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Information flow between asset classes during extreme events

Dora Almeida [a,b,c,*], Andreia Dionísio [b], Paulo Ferreira [a,b,c], Faheem Aslam [d,e], Derick Quintino [a,f]

[a] VALORIZA—Research Centre for Endogenous Resource Valorization, Portalegre 7300-555, Portugal
[b] CEFAGE, IIFA - Center for Advanced Studies in Management and Economics, Universidade de Évora, Largo dos Colegiais 2, Évora 7004-516, Portugal
[c] Portalegre Polytechnic University, Praça do Município, 11, Portalegre 7300-110, Portugal
[d] School of Business Administration (SBA), Al Akhawayn University, Ifrane, Morocco
[e] Department of Management Sciences, COMSATS University Park Road, Islamabad 45550, Pakistan
[f] Faculty of Applied Social Sciences, Federal University of Lavras, Lavras, MG 37203-202, Brazil

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ABSTRACT

The interconnectedness between asset classes becomes particularly relevant during extreme events, as market stress amplifies risk spillovers and impacts asset relationships, influencing risk transmission and financial market stability. While existing studies often examine financial interdependencies, including extended periods, they frequently focus on specific markets or asset classes, limiting the understanding of cross-asset contagion effects. Thus, it is crucial to grasp the interconnectedness among asset classes and how they communicate information under different economic conditions. This research bridges the gap by applying the transfer entropy approach to analyze the evolving connections among various asset classes from April 2017 to September 2024, spanning the COVID-19 pandemic and the Russia–Ukraine war. The findings reveal that stocks and cryptocurrencies consistently are net information transmitters to the system. Currency benchmarks and gold tend to receive information from the system during increased tension, reflecting their role in absorbing risk-driven capital flows. This study challenges the idea that cryptocurrencies are separate from traditional financial markets and shows how they are becoming more integrated. By employing net transfer entropy within a financial network analysis framework, this study uncovers time-varying shifts in market interdependencies and, thus, an enhanced description of financial contagion dynamics. The dynamic nature of such relationships highlights the need for adaptive portfolio strategies and enhanced risk assessment models. Our results have direct implications for portfolio management and risk assessment. Investors can use this study's findings to recognize assets that are sources of systemic risk or safe haven assets, facilitating adaptative changes in their portfolios. Policymakers and regulators can use these findings to forecast systemic vulnerabilities and implement strategies aiming to reduce financial instability in times of crisis.

* Corresponding author at: Portalegre Polytechnic University, Praça do Município, 11, Portalegre 7300-110, Portugal.
E-mail addresses: dora.almeida@ipportalegre.pt (D. Almeida), andreia@uevora.pt (A. Dionísio), pferreira@ipportalegre.pt (P. Ferreira), f.aslam@aui.ma (F. Aslam), derickdq@alumni.usp.br (D. Quintino).

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1. Introduction

The recent globalization of financial markets has resulted in increased integration and interdependence among international stock markets, challenging international diversification and amplifying the transmission of shocks among financial markets [9,47]. This situation implies that an accurate evaluation and understanding of the dynamics of financial assets becomes more crucial than ever for effective international financial planning, forecasting, and risk management [14].

In this context, it becomes relevant to understand how different asset classes—particularly those perceived as segmented, such as cryptocurrencies—interact during periods of heightened economic and geopolitical uncertainty becomes essential.

Recent studies highlight the increasing interdependence between cryptocurrencies and conventional financial markets despite ongoing controversy regarding their potential as diversifiers or systemic risk transmission channels. For example, Bouri et al. [10] demonstrate bidirectional return predictability between "tech titans", i.e., big tech firms (e.g., Apple, Tesla), and "crypto giants", i.e., major cryptocurrencies (e.g., Bitcoin), suggesting overlapping investor behaviors and opportunities for cross-market trading strategies. Likewise, Ghorbel et al. [25] show that during the COVID-19 pandemic, cryptocurrencies served as instruments of equity portfolio diversification in the G7 markets. Meanwhile, Bitcoin had become a significant transmitter of volatility, thus questioning its decoupling from conventional assets. These findings validate Kumar et al. [42], who reported increased cryptocurrency connectedness during the same crisis with Ethereum and Bitcoin spreading shocks—a pattern mirrored in blockchain-exposed equities experiencing co-jumps with crypto markets [59]. These studies all suggest that crises enhance cross-asset connectedness, but there are gaps to be filled to address the nonlinear and asymmetric nature of the interactions.

The present study aims to address a significant gap in financial research by analyzing the complex and nonlinear interactions among different key global financial assets/indices, including cryptocurrencies. These are an important part of the financial market but are sometimes seen as isolated from mainstream assets, although carrying idiosyncratic risks. Our research covers April 2017 to September 2024, which includes two global extreme events—the COVID-19 pandemic and the Russia–Ukraine war. Usually, financial market volatility increases during crises, often resulting in significant interconnectedness and spillovers across various markets [18]. Thus, it is crucial to accurately measure and monitor these interdependencies to establish early warning systems for potential crises and track the development of existing crises. Several studies have found TE to be a valuable early warning signal in various scientific fields. In financial markets, for instance, TE has been used to evaluate causality between stock prices and indices, helping to detect market instabilities and systemic risk [50,56]. Similar applications have also been documented in the field of neuroscience, with transfer entropy (TE) having been used to infer causal relationships in brain dynamics and detect early signs of neurological conditions [16,55,58]. Besides, TE has proven useful in industrial processes in identifying the root causes of faults before they escalate into major failures [60]. These results suggest that TE-based approaches can function as early warning signs of financial instability.

