Network transitions in the cryptocurrency market: The impact of regional conflicts

Yuanyuan Zhang[a], Stephen Chan[b], Nicholas Lord[a], Jeffrey Chu[c,*], Hanfang Yang[c,*], Durga Chandrashekhar[b], Xin Liao[d], Qin Li[e]

[a] *Center for Digital Trust and Society, Department of Criminology, University of Manchester, Oxford Road, Manchester, M13 9PL, UK*

[b] *Department of Mathematics and Statistics, American University of Sharjah, PO Box 26666, Sharjah, UAE*

[c] *Center of Applied Statistics, School of Statistics, Renmin University of China, No. 59 Zhongguancun Street, Haidian District, Beijing 100872, China*

[d] *Business School, University of Shanghai for Science and Technology, Shanghai 200093, China*

[e] *School of Economics, Shanghai University, Shanghai, 200044, China*

Abstract

This paper analyzes the evolution of the cryptocurrency market network structure during two recent military conflicts: the first year of the 2022 Russia-Ukraine war and the first six months of the 2023 Israel-Hamas war, compared with pre-war periods. Analyzing data covering the two periods of 1st January 2020 to 31st December 2022 (Russia-Ukraine), and 1st September 2022 to 29th February 2024 (Israel-Hamas), our findings reveal that before both wars officially began, the cryptocurrency network exhibited high interconnectedness, likely due to investors anticipating conflict and shifting investments into cryptocurrencies. After the conflicts started, the network became significantly disconnected, with the Russia-Ukraine war showing a "small world" effect, where larger cryptocurrencies remained interconnected, while smaller ones were linked to a few larger ones. In contrast, during the Israel-Hamas conflict, larger cryptocurrencies became more disconnected, driving overall network disconnectivity. Further analysis using the TVP-SV-VAR model showed that macroeconomic variables such as geopolitical risk, the U.S. Dollar Index, oil volatility and gold returns, as well as the Google Trend Index had a significant impact on the network's structure, with varying effects across conflicts. Geopolitical risk exerted a stronger positive influence on centrality measures during the Israel-Hamas conflict, the Dollar index had a sharp negative effect on centrality following the Russia-Ukraine war, oil volatility consistently enhanced network centrality and density in both conflicts, gold returns shifted from a negative to a positive effect on network connectivity, especially boosting intermediary roles during the Israel Hamas conflict and the Google Trend Index consistently increased network centrality, highlighting the impact of rising market attention and sentiment. These results are crucial for understanding how military conflicts and economic factors impact cryptocurrency networks, providing valuable insights for academics, investors, policymakers, and legal authorities on market efficiency, risk management, and the potential use of blockchain-based assets in evading sanctions and facilitating cybercrime. As both conflicts are ongoing, future research should focus on analyzing extended war periods and the influence of regulatory actions, sanctions, and cryptocurrency-specific events.

Keywords: Cryptocurrency, Network, Ukraine War, Israel War, Centrality
JEL: G01; G10; G40; H56

1. Introduction

Over the past decade, digital cryptocurrencies have consistently been exposed to significant global events including financial crises, economic cycles, the coronavirus (COVID-19) pandemic, and most recently, regional military conflicts - including the Russian invasion of Ukraine, which has been described as the "largest attack on a European country since World War II (WWII)" (Reuters, 2022), and the Israel-Hamas war, in

*Corresponding author

which Hamas is said to be the "first terrorist organization to use cryptocurrency" in order to financially support its operations (TRM Insights, 2023), albeit eventually being stopped by the Israeli government (Nicolle, 2023).

Prior to 2022, the most significant global event to rock the cryptocurrency market was COVID-19, however, the existing literature remains in the balance regarding its impact. On the one hand, studies such as Yarovaya et al. (2021) and Susana et al. (2020) find no evidence of significant herding behaviour in Bitcoin and Ethereum during COVID-19. Moreover, Mnif et al. (2020) and Fernandes et al. (2022) find that major cryptocurrencies exhibit high market efficiency during this period. On the other hand, Susana et al. (2020) find evidence of herding in smaller cryptocurrencies, whilst Vidal-Tomás (2021) show that the cryptocurrency market was significantly affected and became highly synchronised in the early part of the pandemic. In addition, Kakinaka and Umeno (2022) and Montasser et al. (2022) argue that the cryptocurrency market became inefficient in the short term, with Naeem et al. (2021) noting that the increase in inefficiency hit Bitcoin and Ethereum hardest.

With regards to traditional financial markets, existing studies have noted that previous large scale military conflicts, such as World War II, have significant and direct impacts on financial markets and assets, and global currencies. A common theme is the existence of a "negativity effect", where negative (positive) events stemming from military conflicts lead to a significant negative (positive) effect on stock market returns (Choudhry, 2010; Hudson and Urquhart, 2015, 2022). It is therefore not surprising that on the day of the Russian invasion, the FTSE 100 index dropped by over 2.7% immediately after opening (City A.M., 2022) and the S&P 500 index saw its first correction in two years (Morningstar, 2022). Interestingly, in the case of the Israel-Hamas conflict, the stock market did fall initially, but the effect was not long lasting, as Wall Street was said to be taking 'a wait-and-see approach'. The S&P 500 rose 0.6%, the Nasdaq Composite rose 0.4%, and the S&P/ASX 200 rose 0.2%, whereas a number of European stock indices such as the CAC 40 and DAX fell 0.6% and 0.7%, respectively (Goldman and Toh, 2023). Indeed, numerous studies agree that the Russia-Ukraine conflict negatively impacted stock markets of developed countries both on the day and post event (Yousaf et al., 2022b), due to increased political uncertainty, geographic proximity (Ahmed et al., 2022; Boungou and Yatié, 2022), and trade links (Tajaddini and Gholipour, 2023). When compared with COVID-19, Gaio et al. (2022) find that the impact on stock market efficiency from COVID-19 was significantly greater, and Izzeldin et al. (2023) show that although stock markets reacted earlier to the military conflict, their reactions were more muted compared to COVID-19. With respect to the Israel-Hamas conflict, the few existing studies suggest that total risk spillover has increased (Cui and Maghyereh, 2024b; Lin et al., 2024) and to a higher level than that as a result of the Russia-Ukraine conflict (Cui and Maghyereh, 2024a).

However, a key question is how has the cryptocurrency market reacted to the onset of the wars? Studies investigating the impact of the conflicts on cryptocurrencies remain fairly limited. In the context of the Russia-Ukraine conflict, with regards to investor sentiment, Khalfaoui et al. (2023) find that under bearish (bullish) markets, attention on the war negatively (positively) affects cryptocurrencies in the short run. In terms of diversification and hedging properties, Bedowska-Sójka et al. (2022) find that in the early stages of the conflict geopolitical risk and cryptocurrencies exhibit strong coherence at a mid-frequency. Enilov and Mishra (2023) reveal that cryptocurrencies such as Bitcoin possess safe haven properties against extreme oil prices, and these properties exist for longer periods compared with oil and gold returns during the early part of the war. Similarly, Mohamed (2022) show that cryptocurrencies such as Bitcoin, Ethereum, and Litecoin, exhibit herding during upturns before the war, but do not act as safe havens against the Russian Rouble. Yousaf et al. (2023) show that energy cryptocurrencies are highly connected to Bitcoin but show little correlation with other assets. To the best of our knowledge, no literature has yet comprehensively analysed the impact of the Israel-Hamas conflict on cryptocurrency markets.

Notably, the existing related literature is generally limited to the impact on major cryptocurrencies (Mohamed, 2022; Khalfaoui et al., 2023; Patel et al., 2023; Enilov and Mishra, 2023), and neglects the evolution of the internal dynamics of the overall cryptocurrency market during this period. Although Vidal-Tomás (2021) note that the same appears to have been true for studies investigating the impact of COVID-19 on cryptocurrencies, a number of studies have since examined their dynamic networks during this period. In addition, as cryptocurrencies become increasingly integrated into global finance, their behaviours during geopolitical crises are of interest to both investors and policymakers. Investors, in particular those with diversified portfolios, have a vested interest since the behaviours of non-traditional assets during conflicts may assist them in making informed financial decisions. More generally, changes in the flows and values of cryptocurrencies may have broader economic impacts, especially if they are used to circumvent sanctions or facilitate illicit activities in times of conflict. However, the current literature exploring network structure and interconnectedness in the cryptocurrency markets over the course of the Russia-Ukraine and Israel-Hamas conflicts, thus far, remains limited to studies such as Kumar et al. (2023); Goodell et al. (2023); Mgadmi et al. (2023); Chen et al. (2024); Hamouda et al. (2024).

The primary aim of this study is to perform an in-depth analysis of the evolution of the cryptocurrency market network structure and dynamics during two recent military conflicts, the 2022 Russia-Ukraine war and the 2023 Israel-Hamas war, comparing the findings with a range of pre-war periods. More specifically, the contributions of this study are: i) to provide a comprehensive analysis and comparison between the evolution of the cryptocurrency network structures during the two recent major military conflicts; ii) to analyse the impact of key economic variables on cryptocurrency network structure due to the outbreak of the wars; iii) to investigate the time-varying relationships between key economic variables and changes in cryptocurrency network structure.

The results of our study are significant for academics and investors for identifying when the cryptocurrency market is particularly susceptible (or resilient) to risks from the conflict, diversification, and market efficiency. Furthermore, the results are significant from a legal perspective in ascertaining whether cryptocurrencies may be used to circumvent sanctions or facilitate cybercrime during periods of conflict. We note that this is particularly timely with Elliptic (2023a)'s report that blockchain-based assets are facilitating donations to both the Ukrainian ($212.1 million) and Russian sides ($4 million), with fundraising initiatives relying predominantly on Bitcoin (Russia) and Ethereum (Ukraine). In relation to the Israel-Hamas war, Elliptic (2023b) note that only $21,000 in cryptocurrency has been donated to 'Gaza Now', a pro-Hamas news organization, much of which has now been frozen, whilst donations have reached over $185,000 on the Israeli side in the form of cryptocurrency donations to Crypto Aid Israel.

The contents of this paper are organised as follows. Section 2 describes the data used. Section 3 outlines the methodology for constructing network graphs, the network properties analysed, and the tail risk model. Section 4 discusses the empirical results and Section 5 concludes the paper.

