline in the four periods.

Appendix A. Stationarity tests (ADF)

See [Table A.6](#).

Table A.6

ADF unit root tests for log-returns (complete sample, 4-block layout).

Block 1			Block 2			Block 3			Block 4		
Crypto	ADF	p-val	Crypto	ADF	p-val	Crypto	ADF	p-val	Crypto	ADF	p-val
BTC	-7.595***	0.01	AVAX	-6.893***	0.01	AAVE	-8.093***	0.01	SAND	-8.539***	0.01
ETH	-7.473***	0.01	HBAR	-6.581***	0.01	ICP	-7.977***	0.01	ENS	-8.823***	0.01
XRP	-7.288***	0.01	CRO	-6.472***	0.01	BGB	-6.240***	0.01	FLOW	-8.196***	0.01
BNB	-7.772***	0.01	NEAR	-7.654***	0.01	OKB	-6.571***	0.01	BSV	-8.937***	0.01
SOL	-7.203***	0.01	BCH	-8.155***	0.01	ETC	-8.155***	0.01	SUN	-8.579***	0.01
TRX	-8.469***	0.01	LINK	-7.852***	0.01	KCS	-7.202***	0.01	THETA	-7.504***	0.01
DOGE	-7.353***	0.01	LTC	-8.288***	0.01	ATOM	-7.323***	0.01	MANA	-7.996***	0.01
ADA	-7.304***	0.01	XLM	-7.991***	0.01	ALGO	-7.245***	0.01	NEO	-8.671***	0.01
ZEC	-6.958***	0.01	XMR	-9.389***	0.01	FIL	-8.278***	0.01	CHZ	-8.280***	0.01

(continued on next page)

Table A.6 (continued).

TON	−8.282***	0.01	DASH	−7.800***	0.01	ARB	−7.890***	0.01	RUNE	−7.254***	0.01
XAUt	−7.356***	0.01	XDC	−7.509***	0.01	VET	−7.765***	0.01	EGLD	−8.013***	0.01
PAXG	−7.128***	0.01	JUP	−8.378***	0.01	DOT	−7.653***	0.01	XTZ	−8.484***	0.01
SHIB	−7.406***	0.01	FET	−6.935***	0.01	CRO	−6.472***	0.01	AXS	−7.655***	0.01
LINK	−7.852***	0.01	INJ	−7.409***	0.01	ICP	−7.977***	0.01	FTT	−7.378***	0.01
DOT	−7.653***	0.01	CRV	−7.540***	0.01	NEAR	−7.654***	0.01	CVX	−7.650***	0.01
ADA	−7.304***	0.01	LDO	−7.501***	0.01	AAVE	−8.093***	0.01	SUSHI	−7.884***	0.01
BNB	−7.772***	0.01	ENS	−8.823***	0.01	QNT	−8.037***	0.01	ENJ	−7.968***	0.01
ETH	−7.473***	0.01	SAND	−8.539***	0.01	RSR	−8.322***	0.01	ZIL	−7.955***	0.01
BTC	−7.595***	0.01	MANA	−7.996***	0.01	LPT	−8.012***	0.01	WAVES	−7.151***	0.01
SOL	−7.203***	0.01	AVAX	−6.893***	0.01	GNO	−7.826***	0.01	RLC	−8.338***	0.01

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

Appendix B. Global core

See [Tables B.8–B.10](#).

Data availability

Data will be made available on request.

Table B.7

Cryptocurrencies in the global core in Period 1.

Period 1 (part 1)					Period 1 (part 2)				
Crypto	23/06/22	09/08/22	19/10/22	25/10/22	Crypto	23/06/22	09/08/22	19/10/22	25/10/22
AAVE	X	X			LPT			X	
AIOZ	X				LRC			X	X
APE	X				LUNC	X			
API3			X	X	MANA		X		
ARB	X				METIS		X	X	X
ATOM		X	X	X	MINA		X		
AUDIO			X	X	NEAR		X	X	X
AVAX		X	X	X	NEO		X		X
AXS			X	X	NOW		X	X	
BAL		X			ONT		X	X	X
BAND		X	X	X	PEOPLE				X
CELO		X			QTUM			X	X
CHR		X	X	X	RAY			X	
CRV	X	X		X	ROSE			X	
CTSI				X	RPL			X	
CVX	X	X			RUNE	X	X		X
CVC			X	X	RVN		X	X	X
DCR		X			SAND		X	X	X
DGB			X	X	SKL		X	X	X
DOT		X			SNX		X		
EGLD	X				SOL		X	X	X
ENJ			X	X	SSV		X		
ETC		X	X	X	SUSHI	X			
ETH		X			SXP			X	X
FLOW			X	X	THETA		X		
GNO		X			TORN			X	X
ICX			X		TRAC	X			
ILV				X	WAVES	X	X	X	X
INJ			X	X	YFI		X	X	X
JASMY			X		YGG			X	X
KNC	X				ZEN			X	X
LCX	X				ZIL				X
LDO	X		X	X	ZRX			X	X
LINK				X					

Table B.8

Cryptocurrencies in the global core in period 2.