A substantial proportion of empirical research has traditionally concentrated on linear correlation analysis and other linear statistical tools (e.g., variance ratio tests or autocorrelation measures) to evaluate the Efficient Market Hypothesis (EMH), especially in its weak form [1,11,22,49]. However, contemporary global markets are characterized by their complexity and nonlinear dynamics, thus necessitating an approach that utilizes nonlinear relationships [48]. Additionally, contagion effects between markets, understood as the transmission of financial shocks across markets, are asymmetrical regarding the timing of the arrival of the spillover and the intensity of market response, further complicating these analyses [28]. This situation suggests that markets may exhibit diverse responses to shocks characterized by varying extents of price and volatility movements. This heterogeneity poses a significant challenge to the field of financial linkage studies, necessitating a more nuanced and comprehensive approach to analyzing the intricate dynamics among financial markets. Consequently, despite the extensive literature on financial market relationships, a key research gap remains. Most studies focus on linear relationships and symmetric spillover effects, which may not fully capture the complexity of financial market interactions. Conventional analytical techniques, including correlation-based measures and Granger causality tests, frequently encounter limitations in detecting nonlinear and asymmetric dependencies. Furthermore, while numerous studies have examined financial contagion, they have typically focused on individual episodes of crisis rather than on the temporal evolution of information flow.

To overcome the referred shortcoming, our letter applies an advanced measure of information flow developed by Schreiber [52], TE, which is a directional measure of the dependence between two variables [see, for example, Behrendt et al. [8]], which overcomes the low capability of conventional Granger tests to detect nonlinear causality. We sought to capture the complex interactions and subtle, causal influences that shape global financial markets, thereby enriching the comprehension of their behavior and broader economic implications.

While this study leverages daily return data to capture short-term directional information flows, it also seeks to uncover patterns of information transmission among assets across periods of economic volatility and geopolitical tension. TE allows the capturing of short-term responses in information flow and, at the same time, by analyzing also the changes observed across different economic periods, may even capture broader, enduring shifts in asset interconnectedness, including potential signals of longer-term structural adjustments. The network analysis has also been commonly applied in financial contagion and market connectedness research [see, for example, Diebold and Yilmaz [19], He et al. [33] and Vidal-Tomás [57]], particularly after significant global events. Whereas Diebold and Yilmaz [18] proposed a widely used network approach based on forecast error variance decomposition in vector autoregressions (VAR), our research applies a different approach using net transfer entropy (Net TE). Compared with the VAR-based approach, TE (and consequently Net TE) is a non-parametric, model-free approach that effectively identifies nonlinear relationships and directional information flow among assets without making stringent assumptions regarding their underlying distribution or linearity. The novelty of this study lies in the implementation of Net TE in a financial network analysis system, wherein it is employed to construct the network topology dynamically, following an approach by Diebold and Yilmaz [18] but established on a different methodological basis.

The analysis system facilitates a more adaptive and flexible evaluation of the temporal evolution of market connectedness and information transmission.

This framework allows the evaluation of the complexities of today's financial markets and represents a methodological contribution to the extant literature.

The utilization of a sliding window approach is a well-established concept within the relevant literature [see, for example, Molgedey and Ebeling [46], Mensi et al. [45] or Risso [51]]. Consequently, the present study employs a dynamic analysis through a sliding windows approach to evaluate the temporal evolution of market connectedness and information transmission in a more structured and dynamic manner.

Our findings reveal that cryptocurrencies consistently act as net information transmitters, i.e., they systematically provide information to the system, influencing other assets/indices within the financial network. These results align with Xu et al.'s (2022) observations of crypto-to-equity jumps but extend them by quantifying directional information flows across a broader asset universe. On the other hand, traditional assets like equities, commodities, foreign exchanges, and bonds alternate between transmitting and receiving information depending on economic and geopolitical conditions.

We challenge narratives of crypto-market isolation by demonstrating cryptocurrencies' persistent informational centrality—even amid crises where gold retains safe-haven status [25]. Furthermore, the dynamic network approach provides policymakers and investors with a tool to track structural shifts in market connectedness, such as those triggered by the growth of blockchain ETFs [41] or tech-crypto arbitrage opportunities [10].

The remainder of the letter is structured as follows: Section 2 presents the methods, Section 3 the data, Section 4 presents and discusses the results, and Section 5 presents the conclusions.

2. Methods

The study applies Shannon TE, proposed by Schreiber [52], to analyze the information flow (spillover effects) between pairs of assets/indices, as defined in Eq. 1, under the assumption of a Markovian process of k and l orders for Y and X (where Y and X are two observable scalar random time series), respectively. TE is defined as the amount of information that a source provides about a destination's next state that was not contained in the destination's past and quantifies the ability of the random time series Y to predict the dynamics of the random time series X. Thus, TE from Y to X is equal to the difference between: (i) information about future observation $X(t+1)$ gained from past observations of X and Y; and (ii) information about future observation $X(t+1)$ gained from past observations of X only.

$$TE_{Y\to X}(k,l) = \sum_{x,y} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) \log \frac{p\left(x_{t+1}|x_t^{(k)}, y_t^{(l)}\right)}{p\left(x_{t+1}|x_t^{(k)}\right)} \tag{1}$$

Thus, Eq. (1) measures how much additional information Y provides for the prediction of $X(t+1)$ apart from the historical information provided by X itself. In this context, Y represents the source asset/index (information provider), while X represents the destination asset/index (information receiver). This formulation allows us to determine the directional nature of information flow, distinguishing between net transmitters (i.e., assets that systematically provide information to the system) and net receivers (i.e., assets that predominantly absorb information from other assets). TE is a bidirectional and non-parametric method, and the bootstrap method proposed by Dimpfl and Peter [20] was used to estimate the TE's p-values.