2. Data

The data we analyse comprise the historical daily closing prices of 32 cryptocurrencies in terms of the US Dollar (USD), for the two conflict periods comprising: i) three calendar years from 1st January 2020 to 31st January 2023 for the analysis of the Russia-Ukraine conflict; ii) approximately one and half calendar years from 1st August 2022 to 29th February 2024 for the analysis of the Israel-Hamas conflict, where the daily log returns are computed and used in the empirical analysis.

The two sample periods are each further split into three subsample periods corresponding to "pre-war period 1", "pre-war peiod 2", and "war period", respectively, which account for time periods that capture before the start of the conflict, and during and after the start of the conflict. The starts of the conflicts are defined as 24th February 2022 (Russia-Ukraine) and 7th October 2023 (Israel-Hamas), respectively, allowing us to analyse the cryptocurrency network topology and before and after these periods. The 32 cryptocurrencies were selected based on a combination of their high ranking in terms of market capitalisation, trading volume, and availability for trading consecutively between 1st January 2020 and 29th February 2024. These cryptocurrencies were specifically chosen due to their dominance, as they accounted for between 65-80% of the total market capitalisation of the cryptocurrency market during the sample period. Moreover, the inclusion of a condition for availability of trading ensured that the results would not be impacted by relatively unknown or unimportant coins that may have had a short lifespan and/or had been introduced just before our sample period.[1]

Figure 1 presents the box plots of the combined daily log returns for all 32 cryptocurrencies across three subsample periods: (i) 1st January 2020 to 31st December 2020 (pre-war period 1); (ii) 1st January 2021 to 31st December 2021 (pre-war period 2); (iii) 1st January 2022 to 31st December 2022 (war period) associated with the Russia-Ukraine war. The statistics computed include the minimum, maximum, mean, skewness, kurtosis and standard deviation. Figure 1 shows a clear upward trend in the minimum returns across these periods. Pre-war period 1 records the lowest minimum values, with substantial dispersion. Pre-war period 2 reflects an improvement with the median approaching -0.5, while during the war period, the minimum returns increase significantly, indicating less extreme negative returns. The maximum returns peaked in pre-war period 2, with a median value close to 0.4. Notably, neither the minimum nor maximum returns directly coincide with the official start of the Russian-Ukrainian conflict. The mean returns follow a declining

[1]A complete list of the 32 cryptocurrencies can be found in Supplementary Information Table S1.

trend from pre-war period 1 through to the war period. Pre-war period 2 exhibits the highest median mean returns, but these values decline during the war, reflecting lower average returns amidst the conflict. The skewness of returns is negative in pre-war period 1, shifting towards positive skewness in pre-war period 2 and further in the war period. This suggests that the distribution of cryptocurrency returns becomes more positively skewed as the conflict progresses, indicating a higher frequency of small positive returns. In terms of kurtosis, there is a marked reduction from pre-war period 1 to the war period. However, all periods exhibit a leptokurtic distribution, characterised by more peakedness and heavier tails than a normal distribution. Finally, with respect to volatility, pre-war period 2 demonstrates the highest variability in returns. In contrast, the war period is associated with reduced volatility, as indicated by a narrower spread in the standard deviation of daily log returns. This may suggest stabilization or reduced activity in the cryptocurrency markets during the conflict.

Figure 2 presents the box plots of the combined daily log returns for all 32 cryptocurrencies across three subsample periods: (i) 1st September 2022 to 28th February 2023 (pre-war period 1); (ii) 1st March 2023 to 31st August 2023 (pre-war period 2); (iii) 1st September 2023 and 29th February 2024 (war period) associated with the Israel-Hamas war. Figure 2 shows a clear upward trend in minimum returns across the periods. Pre-war period 1 records the lowest minimum values with a wide dispersion, while pre-war period 2 shows an increase, with the median approaching -0.2. The war period continues this upward trend, reflecting less extreme negative returns during the conflict. Maximum returns peak in pre-war period 2, with a third quartile value (Q3) near 0.3. However, during the war period, maximum returns decline, indicating fewer extreme positive returns compared to the pre-war periods. The mean returns follow a U-shaped trajectory. Pre-war period 1 shows negative mean returns, which decline further in pre-war period 2. In contrast, the war period sees a significant rise, with positive mean returns, suggesting a recovery or upward movement in average daily returns during the conflict. Skewness is slightly positive in all periods, with a notable increase during the war period. This shift indicates that the distribution of returns becomes more positively skewed, suggesting a higher frequency of small positive returns during the conflict. The kurtosis drops significantly from pre-war period 1 to the war period, although all periods exhibit leptokurtic distributions, characterised by higher peaks and heavier tails than a normal distribution. Finally, with respect to volatility, it is highest in pre-war period 1 and decreases progressively through pre-war period 2 and the war period. The war period exhibits the lowest volatility, as indicated by the smallest spread in returns, suggesting reduced market fluctuations during the conflict.

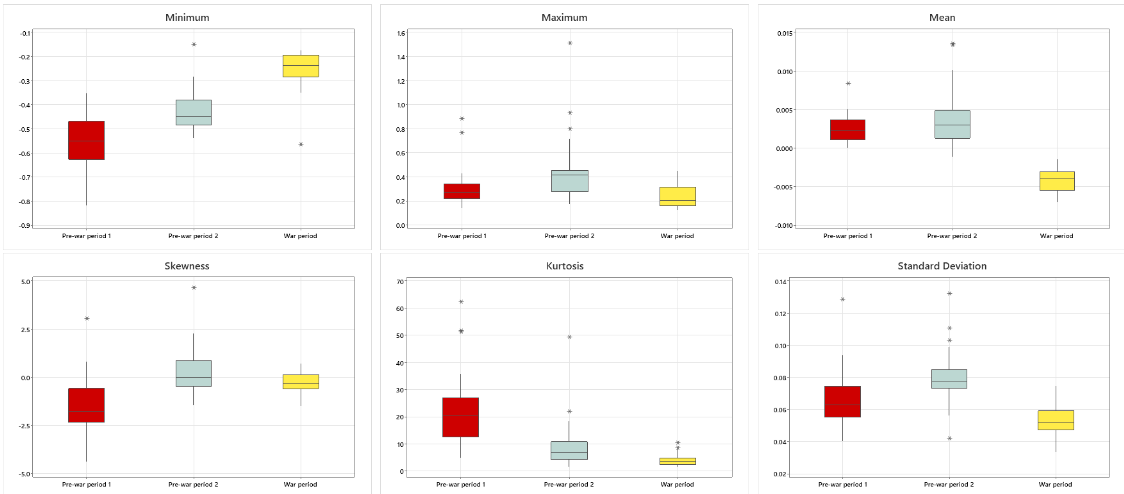

Figure 1: Descriptive statistics of the daily log returns of the 32 cryptocurrencies over the three subsample periods of: i) Pre-war period 1 (red); ii) Pre-war period 2 (blue); iii) War period (yellow), corresponding to the Russian-Ukraine war.

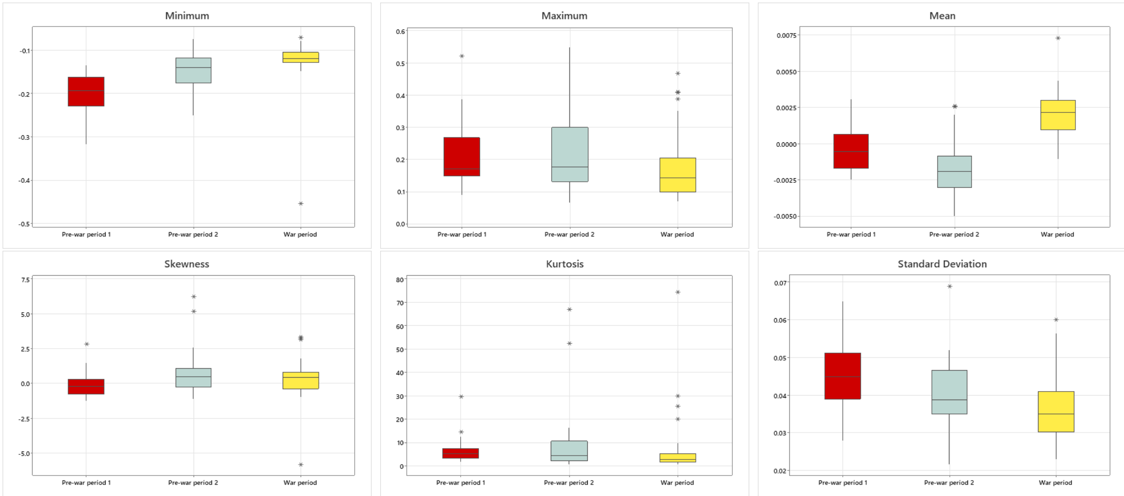

Figure 2: Descriptive statistics of the daily log returns of the 32 cryptocurrencies over the three subsample periods of: i) Pre-war period 1 (red); ii) Pre-war period 2 (blue); iii) War period (yellow), corresponding to the Israel-Hamas war.

3. Method

3.1. Network construction

To construct the networks for the analysis, known as market graphs, we follow closely the methodologies by Boginski et al. (2005) and Vidal-Tomás (2021).[2] We consider the cryptocurrency market as an undirected network $G(V, E)$, where the set of nodes V represent cryptocurrencies and edges $E \subset V \times V$ connect pairs of nodes based on a similarity measure. In this study, pairs of nodes (i, j) are connected by an edge if and only if the corresponding Pearson correlation coefficient C_{ij}, based on the daily log returns of the two cryptocurrencies, exceeds a specified threshold of $\theta = 0.5$. The dynamic nature of the cryptocurrency network is captured using rolling windows of returns, as opposed to a single sample covering an entire subsample period, where network graphs are constructed for each 30-day rolling window of returns over each subsample period.[3]

Our network construction is based on the winner-takes-all approach using a fixed threshold θ, which is in line with numerous related studies such as Boginski et al. (2005), Tse et al. (2010), Heiberger (2014), Nobi et al. (2014), Moghadam et al. (2019), and Vidal-Tomás (2021), to name but a few. As noted by Heiberger (2014), this approach is similar to other reduction techniques, but possesses two key advantages over other methods, such as the multiple spanning tree (MST) and planar maximally filtered graph (PMFG) (Vidal-Tomás, 2021). These are that when using the threshold method, "no essential information about the networks is lost" (Heiberger, 2014) as opposed to MST and PMFG, which may remove highly correlated edges, and "the number of nodes in the network is not mandatory" (Heiberger, 2014), in other words there is no fixed upper bound.