Period 2 (part 1)				
Crypto	18/06/23	28/07/23	06/11/23	22/12/23
ACH	X		X	
ADA		X		
AKT			X	
AMP			X	
ANKR	X			
APE		X		
API3			X	
AR	X			X
ARB		X		
ARK			X	
AUDIO	X		X	
AXS	X			X
BAN		X		
BAND	X			
BSV		X		
CELO	X			
CFX	X			X
CHEEMS			X	X
CHZ	X			
CHR	X			
CKB				X
COTI	X			X
COW			X	X
CTSI	X			
DAG		X		
DASH	X			X
DOT				X
ENJ	X			
ENS	X			X
FET			X	
FIL				X
FLOW	X			X
GAS			X	
HBAR		X		
IAG		X		
ICX	X			
INJ	X			
IOTX			X	
JASMY	X			
JST			X	
JUP			X	
KAVA	X			

Period 2 (part 2)				
Crypto	18/06/23	28/07/23	06/11/23	22/12/23
KEEP	X			
KSM			X	X
LDO	X			
LPT	X			
LQTY	X			
MANA	X			X
NEAR				X
NEO	X			
OG	X			
OM				X
ONT	X			
ORCA		X		
PEOPLE	X		X	X
PUNDIX		X		
QTUM				X
RAIN		X		
RAY	X	X		X
RLC	X			
ROSE			X	
RSR	X		X	X
SAFE			X	
SAND	X			X
SHX		X		X
SKY	X	X		
SOLO		X		
SOL				X
SSV	X			
SUSHI	X		X	
SXP	X			X
TEL			X	
THETA				X
TRB			X	
WAVES				X
WOO			X	
X1INCH	X			X
XLN		X		
XTZ				X
XVS	X			
YGG				X
ZEC	X			
ZEN				X
ZIL	X			X

Table B.9

Cryptocurrencies in the global core in period 3.

Period 3 (part 1)				
Crypto	25/09/24	14/11/24	29/11/24	03/01/25
ACH		X		
ANKR				X
API3				X
AR		X	X	
ATOM			X	
AVAX		X		
AXS			X	
BAND				X
CFX			X	
CHEEMS		X		
CHR	X			X
CHZ			X	X
COTI		X		X
COW	X			
CRO		X		
CRV				X
CTSI				X
CVX				X
DASH			X	X
DOGE		X		
DOT			X	
EGLD			X	
ENJ				X
FIDA	X			X
FIL			X	
FLOW			X	
ILV		X		X
INJ		X		
IOST				X
JASMY		X	X	
KNC				X
KSM			X	
LCX			X	

Period 3 (part 2)				
Crypto	25/09/24	14/11/24	29/11/24	03/01/25
LDO	X	X		
LPT		X	X	
LQTY	X			
LRC			X	X
MANA			X	
METIS	X	X		X
NEAR	X	X		
ONT				X
PEOPLE	X			
PENDLE		X		
RLC				X
RSR		X	X	X
RUNE		X		
RVN				X
SAND			X	
SKL		X	X	
SNX	X			X
SOLO			X	
SUSHI		X	X	X
TEL		X	X	
THETA		X		
TRB		X		
VELO		X		
VET			X	X
VTHO		X		X
VVS		X		
X1INCH			X	
XLM			X	
YGG	X	X	X	
ZEN			X	
ZIL			X	X
ZRX	X			X

Table B.10

Cryptocurrencies in the global core in period 4.

Period 4 (part 1)				
Crypto	27/06/25	17/07/25	11/11/25	16/11/25
AIOZ	X			X
AKT			X	X
APE	X	X		
AXS			X	X
BAND		X		
BICO		X		
CRV		X		
CVX	X	X		
DOT			X	
EGLD			X	
ENJ			X	X
ENS		X		
FET			X	X
FIL			X	X
FLUX			X	X
IAG	X			X
INJ		X	X	X
JASMY	X			
JUP	X	X		
KAVA			X	
KSM		X		

Period 4 (part 2)				
Crypto	27/06/25	17/07/25	11/11/25	16/11/25
LDO		X	X	
LCX	X			
LPT	X			
LRC		X		
MEME		X		X
PEOPLE			X	X
PCI	X			
PHA			X	X
RAY		X		X
ROSE		X		
RPL	X	X		
RSR	X	X		
RVN	X			
SSV		X	X	X
SUSHI		X		X
TEL	X			
THETA			X	X
TRB		X	X	X
VVS			X	X
WOO			X	X

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