The TE provides a framework for identifying asymmetric information flows, allowing for the classification of assets based on their systemic role as information receivers (assets/indices that predominantly absorb information from other assets/indices rather than influencing them) or providers/transmitters (assets/indices that systematically provide information to the system, influencing other assets within the financial network)—something that traditional correlation metrics do not capture. This classification is based on Net TE, which captures the dominant direction of information flow. Assets/indices with a positive Net TE value are net transmitters, while those with a negative Net TE value are net receivers. This classification does not merely reflect market volatility but rather captures deeper economic dynamics that drive shifts in asset roles over time. It encompasses liquidity preferences, inflation expectations, and risk perceptions, which all impact investor behavior and shape the interactions of assets within financial systems. For instance, during periods of high uncertainty, safe-haven assets may act as information receivers, as they absorb demand from risk-averse investors, while speculative assets, like certain cryptocurrencies, typically serve as information providers due to their high sensitivity to market sentiment [12,30,36,40,7]. By identifying these roles, TE reveals the economic mechanisms that govern how assets interact within financial networks, offering insights into the structure and evolution of information transmission within the analyzed financial system, reflecting the interactions among the selected assets and their response to economic conditions. This is done by applying Net TE to quantify the directionality and magnitude of information transfer among various assets on a temporal scale. By calculating each asset's net difference between its outgoing and incoming information flows, our approach enables the categorization of assets as either net information transmitters or receivers. This classification sheds light on their systemic function in the financial network, which is altered by different states of the economy. This classification is not static but responds to various economic conditions, thereby demonstrating the impact of financial conditions on the roles played by assets in relation to systemic risk and contagion. By laying out such time interdependencies, our method offers a dynamic view of financial contagion, systemic risk, and asset interconnectedness that is especially well-suited to financial market analysis under tail events.

The Net TE defined in Eq. 2 was estimated to identify which paired variables influence each other.

$$Net\ TE_{YX} = TE_{Y\rightarrow X} - TE_{X\rightarrow Y} \tag{2}$$

The information flow's dominant direction could be (i) positive if $TE_{Y\rightarrow X}(k,l) > TE_{X\rightarrow Y}(k,l)$, (ii) negative if $TE_{Y\rightarrow X}(k,l) < TE_{X\rightarrow Y}(k,l)$ or (iii) equal to zero if $TE_{Y\rightarrow X}(k,l) = TE_{X\rightarrow Y}(k,l)$.

The Net TE was used to construct information flow networks, facilitating the mapping and visualization of the complex financial interdependencies between different assets.

The market connectedness analysis represents each financial market as a node, with interconnections between markets defined as links, each corresponding to the Net TE between each pair of assets/indices. They are directed and weighted (ensured, in this case, by the representation of $Net\ TE_{YX} > 0$) to reflect the exposure of each asset/index to each other, as outlined by Gai and Kapadia [23].

To identify if each asset/index is a net transmitter of information flow to the system (TO) or a net receiver from the system (FROM), an approach similar to that of Diebold and Yilmaz [18] is applied, with the novelty of utilizing the TE.

A TE matrix (an asymmetric matrix) represents the information flow from one asset/index (rows) to another (columns). The "contribution to" (TO) metric quantifies the contribution of a specific asset/index to the system, calculated as the sum of all TE values in its row. The "contribution from" (FROM) metric measures the impact of the system on an asset/index, summing all TE values in its column. Thus, representing the TE from asset i to asset j (TE_{ij}), where $i, j = 1, 2, \ldots, N$ and N is the total number of assets in the system. Eq. 3 represents how much asset i transmits information to the other $N-1$ assets.

$$TO_i = \sum_{j\neq i}^{N} TE_{ij} \tag{3}$$

Conversely, Eq. 4 represents how much asset i receives information from the other $N-1$ assets.

$$FROM_i = \sum_{j\neq i}^{N} TE_{ji} \tag{4}$$

To determine whether an asset is a net transmitter/receiver of information, the differences between its TO_i and $FROM_i$ values were calculated. A positive difference means it is a net transmitter (represented in blue), while a negative difference indicates a net receiver (represented in red). The node size is proportional to this absolute difference (i.e., larger nodes indicate larger differences).

A crucial property of network graphs is their degree distribution, i.e., the probability distribution describing how many connections (or "degrees") each node in the network has. In a directional graph, each node possesses two distinct types of degrees: the in-degree (the number of incoming links reflecting how much an asset is exposed to others) and the out-degree (the number of outgoing links indicating its influence on other nodes). The overall degree of a node is the sum of its in-degree and out-degree, and the distribution of these sums across all nodes constitutes the overall degree distribution. We can better understand the network's structure by analyzing the three measures separately. Specifically, the in-degree distribution highlights which nodes are more susceptible to external influences, while the out-degree distribution reveals the most influential ones. Thus, the visual analysis is complemented with three degree measures: the degree of a node, in-degree, and out-degree [see Guo [28] for details].

To analyze information flow over time and assess the impact of events like COVID-19 and the Russia–Ukraine war, the TE was estimated considering sliding windows of 500 observations (chosen to provide enough data points for accurate TE estimation while effectively capturing temporal dynamics). This means that we transform our full sample in sequential samples of 500 observations, i.e., starting by calculating the TE for the window form $t = 1, \ldots, 500$; then for $t = 2, \ldots, 501$; and so on, for a total of 1344 estimates for TE for each pair under analysis. Ultimately, we will have a set of TE (and Net TE) values instead of a single TE (or Net TE) value. This approach allows the identification of the time-varying dynamics of TE and net TE. We performed a similar analysis with an SW of 250 observations as a robustness test.

The TE and Net TE of each asset/index to the system was estimated similarly to Eq. 3.

All the TEs' estimates were made using the R package RTransferEntropy.

3. Data

The study used daily closing prices in USD from three cryptocurrencies (selected by market capitalization and covering different types of cryptocurrencies) and eight indices, chosen to cover different world regions and asset classes, obtained from https://www.

Table 1
Description of assets and indices.