The threshold of $\theta = 0.5$ was selected to retain consistency with existing and related studies (Boginski et al., 2005; Tse et al., 2010; Moghadam et al., 2019), while still being reasonable given the data in the present study. As noted by Vidal-Tomás (2021), considering only correlations $C_{ij} > 0.5$ allows us to retain the strongest relationships between cryptocurrencies, without significant loss of important information. Moreover, related studies have shown that using a threshold of $\theta \approx 0.5$ leads to the distribution of degrees having a well-defined structure and following a power law (Boginski et al., 2005), and in networks constructed using price returns the increase in goodness of fit to the power-law distribution tails off at an optimal threshold of approximately $\theta = 0.5$ (Tse et al., 2010). Whilst alternative approaches, such as thresholds based on the mean correlation C_{ij} and its standard deviation, have been proposed by Nobi et al. (2014) and others, we believe that they are not entirely appropriate for the present study. In contrast to these studies, we consider a much smaller sample size of 32 cryptocurrencies and individual rolling window sample periods. However, the key influencing factor is that the distributions of the correlations in our case (over the two main war periods) are significantly negatively and left skewed, as shown in Figure 3 below. It follows that the

[2]For brevity, only the basic methodology is highlighted. We refer readers to Boginski et al. (2005) and Vidal-Tomás (2021) for more detailed explanations.

[3]Shorter rolling windows of 14 days are also found to give similar results.

mean correlations and standard deviations in the present study are much larger compared to other studies. Therefore, implementing a threshold θ that is one, two, or three standard deviations greater than the mean correlation would lead to a threshold close to or even exceeding 1, resulting in very few, if any, edges being retained in the network giving a poor representative analysis.

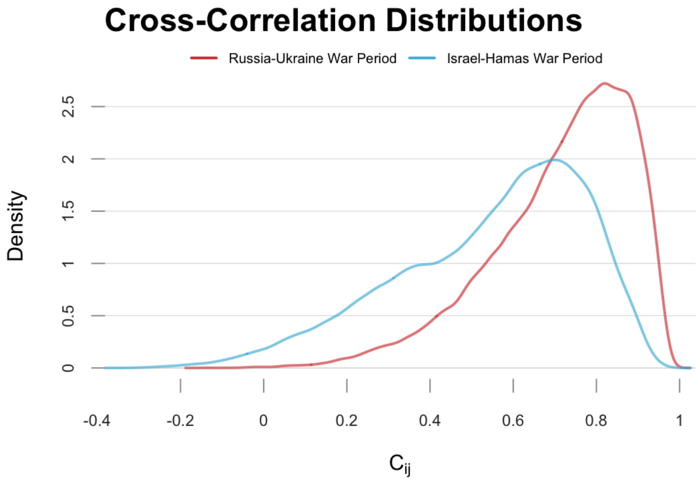

Figure 3: Distribution of daily correlations for the two main war periods.

3.2. Network properties (node level)

The evolution of the cryptocurrency network is analysed through the property of centrality. It is expected that the structure of the network is heterogeneous, where some nodes play a more important role than others. Therefore, the importance of the most central cryptocurrencies can be captured by the centrality, as these are likely to be the most influential and able to propagate information more widely (Rodrigues, 2019). Furthermore, the concept of centrality relates more generally to the spreading and synchronisation in a network. As highlighted in the existing literature, there is generally no single definition or measure of centrality (Gupta et al., 2016; Rodrigues, 2019). Instead, numerous measures have been proposed that focus on various aspects such as importance of specific nodes, degree of control, etc., but here we focus on the three measures of degree centrality, betweenness centrality, and eigenvector centrality.

3.2.1. Degree centrality

The raw degree centrality is the simplest centrality measure, which is defined by the number of edges connecting to each node. However, as noted by Wasserman and Faust (1994), this depends on the number of nodes in the network, therefore, standardizing this measure can allow for comparisons across networks of different sizes. For a given node v_i, this is

$$C_D(v_i) = \frac{\sum_{j=1}^{N} A_{ij}}{N-1},$$

where N is the total number of nodes in the network and from the network's adjacency matrix A, $A_{ij} = 1$ if $C_{ij} > \theta$, and $A_{ij} = 0$ otherwise. It follows that nodes with a higher degree can be considered as more central.

3.2.2. Betweenness centrality

An alternative measure is the raw betweenness centrality, which is based on the number of shortest paths and represents the degree to which a node ranks between other nodes. Similar to the raw degree centrality, this value depends on the number of nodes in the network, and we can therefore standardize it in the same way. For a given node v_i, this is

$$C_B(v_i) = \frac{\sum_{s \neq v_i \neq t} \frac{\sigma_{st}(v_i)}{\sigma_{st}}}{[(N-1)(N-2)/2]},$$

where σ_{st} is the total number of shortest paths from node s to node t, $\sigma_{st}(v_i)$ is the total number of those paths that pass through v_i, and N is the total number of nodes in the network. At a network level, a high betweenness centrality indicates a bridging position, which reflects a node with power and the ability to control the flow of information between its neighbours. We note that in the remainder of the paper, the use of the terms degree centrality and betweenness centrality refers to the standardized versions of the measures as defined above.

3.2.3. Eigenvector centrality

While degree centrality simply measures the number of connections, the eigenvector centrality extends this by offering a relative measure of the influence of a node. For a given node v_i, this is

$$C_E(v_i) = \frac{1}{\lambda} \sum_{j \in M(v_i)} C_E(v_j),$$

where $M(v_i)$ is the set of neighbours of v_i, and λ is a constant eigenvalue. As connections to other nodes with a high eigenvector centrality contribute more to the score of a node, a high eigenvector score implies that a node is connected with many high scoring nodes and receives a higher endorsement from important nodes.

The three centrality measures reflect the level of interconnectedness: high centrality scores correspond with cryptocurrencies being highly connected, having a greater influence in the network, and greater co-movement in their returns. As noted by Raddant and Kenett (2021), greater interconnectedness in financial markets can be both positive and negative - it can help absorb shocks and lead to greater robustness, but it can help propagate shocks and create greater fragility. In addition, high co-movement relates to the behaviours of individual assets and may suggest common underlying factors or economic linkages at play. Raddant and Kenett (2021) also show that stocks form large connected components during financial crises, connections become more dense, and there is a synchronisation in the dynamics of the number of edges. Thus, the greatest number of edges generally exist during crises (i.e. a large and connected network), but can similarly exist when the network is small and dense. However, as the average degree relates to changes in both network size and structure, even in times of crisis not everything is always guaranteed to be interconnected.

The level of interconnectedness further relates to herding. As suggested by Yousaf et al. (2023), cryptocurrency investors may follow each other due to lack of information or fear of losses, and this behaviour may become stronger during crises or bubbles. More generally, herding behaviour among financial market participants also has direct implications on market efficiency and asset pricing, as high levels of herding are generally associated with market volatility and instability. During periods of market stress or extreme price movements individuals are more likely to ignore their own thoughts and instead follow the majority, which is in contrast to the efficient market hypothesis. Thus, resulting in individual stock returns clustering around the overall market return. Indeed, a recent body of work suggests that inefficiency in cryptocurrency markets can be attributed to investor herding (Bouri et al., 2019; Vidal-Tomás, 2019; Ballis and Drakos, 2020).

Both the herding of market participants and connectivity between assets are of interest to investors and policymakers (Yao et al., 2014). The dynamic relationship between assets relates to diversification properties (Umar et al., 2022), and the overall level of connectivity may explain the risk transmission in financial markets. The financial stability of markets is also essential to ensure that investments are secure and safe (Mnif et al., 2020). Therefore, understanding these interactions can help to interpret the changes that occur during crises and assist with possible responses.

3.3. Network properties (network level)

To complement the analysis of node level centrality, in addition to the above network centrality measures, we also consider the following four additional global network properties of density, transitivity, mean shortest path, and assortativity, which capture and reflect the level of interconnectedness in slightly different ways.

3.3.1. Density

The (global) network density relates closely to centrality but provides a reflection of the interconnectedness across the entire network rather than individual nodes, and is defined by the ratio of the actual number of edges to the maximum number of possible edges. For a given undirected network graph G, this is

$$\rho = \frac{2M}{N(N-1)},$$

where M is the number of edges, N is the number of nodes, and $0 \leq \rho \leq 1$. The greater the number of connections between individual nodes the denser the network, indicating a more tightly coupled and highly influential network.

3.3.2. Transitivity

The transitivity of a network captures the tendency for nodes to form triangles, or the degree to which nodes that each have relationships with a common node are likely to have a direct relationship - i.e. "the friend of my friend is also my friend" (Newman, 2010). This is defined by the number of closed triples and open triples, or more commonly the number of triangles and connected triples. For a given undirected network graph G, this is

$$T = \frac{(3 \times \text{number of triangles in the network})}{(\text{number of connected triples of vertices})},$$

where 'connected triples" means three vertices uvw with edges (u, v) and (v, w), and the factor of three results from each triangle being counted three times when counting the connected triples (Newman, 2010). As transitivity measures the fraction of connected triples that are closed into triangles, the higher the transitivity the more tight-knit the community structure. Note that here we consider transitivity in the form of triangles and triples (Wasserman and Faust, 1994), which is often referred to as the (global) clustering coefficient for directed and undirected networks. However, even though the two terms are frequently used interchangeably in the literature, we use transitivity here (as a global measure) to avoid confusion with the local (or average) clustering coefficient, which are local node level measures with the main difference being how the methods sample.

3.3.3. Mean shortest path

The mean shortest path (characteristic path length) of a network provides a measure of the efficiency of information in the network, and is defined as the average number of steps along the shortest paths between all possible pairs of nodes. For a given undirected network graph G, this is

$$l_G = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \neq j} d_{v_i, v_j},$$

where N is the number of nodes, and d_{v_i,v_j} denotes the shortest path between node v_i and v_j. The mean shortest path length forms one of the key measures for evaluating the small-world effect in networks, along with the level of clustering (Watts, 1999; Newman and Watts, 1999; Albert and Barabasi, 2002; Nishikawa et al., 2002; Arnaboldi et al., 2015). A shorter average path length may be more likely to indicate a "small world" network, where nodes are connected via very short paths, however, the level of clustering may also influence this.