Asset/index	Asset class	Symbol
Bitcoin	Cryptocurrency	BTC
Ethereum	Cryptocurrency/Smart contracts platform	ETH
Tether	Cryptocurrency (Stablecoin)	USDT
MSCI_USA Index	Equities (USA)	MSCI_USA
MSCI_EUROPE Index	Equities (Europe)	MSCI_EUR
MSCI_CN Index	Equities (China)	MSCI_CN
Traditional US Dollar Index	Foreign exchange	USDI
ICE gold future price	Commodities (precious metals)	GOLD
Dow Jones Commodity Index	Commodities (energy, metals, agriculture)	DJCI
CBOE Volatility Index	Volatility index (derivatives)	VIX
Vanguard Total Bond Market Index Fund Admiral Shares (bonds)	Bonds	VBTLX

investing.com/ (Table 1). The selected assets are three of the biggest cryptocurrencies chosen by their market capitalization and specific roles in the digital asset ecosystem. Bitcoin (BTC) and Ethereum (ETH) are two of the most actively traded cryptoassets and tend to influence general market sentiment. At the same time, Tether (USDT) is a stablecoin widely used as a liquidity instrument in cryptocurrency markets. Despite its price stability, USDT plays a central part in cryptocurrency markets, frequently serving as a safe haven in the digital asset space in times of increased market volatility. Its market forces, such as volatility in trading volume, liquidity supply, and investor demand changes, can affect the broader context of information transmission in financial networks. By adding USDT to our analysis, we sought to evaluate whether stablecoins act as net information receivers or transmitters, especially during the episode of extreme events, and explore their impact on the interlinkages between cryptoassets and traditional finance markets. We also add broad equity indices (MSCI_USA, MSCI_EUR, MSCI_CN) to cover the US, European, and Chinese stock markets, commodities (GOLD, DJCI) to represent the behavior of safe-haven and diversified commodity investments, foreign exchange (USDI) to track global currency market trends, a volatility index (VIX) as a proxy for market uncertainty, and a bond index (VBTLX) to account for the contribution of fixed-income assets. This diversified combination guarantees that we address the interaction between conventional financial assets and new digital assets and the information flow to different market segments during both crisis and regular periods.

The period spans from April 18, 2017, to September 6, 2024, with 1843 observations. This period was selected to span two of the most extreme global crises—the COVID-19 pandemic and the Russia–Ukraine war—which enormously affected financial markets. This period enables the consideration of market interconnectedness changes during periods of high uncertainty. The selection of the data

Table 2
Descriptive statistics.

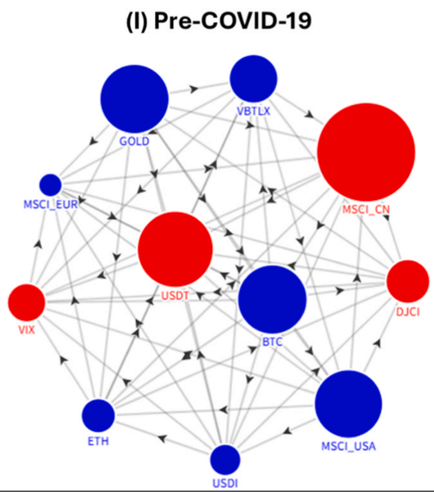
	Mean	Standard deviation	Skewness	Kurtosis	Shapiro–Wilk test	ADF test
Full sample						
BTC	0.0021	0.0458	−0.7270	10.6000	0.9170***	−10.3057***
ETH	0.0021	0.0611	−0.3280	9.0500	0.9100***	−10.7336***
USDT	0.0000	0.0038	1.1700	26.5000	0.5420***	−13.6227***
MSCI_USA	0.0005	0.0123	−0.8680	15.1000	0.8710***	−11.8211***
MSCI_EUR	0.0002	0.0115	−1.1300	16.5000	0.8990***	−12.0343***
MSCI_CN	−0.0001	0.0153	0.2770	5.4900	0.9580***	−11.9627***
USDI	0.0000	0.0042	−0.0747	1.7500	0.9850***	−12.3333***
GOLD	0.0004	0.0092	−0.2290	4.1900	0.9530***	−11.7641***
DJCI	0.0003	0.0100	−0.8420	6.1800	0.9410***	−11.0727***
VIX	0.0002	0.0802	1.5000	8.7400	0.9070***	−13.2046***
VBTLX	0.0000	0.0032	−0.0990	3.0400	0.9620***	−11.6234***
Pre-COVID−19						
BTC	0.0026	0.0501	0.0575	3.1100	0.9510***	−8.3337***
ETH	0.0020	0.0687	0.3640	3.6500	0.9400***	−8.3334***
USDT	0.0001	0.0061	0.7090	8.7800	0.7910***	−11.5261***
MSCI_USA	0.0003	0.0098	−1.1300	10.5000	0.8540***	−8.1323***
MSCI_EUR	−0.0001	0.0085	−1.2900	8.3600	0.9200***	−7.4550***
MSCI_CN	0.0003	0.0117	−0.5390	1.8200	0.9760***	−9.2709***
USDI	−0.0001	0.0037	−0.0335	1.1200	0.9920***	−9.7443***
GOLD	0.0004	0.0073	−0.1940	4.1900	0.9590***	−9.4416***
DJCI	−0.0001	0.0078	−0.8980	7.2400	0.9390***	−7.9288***
VIX	0.0016	0.0886	1.7100	10.0000	0.8920***	−10.2125***
VBTLX	0.0001	0.0020	−0.0963	3.1300	0.9610***	−9.0087***
Between COVID−19 and Russia–Ukraine war						
BTC	0.0033	0.0504	−1.9300	20.1000	0.8760***	−7.6411***
ETH	0.0053	0.0676	−1.3400	14.5000	0.8870***	−8.0034***
USDT	0.0000	0.0008	3.3100	66.2000	0.6710***	−12.3393***
MSCI_USA	0.0008	0.0159	−1.0600	16.9000	0.8100***	−11.7706***
MSCI_EUR	0.0006	0.0144	−1.8400	21.5000	0.8450***	−10.9857***
MSCI_CN	0.0000	0.0158	−0.2380	1.4200	0.9840***	−9.1827***
USDI	0.0000	0.0040	0.4640	2.4100	0.9760***	−11.3702***
GOLD	0.0003	0.0115	−0.3110	4.5200	0.9310***	−9.6886***
DJCI	0.0014	0.0117	−1.3600	8.1200	0.9110***	−9.3073***
VIX	−0.0011	0.0854	1.2300	5.0200	0.9250***	−9.5293***
VBTLX	−0.0001	0.0027	−0.6610	6.9800	0.9130***	−9.9651***
During Russia–Ukraine war						
BTC	0.0005	0.0360	−0.5570	6.9400	0.9220***	−7.8178***
ETH	−0.0003	0.0444	−0.5690	8.2500	0.9060***	−7.4869***
USDT	0.0000	0.0004	−0.2750	23.3000	0.8030***	−10.8965***
MSCI_USA	0.0003	0.0116	−0.1920	1.7600	0.9790***	−7.8524***
MSCI_EUR	0.0001	0.0119	0.0019	2.8500	0.9690***	−8.6368***
MSCI_CN	−0.0006	0.0182	0.8070	6.6200	0.9380***	−8.6480***
USDI	0.0001	0.0049	−0.3280	1.2400	0.9860***	−8.1993***
GOLD	0.0004	0.0092	−0.0819	0.7570	0.9900***	−8.6681***
DJCI	−0.0002	0.0107	−0.3470	2.4000	0.9750***	−10.3592***
VIX	−0.0003	0.0647	1.1300	7.3000	0.9280***	−9.3774***
VBTLX	−0.0001	0.0045	0.0711	0.4460	0.9950***	−8.0540***

series and the time horizon is driven by the desire to analyze the dynamics of information flows across different asset classes during different economic regimes, especially during extreme disruptions.

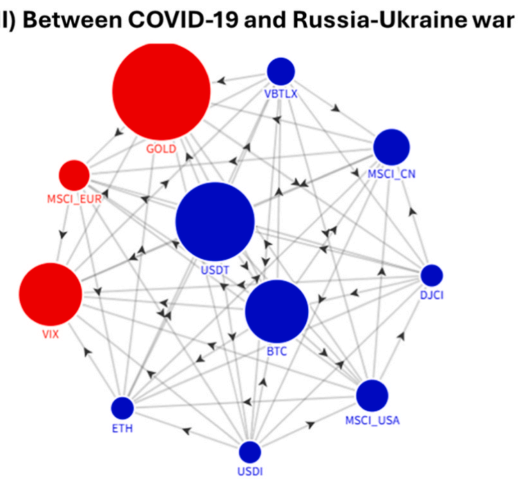
4. Results and discussion

The returns were calculated according to $r_t = \ln(P_t) - \ln(P_{t-1})$, where P_t and P_{t-1} represent the daily values of a given series on days t and $t-1$, respectively.

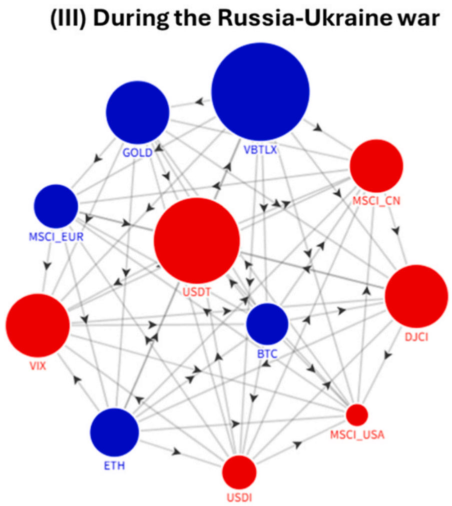
Considering all the analyzed periods, the descriptive statistics (Table 2) reveal: (i) that, particularly between COVID-19 and the Russia–Ukraine war, BTC and ETH show the highest mean returns, while USDT consistently shows near-zero mean returns; (ii) negative skewness for most assets/indices, except for USDT, MSCI_CN and VIX for the full sample; all the cryptoassets and VIX in the Pre-COVID-19 period; USDT, USDI, and VIX in the period between COVID-19 and the Russia–Ukraine war; MSCI_EUR, MSCI_CN, VIX and VBTLX in the Post-Russia–Ukraine war period, meaning a higher probability of negative returns than positive ones; (iii) positive kurtosis (especially for USDT), meaning fat-tailed distributions. The normality and stationarity of the distribution were assessed using, respectively, the Shapiro–Wilk test, which assumes that the variable follows a normal distribution [53], and the Augmented



	BTC	ETH	USDT	MSCI_USA	MSCI_EUR	MSCI_CN	USDI	GOLD	DJCI	VIX	VBTLX
d_i	10	10	10	10	10	10	10	10	10	10	10
d_{in}	2	5	8	3	7	7	3	2	6	8	4
d_{out}	8	5	2	7	3	3	7	8	4	2	6



	BTC	ETH	USDT	MSCI_USA	MSCI_EUR	MSCI_CN	USDI	GOLD	DJCI	VIX	VBTLX
d_i	10	10	10	10	10	10	10	10	10	10	10
d_{in}	3	5	3	4	6	5	5	7	5	8	4
d_{out}	7	5	7	6	4	5	5	3	5	2	6



	BTC	ETH	USDT	MSCI_USA	MSCI_EUR	MSCI_CN	USDI	GOLD	DJCI	VIX	VBTLX
d_i	10	10	10	10	10	10	10	10	10	10	10
d_{in}	5	4	7	6	6	7	3	3	6	7	1
d_{out}	5	6	3	4	4	3	7	7	4	3	9

Fig. 1. Net TE networks.Note: (I), (II), and (III) correspond to the periods before the COVID-19 pandemic (04/18/2017–03/10/2020), between the COVID-19 pandemic and the onset of the Russia–Ukraine war (03/11/2020–02/18/2022), and after the onset of the Russia–Ukraine war (02/22/2022–09/06/2024), respectively.

Dickey–Fuller stationarity test, which assumes the existence of a unit root, i.e., the non-stationarity of the series under study [17]. The null hypotheses of the Augmented Dickey–Fuller and Shapiro–Wilk tests were rejected at a 1 % significance level (***) for all assets/indices.