3.3.4. Assortativity

The (degree) assortativity of a network measures the level of homogeneity in terms of edges, and is defined as the Pearson correlation of the degrees of connected nodes. For a given undirected graph G, this is

$$r = \frac{1}{\sigma_q^2} \sum_{jk} jk(e_{jk} - q_j q_k),$$

where $q_i = \sum_j e_{ij}$, σ_q is the standard deviation of q, and $-1 \leq r \leq 1$. At a network level, positive assortativity generally indicates that nodes tend to be connected with nodes that have a similar number of degrees, whilst negative assortativity (disassortativity) indicates that nodes with few edges tend to be connected with those that have many edges, and vice versa.

As with the centrality measures in Section 3.2, the above four global network properties are also key indicators in the context of financial networks. Network density provides information about the relationship between individual stocks in a correlation network, with a higher density signifying a tighter connection between nodes within the network, and an increased correlation (Isogai, 2016). In this case, higher density implies a more tightly connected cryptocurrency network, with greater co-movement between cryptocurrencies. In terms of clustering, evidence suggests that in most physical and social networks, nodes have a strong tendency to form clusters.

A high clustering coefficient indicates a "high local interconnectedness," (Markose et al., 2012) and a more effective transmission of contagion (Torri and Giacometti, 2023). Transitivity has been found to result in a stronger community structure (Orman et al., 2013) and be high in networks with communities (Torri and Giacometti, 2023). Similarly, a number of studies have also revealed that community structure is a sufficient condition to cause high transitivity (Pastor-Satorras et al., 2003; Liu and Bambi , 2005; Clauset et al., 2008). Whilst communities have been studied extensively in traditional financial networks (i.e. banks, stock markets, and firms) (Buccheri et al., 2013; Wang and Xie, 2015; Wang et al., 2017; Huang and Chen, 2021; Batrancea et al., 2024), they have only recently started gaining traction with respect to cryptocurrency markets (Stosic et al., 2018; Wu et al., 2021b; Kitanovski et al., 2022; Brigatti et al., 2023).

The average or mean shortest path length is a measure of the network's informational efficiency such that a shorter mean typically signifies a greater rate of diffusing information across the network, although there are exceptions to this behaviour owing to potential disturbances (Papana et al., 2017). In the context of cryptocurrencies, this links back to the idea of interconnectedness where a shorter path length indicates that the cryptocurrency market is more tight knit. Indeed, analyses of stocks by Kauê Dal'Maso Peron et al. (2012), during times of financial crisis, shows that the mean shortest path seems to increase, implying a reduced network where the value of the path length varied most when the financial situation was unstable.

In addition, mean shortest path length also relates to betweenness centrality as a shorter path length may correspond with less network dominance or control coming from individual cryptocurrencies. Assortativity is one of a number of factors that plays an important role in determining the existence of a core-periphery structure, where peripheral nodes are likely to connect to dissimilar core nodes, and the concepts of assortativity and core-periphery often coexist and reinforce each other (Wang et al., 2025). Higher assortativity can strengthen a core-periphery structure leading to a highly interconnected core, but the presence of a core does not automatically imply positive assortativity (Mondragón, 2020), as disassortativity can relate to a more hub-and-spoke core-periphery structure (Csermely et al., 2013; Hurd et al., 2017). In addition, core-periphery structures often lie between the extremes of common properties (i.e. random/condensed structures, clique/star configurations, symmetry/asymmetry, assortativity/disassortativity, etc.) (Csermely et al., 2013). Whilst social networks often exhibit positive degree assortativity (Mondragón, 2020), other common networks exhibit core-periphery structures but with negative assortativity - i.e. technological and infrastructure networks (Newman, 2003), and also biological networks.

3.4. TVP-SV-VAR for tail risk driving factors

To further study the evolving and non-linear dynamic impacts of tail risk factors on the network transitions over time, we employ the Time-Varying Parameter Stochastic Volatility Vector Autoregression (TVP-SV-VAR) model by Primiceri (2005). Note that economic variables usually exhibit drifting coefficients and shocks of stochastic volatility. Compared to other Vector Autoregressive model, the TVP-SV-VAR model assumes that both the coefficient matrix and the covariance matrix are time-varying, which can capture the dynamic nature of parameters and structural changes within the economic system, and helps to improve the accuracy and explanatory (Boufatech and Saadaoui, 2021; Hu et al. , 2023). In general, the TVP-VAR method has a few limitations such as the use of complex methods for estimation and inference as the "model is fundamentally nonlinear" (Lubik and Matthes, 2015) leading to computational challenges. However, this can be possibly mitigated by employing a Gibbs sampler technique (Lubik and Matthes, 2015). In addition, high dimensional TVP-SVAR is not as common and is challenging to deal with due to the issues of inaccurate estimation, over-fitting, and high computational demand (Zheng et al., 2023), but possible mitigation strategies include the implementation of a generalized recentering approach combined with a rank-reduced state covariance matrix and parameter expansions simplify high-dimensional TVP-SVAR (Chan et al., 2020). By applying this model, we aim to analyse the dynamic relationships between geopolitical risk (Geopolitical Risk Index, GPRD), the US Dollar Index (DXY), oil market volatility (CBOE Crude Oil ETF Volatility Index, OVX), the Gold price (GOLD), the Google Trend Index (GTU) and the above cryptocurrency network characteristics. In this case, the approach provides a framework for understanding the complex interactions between key economic variables and network transitions during critical times. In this study, the parameters of the TVP-SV-VAR model are estimated using the *OxMetrics* software. However, the software restricts the TVP-SV-VAR model to a maximum of four variables. Consequently, we construct two separate TVP-SV-VAR models: the first incorporates GPRD, DXY, OVX, and cryptocurrency network characteristics; the second includes GOLD, GTU, and the network characteristics.

The five external variables were selected based on their relevance to the impact of military conflicts on financial markets. More specifically, the Geopolitical Risk Index by Caldara and Iacoviello (2022) measures the "threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations". Daily geopolitical risk index data was sourced from the iFinD (2024) database and is constructed based on articles from 10 major US newspapers, by counting the number of articles related to adverse geopolitical events in each newspaper for each month (as a share of the total number of news articles). Such a measure is commonly reported to be a key indicator determinant of economic decisions by policy makers, investors and the media Caldara and Iacoviello, 2022. Oil is a key driver in the global economy and volatility can influence global economic stability, the hedging behaviour of investors managing energy risk, capital market uncertainty, and political stability - especially for those nations who are major oil exporters. Oil volatility was measured by the daily closing price of the CBOE Crude Oil ETF Volatility Index and was obtained from Investing.com (2024a). The US Dollar remains a critical component of the currency market and the US Dollar Index measures the value of the US Dollar relative to a basket of six major world currencies, providing context for understanding global economic trends. It also relates to oil and commodities, as oil and others are priced in US Dollars, and impacts the hedging strategies of those invested in commodities. Furthermore, the index is one of a number of key determinants in the Federal Reserve's decision making on interest rates. The currency market was measured by the daily closing price of the US Dollar Index and was obtained from Investing.com (2024b). Some literature has suggested the interconnectedness of gold with cryptocurrencies, especially during the COVID-19 pandemic (Foroutan and Lahmiri, 2024; Mensi et al., 2023), while others assert the "safe-haven" nature of gold, especially during times of conflict. For example, Ari et al. (2023) found that variations in gold returns typically did not lead to variations in the returns of firms in the energy sector. Similarly, a very recent study by Mchirgui et al. (2025) who examined Bitcoin, gold, gold-backed cryptocurrencies, and energy commodities found that gold demonstrated some safe-haven characteristics specifically during the Russia-Ukraine war, unlike during the COVID-19 pandemic. Hence, the closing prices of gold data from Investing.com (2025) were obtained and analyzed. To aid in distinguishing between idiosyncratic risk and overall market risk as proxied by the above external variables, we capture cryptocurrency market attention and sentiment by employing the Google Trends (Cryptocurrency) Index as proposed by Aslanidis et al. (2022), which adapts the original Google Trends Uncertainty Index from Castelnuovo and Tran (2017) for cryptocurrencies. The index was computed using daily Google Trends search volume data following the procedures in Castelnuovo and Tran (2017) and Aslanidis et al. (2022), using the set of 21 cryptocurrency-related terms that form 'Subset 1' in the study by Aslanidis et al. (2022). This set of cryptocurrency-oriented keywords were originally selected based on a bibliometric analysis of existing relating literature (Aslanidis et al., 2022).

Table 1 and Table 2 show the summary statistics for the daily global geopolitical risk index, oil volatility index, US Dollar Index, Gold, Google Trend Index and the seven network properties, over the full sample period of 1st January 2020 to 29th February 2024, inclusive. Note that the final sample of data analysed includes only trading days when data for all variables are available, this means holidays and weekends were excluded due to the lack of oil volatility and US Dollar Index data. For consistency, the summary statistics computed were the same as those computed in Figures 1 and 2. Also note that a prerequisite for the TVP-SV-VAR model is that all data is stationary. As can be seen from Table 1 and Table 2, all series were found to be stationary according to the Augmented Dickey Fuller (ADF) test, except for the US Dollar index and the gold price. To achieve stationarity, logarithmic differencing was applied to the US Dollar Index and the gold price, resulting in return series. In addition, to align the variable ranges, the GPRD, OVX and GTU were pre-processed by taking logarithms, which still remained stationary. According to the Jarque-Bera test for normality, the distributions of all series exhibit significant deviations from the normal distribution.

	DC	BC	EC	Density	Transitivity	MSP	Associativity
Observations	1046	1046	1046	1046	1046	1046	1046
Minimum	0.225	0.000	0.453	0.225	0.509	0.713	-0.229
Median	0.808	0.007	0.879	0.808	0.911	0.828	-0.095
Mean	0.756	0.010	0.847	0.756	0.887	0.851	-0.080
Maximum	1	0.049	0.985	1	1	1.434	0.475
Skewness	-0.643	1.176	-1.151	-0.643	-0.954	1.792	2.233
Kurtosis	-0.611	1.048	0.886	-0.611	0.216	4.681	8.302
SD	0.194	0.009	0.101	0.194	0.093	0.094	0.087
Jarque-Bera	88.331***	287.152***	263.874***	88.331***	159.983***	1502.036***	3682.556***
Augmented Dickey-Fuller	-4.214***	-4.003***	-5.216***	-4.214***	-3.959***	-4.798***	-4.999***

Table 1: Summary statistics of daily means of the seven network properties, over the full sample period. *** indicates statistical significance at the 1% level of significance for test statistics.

	OVX	$\ln OVX$	DXY	r_{DXY}	GPRD	$\ln GPRD$	GOLD	r_{GOLD}	GTU	$\ln GTU$
Observations	1046	1046	1046	1046	1046	1046	1046	1046	1046	1046
Minimum	24.23	3.188	89.44	-0.021	22.26	3.103	1477.9	-0.051	80.5	4.388
Median	40.31	3.697	99.32	0.000	110.515	4.705	1836.1	0.0005	168.75	5.128
Mean	46.989	3.776	99.119	$6.956e-05$	122.905	4.689	1838.571	0.0003	174.970	5.129
Maximum	325.150	5.784	114.110	0.016	540.830	6.293	2083.5	0.058	317.567	5.761
Skewness	4.724	2.222	0.170	-0.155	2.014	-0.080	-0.301	-0.237	0.171	-0.376
Kurtosis	29.506	6.898	-0.940	1.596	7.194	0.351	-0.255	3.945	-0.679	-0.398
SD	25.470	0.334	5.897	0.005	65.697	0.497	118.750	0.010	45.494	0.272
Jarque-Bera	41448.408***	2908.619***	43.687***	113.322***	2935.166***	6.265**	18.661***	678.400***	25.332***	31.587***
Augmented Dickey-Fuller	-3.375**	-3.276**	-1.010	-14.653***	-5.539***	-3.101**	-2.493	-14.408***	-3.441***	-3.459***

Table 2: Summary statistics of the daily geopolitical risk, oil volatility, US Dollar Index, gold and Google Trends attention index, over the full sample period. *** indicates statistical significance at the 1% level of significance for test statistics.

The TVP-SV-VAR model is based on the assumption that the coefficient matrix and the covariance matrix are both time-varying, which allows to us to analyse the impulse effects between the variables at a specific time. First, we construct a basic model as follows:

$$y_t = B_{1t}y_{t-1} + \cdots + B_{st}y_{t-s} + e_t, \quad e_t \sim N\left(0, \Omega_t\right), \quad t = s+1, \cdots, n \tag{1}$$

where y_t is a $k \times 1$ vector, $B_{1t}, \cdots, B_{st}$ is a $k \times k$ coefficient matrix with time t, Ω_t is a $k \times k$ covariance matrix and is decomposed as $\Omega_t = A_t^{-1} \sum_t \sum_t A_t^{-1'}$, and A is a lower triangular matrix. In this setup, the dynamic relationship of each cryptocurrency network characteristic is analysed individually, such that the model includes a total of four variables: GPR, OVX, DXY, and the cryptocurrency network characteristic, giving a value of $k = 4$.

Now consider that the model is time-varying, such that we have A_t and $\sum_t = diag(\sigma_{1t}, \cdots, \sigma_{kt})$, where

$$\sum = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}, \tag{2}$$

and

$$\mathrm{A} = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{kk-1} & 1 \end{pmatrix}. \tag{3}$$

β_t is a stacked row vector of $B_{1t}, \cdots, B_{st}$, $a_t = (a_{1t}, \cdots, a_{qt})'$ is the stacked row vector of A_t, and $h_t = (h_{1t}, \cdots, h_{kt})'$, where $h_t = \log \sigma_{it}^2$.

The time-varying parameters of β_t, a_t, and h_t follow the random-walk process as follows:

$$\beta_{t+1} = \beta_t + \mu_{\beta_t}\alpha_{t+1} = \alpha_t + \mu_{\alpha t}h_{t+1} = h_t + \mu_{ht}, \tag{4}$$

and

$$\begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{pmatrix} \sim N\left[0, \begin{pmatrix} I & O & O & O \\ O & \Sigma_\beta & O & O \\ O & O & \Sigma_\alpha & O \\ O & O & O & \Sigma_h \end{pmatrix}\right], \quad e_t = A_t^{-1} \sum_t \varepsilon_t, \quad t = s+1, \cdots, n \tag{5}$$

where I, Σ_β, Σ_α and Σ_h are both diagonal, and obey normal distributions as

$$\beta_{t+1} \sim N\left(u_{\beta 0}, \sum_{\beta 0}\right), \quad a_{t+1} \sim N\left(u_{a0}, \sum_{a0}\right), \quad h_{t+1} \sim N\left(u_{h0}, \sum_{h0}\right).$$

4. Results and Discussion

Figures 4 and 6 (a, b, c) plot the evolution of the three node level centrality measures for individual cryptocurrencies and the average, over the Russia-Ukraine war period and Israel-Hamas war period, respectively. Figures 4 and 6 (d, e, f, g) plot the evolution of the four global network measures over the war periods for the two conflicts. Note that in Figures 4 and 6 (d, e, f, g), since these are global network measures there is only a single line denoting the network measure for the whole network. For clarity, the results are only plotted for the major cryptocurrencies of Bitcoin, Ethereum, and Litecoin, and a minor cryptocurrency of Dogecoin. The results for other major (minor) cryptocurrencies are found to be similar to Bitcoin, Ethereum, and Litecoin (Dogecoin). The averages are computed as the mean of the correspnding measure for all cryptocurrencies that exist in the network corresponding to each rolling window. In Figures 4 and 6, plots highlight the starts of the conflicts on 24th February 2022 and 7th October 2023, respectively (dotted lines). For comparison purposes, corresponding plots for the two pre-war periods for the Russia-Ukraine conflict are shown in Appendix Figures A1 and A3, and in Appendix Figures A5 and A7 for the Israel-Hamas conflict.

4.1. Russia-Ukraine Conflict

In Figure 4, prior to the start of the war, the cryptocurrency market appeared relatively interconnected, but in the immediate aftermath became almost fully connected. However, the betweenness centrality simultaneously tended towards zero, suggesting that no cryptocurrencies dominated and acted as bridges. Through March 2022 to the beginning of April 2022, the cryptocurrency market became significantly disconnected, with smaller cryptocurrencies such as Dogecoin becoming isolated and almost fully disconnected. Though major cryptocurrencies also became less interconnected, the betweenness and eigenvector centralities suggest that: i) they played a role as power players in influencing the market during this time; ii) they became interconnected with a small number of other influential cryptocurrencies, which did not include smaller cryptocurrencies. A repeat of this trend is also found around mid-November 2022. Moreover, in a significant proportion of rolling windows, Dogecoin and other smaller cryptocurrencies became isolated from the whole network and specifically from influential cryptocurrencies.

Through April 2022, the cryptocurrency market exhibited a sharp increase in interconnectedness to a level similar to the pre-war period. Interestingly, the cryptocurrency market also became fully connected for an extended period of around one month, at around June 2022 and December 2022. Moreover, the trend in the betweenness centrality suggests that major cryptocurrencies such as Bitcoin, Ethereum, and Litecoin had significant influence over the network immediately before these periods.

With respect to the global network properties, in Figure 5, the measures of density and transitivity exhibit almost exactly the same trend as degree centrality, which may be expected since density and transitivity relate to the number of node, edges, and edges between nodes. The high level of transitivity (above 0.9) throughout the majority of this war period suggests that the strength and level of community structure may also be relatively high. Notably, the mean shortest path did not immediately experience a significant change in response to the start of war, but rather peaked when the cryptocurrency network become severely disconnected through March and April 2022. However, throughout this war period, the mean shortest path remained relatively stable and small in magnitude, suggesting a small world effect where information could be transmitted through the network relatively efficiently. This is supported by our estimates of a dynamic rolling small-world index in line with the methodology proposed by Humphries and Gurney (2008) for each rolling window, as shown in Figure S1(a). The index characterizes the small-worldness of a network based on the difference between the mean shortest path lengths and clustering coefficients of the cryptocurrency network and Erdös–Rényi random graphs, respectively (see Appendix B.1 for extended methodological details). It can be seen that the small-world index exceeds the threshold value of 1, as defined in Humphries and Gurney (2008), for the whole war period, with a mean value of 1.389, suggesting an extended small world effect. Similarly, during the war period, network assortativity generally remained negative but, again, peaked when the network became very disconnected. This suggests that for the most part, smaller cryptocurrencies tended to connect with larger cryptocurrencies rather than other smaller currencies (similar to traditional banks), thus supporting the view that larger cryptocurrencies overall were more dominant, with little change throughout this period.

Figures S5 and S6 plot the network structures of the cryptocurrency market based on degree and betweenness centrality, respectively. Networks based on eigenvector centrality are also found to be similar to those based on degree centrality.[4] Larger and lighter (smaller and darker) coloured nodes reflect higher (lower) centrality, and darker (lighter) coloured edges reflect higher (lower) correlation between nodes. The highlighted sections of the average centrality plots indicate the rolling window period for which the network structure was computed, and the network graphs constructed correspond with the end date of the rolling window.

The network structures appear to be in line with the trends of the centrality measures. As in Vidal-Tomás (2021), we find evidence that the cryptocurrency market is characterised by a core-periphery structure over much of the sample period. Visually, on the first day of the conflict, the network structure did not change significantly but quickly became fully connected. However, in March 2022 the network became significantly disconnected with a smaller core and much weaker correlation overall. In the periods where the network becomes highly interconnected, the core-periphery structure essentially disappears (Figure S3). Interestingly, irrespective of the network structure, there are only ever a few cryptocurrencies in each network graph that exhibit a high betweenness centrality. Many are located at the periphery suggesting that they may not necessarily be the most interconnected cryptocurrencies. This is supported by our estimates of a dynamic rolling core-periphery index in line with the methodology proposed by Borgatti and Everett (1999) for each

[4] Network plots based on eigenvector centrality are available upon request.