As shown in Fig. 1 (I), before COVID-19, the MSCI_CN, USDT, DJCI, and VIX were mostly receivers of information, while others were transmitters. The VIX, a measure of market volatility, was consistently a net information receiver, reflecting its role in responding to market uncertainty rather than driving it. The DJCI, which tracks commodity prices, was also a net receiver in this period (and after the onset of the Russia–Ukraine war), indicating its sensitivity to global supply–demand dynamics and economic expectations around growth and inflation [27].

During the COVID-19 pandemic and before the Russia–Ukraine war, Fig. 1 (II), GOLD, VIX, and MSCI_EUR received more information [corroborating Assaf et al. [2], which found that gold and VIX maintained their roles as safe hedging tools during the pandemic], while DJCI, USDT, and MSCI_CN transmitted information. VIX absorbed uncertainty from the pandemic, and DJCI and MSCI_CN reflected commodity market volatility due to China's global trade role. China's quick recovery made MSCI_CN a transmitter. GOLD, usually a safe-haven asset, acted as a net information receiver during this period due to the impact of expansionary fiscal policies and low interest rates, which reduced its attractiveness. Real interest rates dropped due to pairing aggressive monetary easing with fiscal stimulus, decreasing the opportunity cost of gold and inducing a shift in investors' preference towards riskier assets.

After the Russia–Ukraine war onset, Fig. 1 (III), USDT, DJCI, VIX, MSCI_CN, USDI, and MSCI_USA were net information receivers. At the same time, VBTLX, GOLD, ETH, MSCI_EUR, and BTC were net information transmitters, suggesting that bonds and gold may not be safe havens for cryptocurrencies, corroborating Karim et al. [37]. The present study further supports the argument that conventional bond markets are not necessarily a hedge for cryptocurrency volatility. This finding aligns with the conclusions of Karim et al. [37], who found that most bonds did not act as safe-haven assets for crypto markets. Furthermore, our findings suggest that gold, which is conventionally regarded as a safe-haven asset, did not fulfill this role in the post-Russia–Ukraine war era. Consequently, our results indicate that the role of gold in financial networks is subject to change and is responsive to macroeconomic environments. The war caused disruptions in global supply chains, particularly in energy and grain markets, impacting DJCI. USDT became a refugee of liquidity during market volatility [24,26,4,5], MSCI_CN also became a receiver, reflecting China's delicate geopolitical position and the impact of global tensions on its economy. The geopolitical dynamics of China are characterized by its substantial involvement in international trade and finance amidst enduring economic and diplomatic tensions, particularly with Western nations. Its stance on major geopolitical events, such as the Russia–Ukraine conflict, has the potential to impact market stability and investor sentiment, consequently influencing financial interconnectedness. The ongoing war has had a notable impact on global currencies against the US dollar, with European currencies like the Russian rouble, Czech koruna, and Polish zloty depreciating significantly. Conversely, Pacific currencies risen appreciably [15]. USDI, previously a net information transmitter, became a net information receiver. USDI, which measures the US dollar against a basket of currencies, shifted to becoming a net information receiver, possibly reflecting global tensions and supply chain disruptions, particularly in energy markets, as the pattern identified by Chortane and Pandey [15].

The sliding windows approach evaluated the dynamic relationship between each asset/index within the financial markets (Fig. 2).

Before COVID-19, BTC, MSCI_USA, MSCI_EUR, USDI, GOLD, and VBTLX acted as net information transmitters to the system, leading market expectations for assets like stocks and gold. In contrast, ETH, USDT, MSCI_CN, DJCI, and VIX were mainly net information receivers. In the post-pandemic setting, MSCI_EUR, GOLD, and VBTLX became net information receivers due to increased risk aversion. At the same time, VIX, USDT, and ETH shifted to net transmitters, corroborating Elsayed et al. [21] and Shu and Chang [54], Hairudin and Mohamad [29], Harasheh et al. [31] and Harb et al. [32], respectively. These results partially corroborate those of Ghorbel et al. [25] or Jeribi and Kammoun Masmoudi [35], whose empirical results proved that the stock and crypto markets responded to COVID-19.

The rise of decentralized finance (DeFi) and Non-Fungible Tokens (NFTs) drove ETH's transition. The shift seen can be explained by the growth of DeFi, which is defined as financial services that are constructed on blockchain technology, including decentralized exchanges (DEXs), lending and borrowing protocols, and decentralized derivatives, which are primarily built on the Ethereum network [38]. Simultaneously, Ethereum has become the platform of choice for NFTs, cryptographic tokens that signify ownership of one-of-a-kind digital assets like digital art and collectibles [13,39]. Elevated activity in DeFi and NFT interest has meaningfully driven volumes of transactions on the Ethereum network, thereby enhancing ETH's position as a significant net transmitter during the Russia–Ukraine war [43].

Following the Russian invasion of Ukraine, ETH and MSCI_USA shifted from transmitters to receivers, indicating that geopolitical risks affected them, as this period coincided with shifts in asset roles within the information network. This evidence aligns with previous studies that conclude that the Russian invasion of Ukraine caused significant shifts in the roles and behaviors of various financial assets due to heightened geopolitical risks [e.g., Będowska-Sójka et al. [6] or Li et al. [44], among others]. Meanwhile, BTC and USDT continued as net information transmitters, and USDI, VBTLX, and MSCI_EUR shifted to net information transmitters, driven by demand for safe-haven assets. GOLD initially remained a receiver but reverted to a transmitter as inflation expectations adjusted.

An analogous analysis was conducted with a SW of 250 observations as a robustness test, yielding analogous qualitative results (results available upon request).