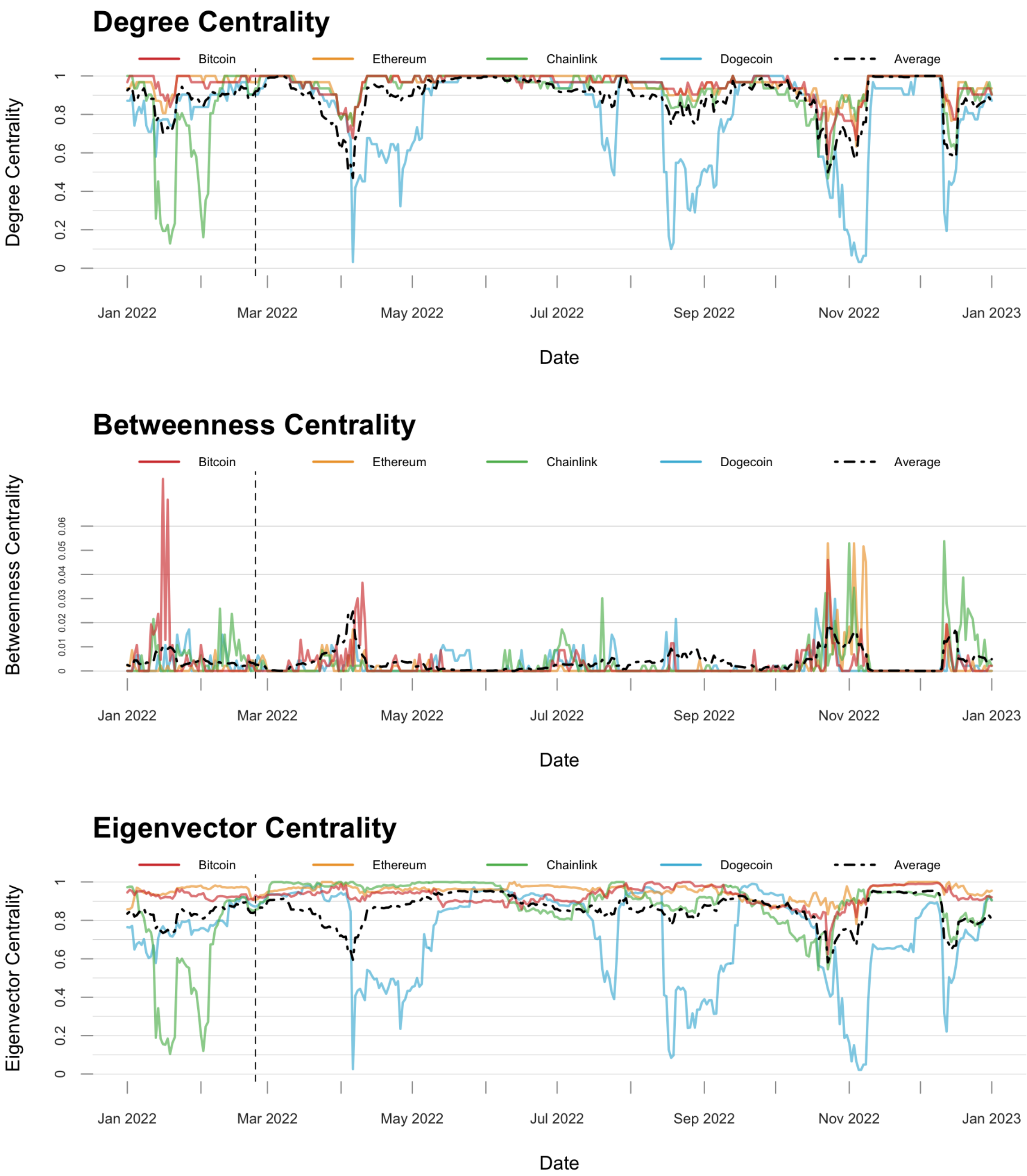

Figure 4: Plots of the (a) degree centrality (top), (b) betweenness centrality (middle), and (c) eigenvector centrality (bottom), for the Russia-Ukraine conflict war period of January 2022 to January 2023.

rolling window, as shown in Figure S2(a). This index is based on the maximal (Pearson) correlation of the network's adjacency matrix with a core-periphery model (optimal pattern matrix) (see Appendix B.2 for further methodological details). We note that as the index tends to a maximum value of 1, the network structure tends towards a strong core-periphery topology (Borgatti and Everett, 1999). It can be seen that the core-periphery index maintains a value in excess of approximately 0.75 for the majority of the war period, with a mean value of 0.813, reaching and maintaining the maximum value of 1 for extended periods. The increase and subsequent decrease in the network interconnectivity before and after the start of the war, respectively, is also reflected by the peaking of the index at 1 and subsequent dip to below 0.5. The overall negative level of assortativity, as has been found in financial markets (Hurd et al., 2017), suggests that the structure may be more of a hub-and-spoke form.

In comparison to the two pre-war periods, shown in Appendix Figures A1 and A3, away from the war period the centrality measures also show significant transitions and cycles between interconnectedness and

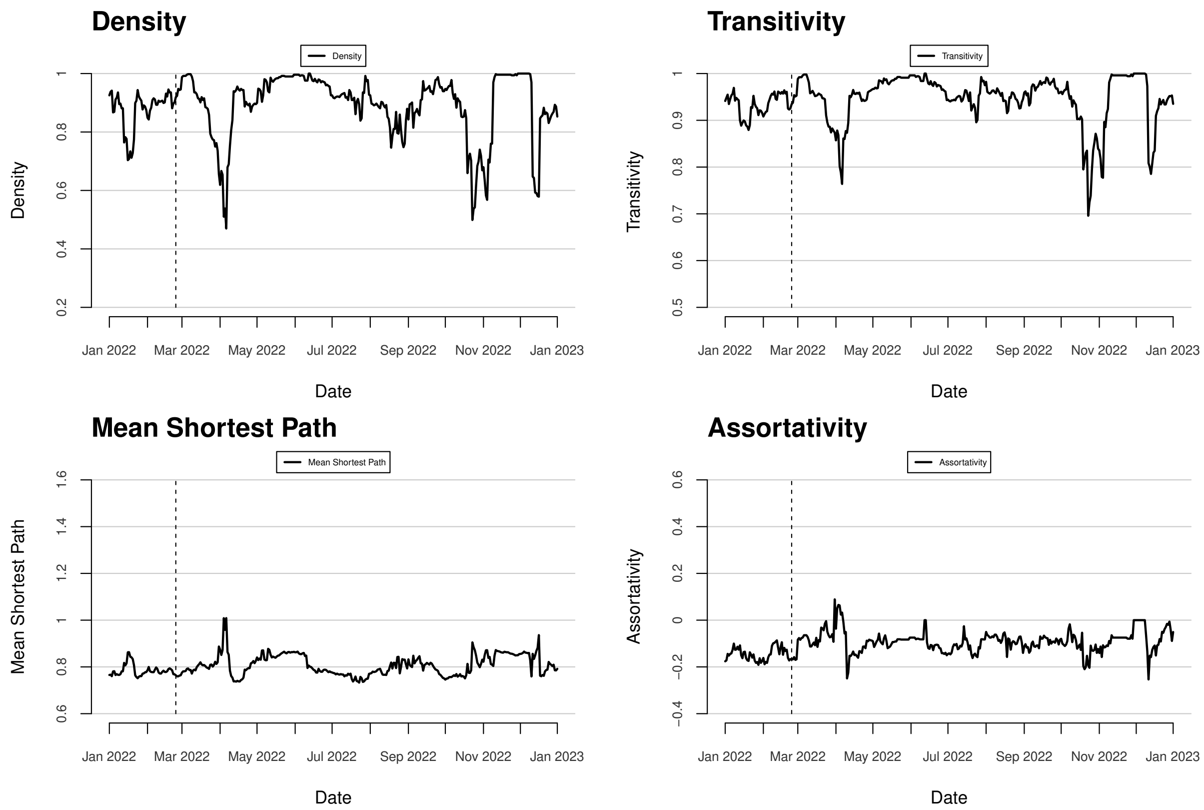

Figure 5: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Russia-Ukraine conflict war period of January 2022 to January 2023.

disconnectedness. For example, the highly interconnected nature of the cryptocurrency network in March 2020 corresponding with COVID-19 (Vidal-Tomás, 2021) and mid-2021, but also the disconnected nature in the first half of 2021 and October 2021. In addition, during the COVID-19 pandemic in 2020, large cryptocurrencies such as Bitcoin and Ethereum appeared dominant in terms of degree and eigenvector centrality, however, interestingly in the first half of 2021, larger cryptocurrencies were significantly less dominant. Density and transitivity similarly exhibit significant variations in the two pre-war periods. Likewise, in the time preceding the war period, the mean shortest path appears similar and fairly stable, but in the first pre-war period covering the COVID-19 pandemic, mean shortest path appears unstable with significant peaks. Assortativity also appears significantly more unstable during the pre-war periods, possibly indicating more significant changes in the cryptocurrency network structure and connectivity, compared with the war period.

4.2. Israel-Hamas Conflict

In comparison with the results for the Russia-Ukraine war period, we see both similarities and differences for the Israel-Hamas war period in Figure 6. The situation is somewhat similar just before the start of the war, as the cryptocurrency network appears relatively interconnected, though not as connected as before the start of the Russia-Ukraine conflict. In the immediate aftermath of the war, the cryptocurrency network gradually becomes disconnected before degree centrality reaches a minimum around one month later, similar to what was observed for the Russia-Ukraine conflict. Towards the end of 2023 and the beginning of 2024, the network shows signs of recovery and increased connectivity, but fails to sustain pre-war levels. A number of interesting observations emerge during this period. As the network becomes more disconnected, large cryptocurrencies exhibit a significant decline in their degree centrality, suggesting they may not be as resilient as expected. However, there is a notable spike in Bitcoin's betweenness centrality at the most disconnected point, implying that Bitcoin may be acting as a bridging point and power player, possibly even contributing to the network's disconnectedness. Additionally, the eigenvector centrality shows that in these disconnected periods, major cryptocurrencies like Bitcoin and Ethereum are less connected with other highly interconnected cryptocurrencies. This is similar to what was seen for smaller cryptocurrencies during disconnected periods in the Russia-Ukraine war period.

The behaviours of the global network properties appear somewhat similar to those observed for the

Russia-Ukraine war period. Density and transitivity exhibit almost the exact trends as for degree centrality, but for the case of the Israel-Hamas conflict, the magnitude of change in these metrics is much more significant especially when the network became disconnected, suggesting that the network structure overall may have experienced more significant changes, compared with during the Russia-Ukraine war. This is particularly evident in the level of transitivity - although it remains above 0.8 for the majority of the war period suggesting a relatively strong level of community structure, it does not peak as high as that for the Russia-Ukraine conflict period but drops much lower. Similarly, the mean shortest path transitions from being fairly stable prior to the start of the war, peaking significantly when the network becomes disconnected, and then more volatile after this - even more so than after the start of the Russia-Ukraine war. Once again, highlighting that the cryptocurrency network does not recover and become as interconnected after the start of the war. Similar to the Russia-Ukraine war period, there is evidence of a small world effect as indicated by our estimates of the dynamic rolling small-world index as shown in Figure S1(b). It can be seen that the small-world index exceeds the threshold value of 1, as defined in Humphries and Gurney (2008), for the whole war period, with a mean value of 1.591 and peaking higher than in the Russia-Ukraine war period, suggesting an extended small world effect. The level of assortativity appears very similar to that during the Russia-Ukraine war remaining negative but fairly stable throughout war period but exhibiting a significant peak in the aftermath of the start of the war, which is much greater in magnitude than that seen for the Russia-Ukraine conflict. The overall negative level may also suggest that the structure may be more of a hub-and-spoke form. Also similar to the Russia-Ukraine war period is the evidence of a strong core-periphery network structure, as indicated by our estimates of the dynamic rolling core-periphery index as shown in Figure S2(b). It can be seen that core-periphery index also maintains a value in excess of approximately 0.8 for the majority of the war period, with a mean value of 0.861. However, in contrast to the Russia-Ukraine war period the core-periphery structure appears to be less impacted by the start of the Israel-Hamas war, with the core-periphery index decreasing but only to a minimum of approximately 0.7.

Comparing these results with the two pre-war periods for the Israel-Hamas conflict, shown in Appendix Figures A5 and A7, we note a number of contrasting observations. In the pre-war periods, the level of network interconnectedness appears to be more stable, and the transitions between being more interconnected or more disconnected are not as volatile as in the war period. However, larger cryptocurrencies appear to dominate whereas smaller cryptocurrencies become very disconnected at various time points. In particular, the betweenness centrality in the second pre-war period shows similarities with the war period, but it can be observed that both Bitcoin and Ethereum exhibit high individual centrality in the second half of this period. Moreover, on average, the eigenvector centrality is relatively high in the pre-war periods, but in contrast to the war period, smaller cryptocurrencies exhibit significantly lower eigenvector centrality for extended periods. This suggests that pre-war, smaller cryptocurrencies seem to be less connected with other cryptocurrencies, and post-war, larger cryptocurrencies seem to be less connected with other cryptocurrencies. Whilst density, transitivity, and mean shortest path exhibit variations pre-war, compared with the war period they are generally much more stable. Pre-war assortativity is also negative like the war period, although there are a couple of periods where it peaks above zero becoming positive.

To further confirm the robustness of our results, we also repeated the above analysis for the two conflict periods, using networks constructed based on threshold values of both $\theta = 0.3$ and $\theta = 0.75$. As an example, the plots of the corresponding centrality measures over the Russia-Ukraine war period are shown in Supporting Information Figures S1 and S2, respectively. Similar trends and shapes exist in the centrality measures for these networks, with the magnitude of the trends under $\theta = 0.3$ ($\theta = 0.75$) being smaller (larger) compared with those obtained for $\theta = 0.5$. However, the patterns exhibited are consistent across the board, for example, the high level of interconnectedness after the start of the war, the transition between high and low interconnectedness between February and April 2022, the extended periods of high interconnectedness, etc. Unsurprisingly, the trends in the centrality measures for $\theta = 0.3$ are much smaller in magnitude as the corresponding networks constructed may include relatively weak comovements between cryptocurrencies, i.e. correlations close to 0.3. Arguably, these weakest comovements may be closer to being noise rather than a significant relationship, which dampens the overall trends. In contrast, the patterns in the centrality measures for $\theta = 0.75$ are much larger in magnitude, but using a high threshold results in networks that are constructed based only on extreme comovements between cryptocurrencies. Whilst these results may be more significant and perhaps reliable, the high threshold may lead to some relatively important comovements being omitted. Therefore, the results corresponding to $\theta = 0.5$ provide a reasonable middle ground and balance between the two cases of $\theta = 0.3$ and $\theta = 0.75$, and the above patterns were found to hold true for both the two war periods and for the global network properties.

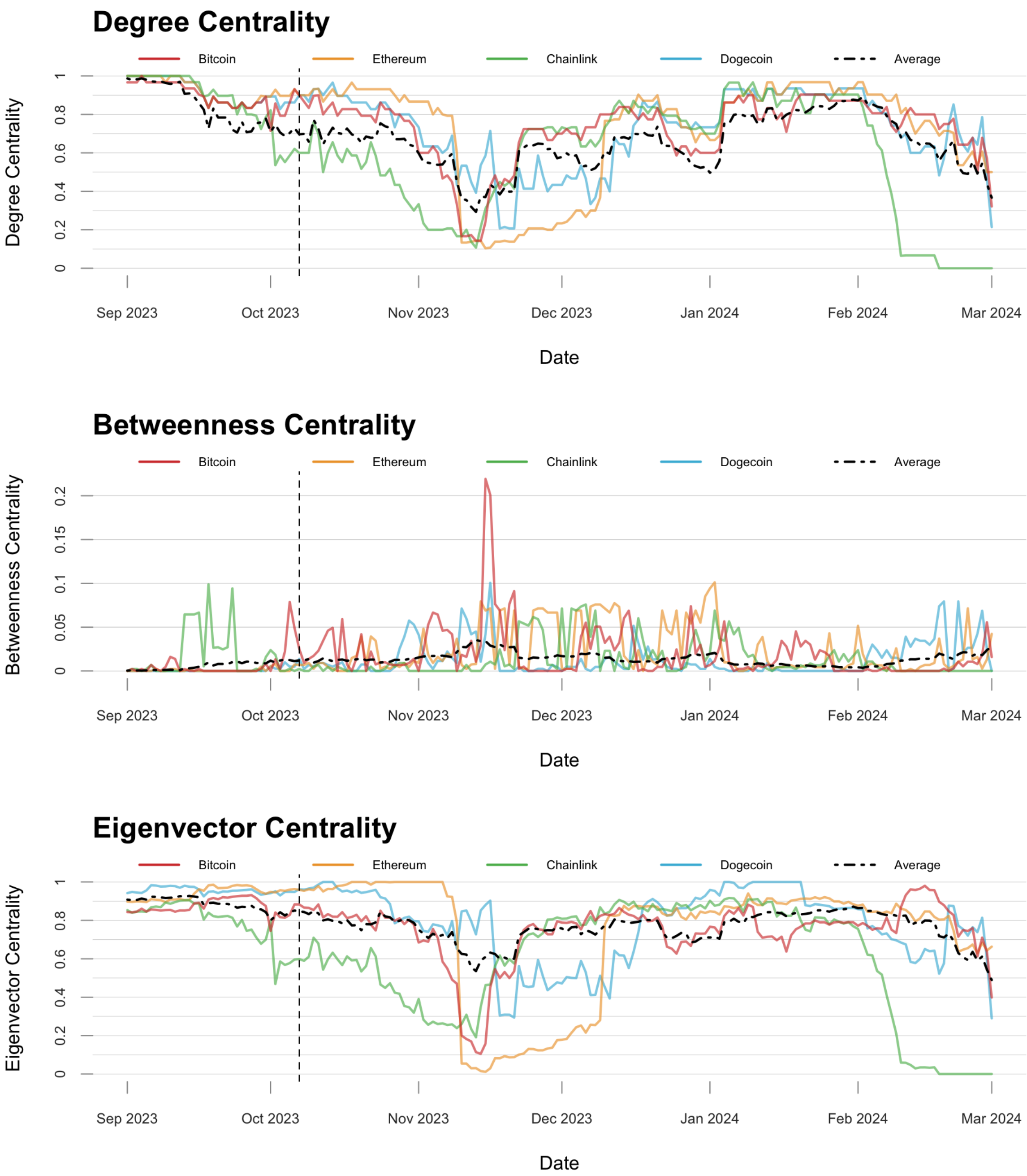

Figure 6: Plots of the (a) degree centrality (top); (b) betweenness centrality (middle); (c) eigenvector centrality (bottom), for the Israel-Hamas conflict war period of October 2023 to February 2024.

4.3. Network Analysis Discussion

For much of the Russia-Ukraine (Israel-Hamas) war period, the average degree centrality is above (below) 25, which is greater (less) than that found during the COVID-19 pandemic in Vidal-Tomás (2021). At key event times during the Russia-Ukraine conflict, such as the immediate aftermath of the start of the war, the degree centrality peaks, reflecting a highly interconnected environment that is traditionally related to financial crises. Whilst this is similar to what is found in Vidal-Tomás (2021) after key COVID-19 events, the same cannot be said for the Israel-Hamas conflict, where the outbreak of war is followed by an increase in disconnectedness. This suggests a slight difference in the impact of the wars on herding, connectedness, and market inefficiency.

The relatively high levels of pre-war connectedness in the run up to both the Russia-Ukraine and Israel-Hamas conflicts are in line with Mohamed (2022) who find evidence of herding behaviour between major

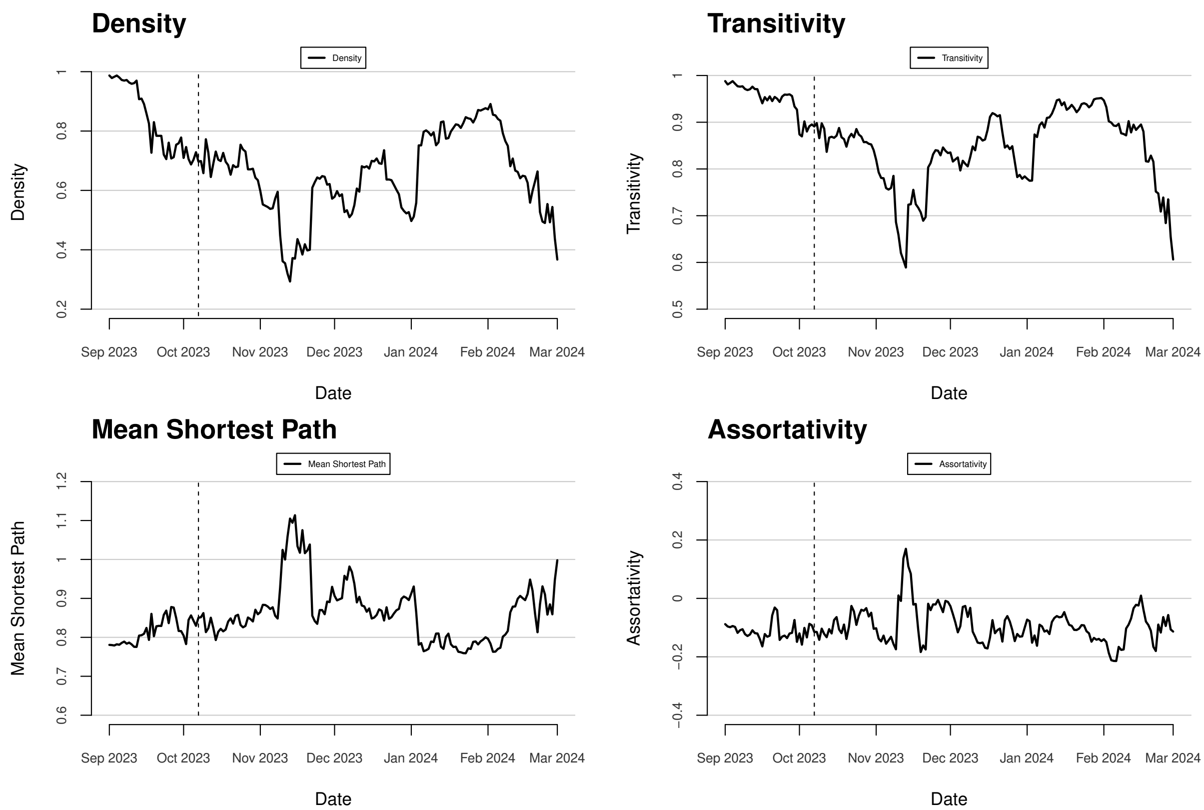

Figure 7: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Israel-Hamas conflict war period of October 2023 to February 2024.