5. Concluding remarks

The study deeply explores the interconnectedness between global assets/indices during extreme events using a nonlinear approach based on TE. The network analysis findings reveal that BTC and ETH act as net information transmitters, challenging the perception that cryptocurrencies are isolated from traditional markets. These findings are consistent with Bouri et al. [10], who found that major

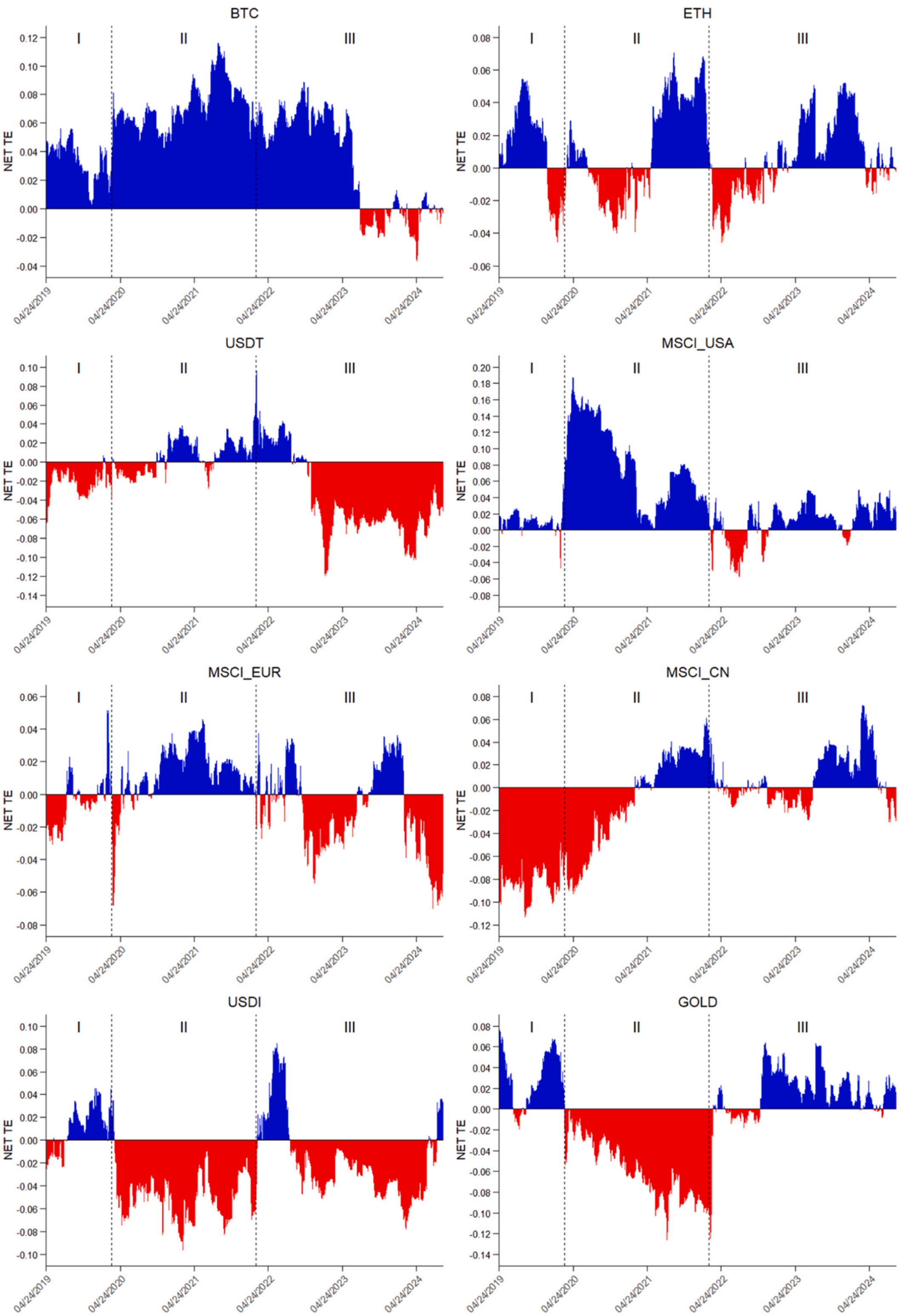


Fig. 2. Time evolution of the Net TE between each asset/index and the system.Notes: (i) The blue (red) area means the period on which the asset/index identified in each graph is a net information flow transmitter (receiver) to (from) the system; (ii) I, II, and III correspond to the periods before the COVID-19 (04/18/2017–03/10/2020), between the COVID-19 and the onset of the Russia–Ukraine war (03/11/2020–02/18/2022), and after the onset of the Russia–Ukraine war (02/22/2022–09/06/2024); (iii) The dashed vertical black lines correspond to 03/11/2020 and 02/22/2022. The first date corresponds to the official declaration of the COVID-19 pandemic as a global pandemic by the World Health Organization, which

triggered significant market volatility and economic uncertainty. The second date represents the deepening of the crisis between Russia and Ukraine, with Russia moving forces into separatist-controlled regions.

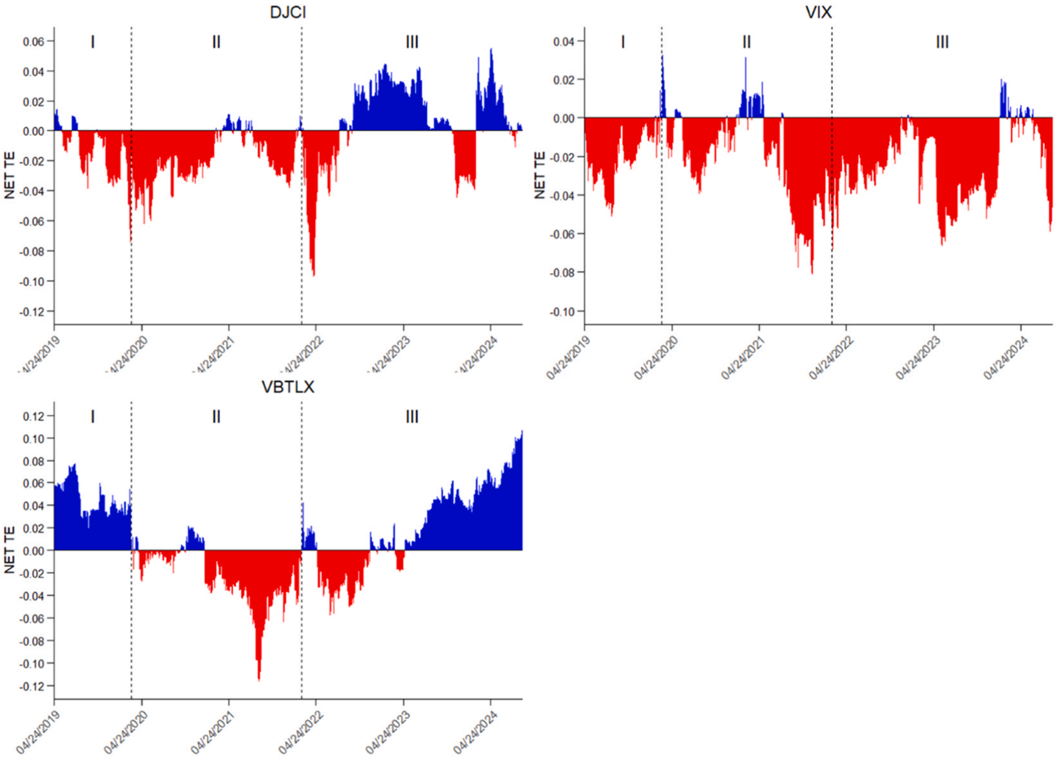


Fig. 2. (*continued*).

cryptocurrencies have significant positive impacts on stock returns. Although both BTC and ETH act as net information transmitters to the system most of the time, the influence of BTC on the system is higher than that of ETH, contrasting Kumar et al. [42], who found ETH more influential than BTC. At the onset of the COVID-19 pandemic, MSCI_CN and DJCI changed from receivers to transmitters, potentially due to China's economic recovery and global commodity volatility. GOLD oscillated between transmitter and receiver roles. USDT, generally identified as a connector between digital and traditional financial markets, is a net information receiver, except after the onset of the COVID-19 pandemic. The dynamic analysis showed BTC and ETH continuing as transmitters. At the same time, GOLD shifted from transmitter to receiver at the onset of the COVID-19 pandemic, remaining a receiver at the onset of the Russia–Ukraine war. MSCI_USA changed from transmitter to receiver after the Russia–Ukraine war onset.

This study allowed us to identify six significant transitions in asset roles following the COVID-19 pandemic and five after the Russia–Ukraine war. Following the COVID-19 pandemic, ETH, USDT, and VIX changed from net information receivers into net information transmitters, suggesting that these assets played an increasingly influential role in shaping market expectations. In contrast, MSCI_EUR, GOLD, and VBTLX became net information receivers, indicating a heightened sensitivity to external market dynamics, likely driven by increased risk aversion and macroeconomic uncertainty. Following the onset of the Russia–Ukraine war, additional shifts in market structure emerged. ETH and MSCI_USA transitioned from net information transmitters to receivers, suggesting that geopolitical risks substantially impacted these assets. Meanwhile, MSCI_EUR, USDI, and VBTLX became net information transmitters, indicating a stronger influence on the overall market. The shift in USDI to a net transmitter role aligns with the increased demand for the US dollar as a safe-haven asset during geopolitical tensions. While these changes occurred at the onset of the war, GOLD transitioned to a net transmitter slightly later, likely reflecting its increasing role as a safe-haven asset as market participants adjusted their portfolios in response to prolonged geopolitical uncertainty and shifting risk perceptions. This transition aligns with the well-documented tendency of gold to act as a key reference asset during periods of financial stress, with its strengthening influence as investors seek stability amid geopolitical tensions. These transitions underscore the dynamic nature of financial market interconnectedness and highlight how systemic shocks can reshape the flow of information across asset classes, with assets/indices adjusting their roles as transmitters or receivers in response to macroeconomic and geopolitical uncertainty.

These results have implications for portfolio diversification and risk management. While cryptocurrencies have emerged as significant players in financial networks, traditional assets remain sensitive to macroeconomic and geopolitical events.

The implications of this study extend beyond descriptive analysis, offering potential applications for portfolio management, risk assessment, and policymaking. Recognizing asset roles as net information transmitters or receivers aids portfolio managers in adjusting asset allocations during crises, with net transmitters likely influencing broader market expectations. For risk assessment, identifying critical periods where assets switch roles informs stress-testing scenarios and liquidity management. Policymakers can also monitor these directional flows to identify early warning signals for systemic risk, facilitating preemptive interventions to stabilize markets during crises. While our findings suggest that Net TE can capture shifts in market interdependencies preceding financial stress, this study does not directly compare Net TE with traditional early-warning indicators (EWIs). Moreover, our findings indicate that cryptocurrencies are increasingly embedded in conventional financial markets. Thus, from a policy-making point of view, it is essential to design regulatory frameworks reflecting their impact on financial contagion and systemic risk. Further, the evolving dynamics of different asset classes (including traditional safe-haven assets) mean that liquidity management strategies must be responsive to evolving market circumstances. In this context, Net TE is a useful instrument for policymakers because it allows real-time monitoring of systemic risk and timely identification of the changes in market interdependence, thus enhancing the capacity to implement more responsive regulation and intervention.

Future research should focus on a broader range of events to better comprehend the interconnectedness among markets through extreme events of various origins. Future research could build upon the current study by utilizing higher-frequency data to create intraday representations of asset interconnectivity during extreme events. Integrating additional sentiment indicators, such as news-based or social media sentiment analysis, could offer a more comprehensive understanding of how psychological and behavioral factors impact market connections. Employing machine learning techniques holds promise for enhancing forecast capabilities and identifying early warning signals of systemic risk. Furthermore, exploring the role of DeFi and stablecoins in financial systems can illuminate their influence on traditional assets, especially amid economic uncertainty. While Net TE offers a framework for detecting changes in financial interconnectedness, its effectiveness as a real-time EWI requires further investigation. A key area for future research is assessing its ability to detect financial distress compared to conventional EWIs, like those considered by Babecký et al. [3] or Kaminsky et al. [34], and traditional financial stability indicators.

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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.

Data availability

Data will be made available on request.

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