cryptocurrencies such as Bitcoin, Ethereum, and Litecoin before the Russia-Ukraine conflict. Similarly, Bedowska-Sójka et al. (2022) show that shortly before the start of 2022, all stock markets experienced an increase in coherence with geopolitical risk at mid-frequency, which lasted through the first month of the Russia-Ukraine war, while Bitcoin and Ethereum also experienced something similar. A possible explanation is that the anticipation of such a geopolitical event may already have been factored into investors' decision making. This is not unreasonable given that growing tensions between Russia and Ukraine had been reported as early as late October 2021 (Diaconaşu et al., 2022), a number of months prior to the official start of the conflict. Similarly, tensions between Israel and Hamas have existed for many years, and had grown once again in the year before the start of the most recent conflict (Britannica, 2024). Additionally, Jackson and Mitts (2023) found that there was "a significant spike in short selling" in exchange-traded funds (ETF) by the principal Israeli-company and other Israeli companies a few days days before the Hamas attack on October 7, 2023, and this short selling was much greater than that observed for other conflicts/crises. Moreover, they observed that more than 4 million new shares were sold between September 14 and October 5 yielding profits just for one Israeli company alone. Other supporting recent research by Bhattacharjee et al. (2025), who conducted an event study to examine the impact of the war on the stock markets of trading partners, stated that "investors may have anticipated the war" due to fear among investors as observed in the positive CAR value before the event changing into negative after. Due to uncertainties looming over traditional markets, many investors may have pre-emptively swapped out traditional assets for cryptocurrencies, leading to relatively high interconnectedness in the build up to the starts of both conflicts.

The short term increase in interconnectedness after the start of the Russia-Ukraine war shows similarities with the effect from COVID-19 found in Caferra and Vidal-Tomás (2021). This also supports the results of Bedowska-Sójka et al. (2022) who find that after the war began, major cryptocurrencies showed varying levels of correlation with geopolitical risk and coherence at short frequencies. However, this does not appear to be the case for the Israel-Hamas conflict. On the one hand, the levels of synchronicity and interconnectedness may be associated with the levels of attention that cryptocurrencies had received since the starts of the respective wars. As illustrated in Figure 8, taking Google search trends[5] of the terms 'Bitcoin' and 'Ethereum' as proxies for attention, we find that the attention in the aftermath of the Russia-Ukraine conflict was

[5] (Add footnote about how Google Trends search volume is computed)

significantly higher than that immediately following the outbreak of the Israel-Hamas conflict. Moreover, upward changes in attention in the aftermath of war were far greater for the Russia-Ukraine conflict. This suggests that as geopolitical risks surged, there was a significantly heightened interest in cryptocurrencies after the Russia-Ukraine conflict, possibly seen as alternative assets, safe havens or a viable path to transfer money away from conflict zones during this period of unease. Historically, during times of geopolitical strife, non-traditional assets like gold have been seen as safe havens. Thus, this interconnectedness might suggest that cryptocurrencies were increasingly being viewed in a similar light. Indeed, Koch and Dimpfl (2023) show that increased attention and herding-like behaviour cause major cryptocurrency prices to move in sync, while this influence weakens with a lower market capitalisation. The lack of a jump in interconnectedness following the outbreak of the Israel-Hamas conflict could be attributed to investors learning from the Russia-Ukraine conflict, and being ready and aware of which cryptocurrencies to invest in to reduce the impact of the geopolitical risk.

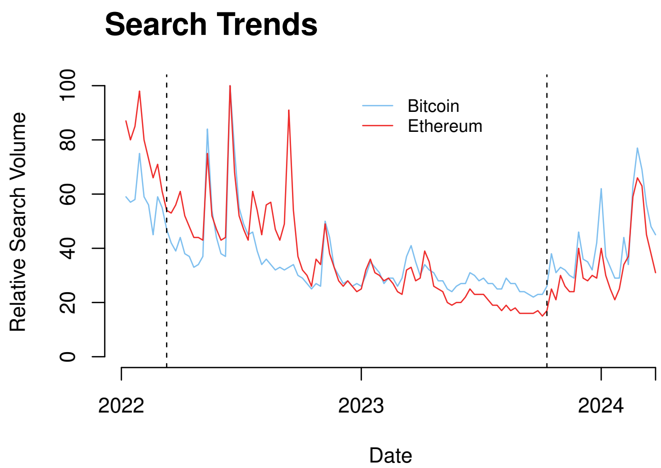

Figure 8: Plot of the Google search trend volume data for the terms 'Bitcoin' and 'Ethereum', over the period of January 2022 to March 2024.

Furthermore, the transitions between high and low interconnectedness in the war periods for both conflicts may also reflect changes between market states. Specifically, the immediate aftermath of the Russia-Ukraine conflict may correspond with a bearish market. This is confirmed when cross referencing the trend in cryptocurrency prices at this time, where prices were found to be falling together across the market and reaching a local minimum. A possible bullish phase followed where cryptocurrencies are recovering and rising but not in sync. Similarly, the aftermath of the Israel-Hamas conflict may correspond with a bullish phase, as some cryptocurrencies showed stable increases in prices of varying degrees, whilst others showed stable prices. These transitions are supported by the results of Khalfaoui et al. (2023) who find the existence of a short term negative (positive) effect of war attention on cryptocurrencies under bearish (bullish) markets leading to greater (less) coherence.

On the other hand, however, these transitions may still be linked to the stock markets, as Gambarelli et al. (2023) find that major cryptocurrencies such as Bitcoin and Ethereum show strong positive correlation with European stock markets during the early Russia-Ukraine conflict period. We note that Yousaf et al. (2022a) find that post-COVID-19, European and Asian stock markets were significantly and negatively affected. Given that the cryptocurrency market, during the Russia-Ukraine conflict, exhibits a similar behaviour in response to COVID-19, this might suggest that cryptocurrencies are influenced by the reactions of, in particular, European stock markets shortly after the start of the war. This would be in line with Santorsola et al. (2022) who note that the Eurozone and UK stock markets were most affected by the start of the Russia-Ukraine war.

However, the general relation between cryptocurrencies and stock markets in the short run after the two conflicts appears to be differ. The cryptocurrency network becoming disconnected is in line with Kumar et al. (2023), who show that cryptocurrencies are able to absorb volatility shocks from the war, and exhibits similarities to the "political property" of oil (Diaconaşu et al., 2022) corresponding with short term increases in cryptocurrency prices after the conflicts start. Furthermore, these results support the "proximity penalty" concept noted by (Diaconaşu et al., 2022) where markets "closer" to the war are more negatively impacted.

This importance of geographical location is highlighted by Martins (2024) who analyse stock indices and sovereign bond yields for the seven largest debt-issuing countries, Israel and the Eurozone. Results indicate that "negative abnormal returns in global equity markets are limited to the Middle East region", closest to the war zone. Bhattacharjee et al. (2025) also analyse the Morgan Stanley Capital Index (MSCI) during 2023, with similar results showing an asymmetric response among Israel's trading partners that varied due to different factors such as geographic proximity to Israel and economic standing. Khan and Rehman (2023) apply the TVP-VAR approach to leading global stock indices during the first three months of the Israel-Hamas conflict, and find "a robust interconnectedness of 82.58% among MSCI ACWI, MSCI World, MSCI Emerging Markets, Israel Index, S&P GCC Composite, and Dow Jones Global Index in the full sample". In other words, cryptocurrencies appear to able to avoid this negative influence of close geographic proximity to the warring nations due to their global and location-independent nature.

It is possible to find events that coincide with these changes in the level of interconnectedness, for example, in April 2022 the Russian Rouble rebounded to pre-war levels; Ukraine reclaimed the entire Kyiv region; Shell exited Russia resulting in a £3.8 billion hit, and in late October 2022 Russia agreed to reinstate the Black Sea grain deal to support crucial food exports from Ukraine. In relation to the Israel-Hamas conflict, since November 2023 Yemen's Iran-backed Houthi rebels have been hijacking and attacking crude oil tankers in the Red Sea; Israel's Supreme Court struck down a controversial change to the judiciary in January 2024; Israeli troops raidied and carryied out an operation at al-Amal Hospital in Khan Younis in February 2024 (BBC, 2023; CNN, 2024; Alarabiya News, 2024). On the surface, this may suggest that signs of greater economic or financial stability may potentially be correlated with less dependence on cryptocurrencies and thus lower interconnectedness.

Taken together, all of the results above suggest that the cryptocurrency markets may experience varying levels of market (in)efficiency after the onset of war, which may provide investors with an opportunity to profit from this and similar conflicts. However, further investigations are required to determine whether these transitions in interconnectedness (and possible market inefficiency) are statistically and significantly connected with war-related events, cryptocurrency-related events, and/or other events.

4.4. TVP-SV-VAR model

In this section, due to limitations of the *Ox Metrics* software as mentioned earlier, we construct one TVP-SV-VAR model to investigate the time-varying relationships between the logarithm of global geopolitical risk index ($\ln GPRD$), the logarithm of crude oil volatility index ($\ln OVX$), the return of US Dollar Index (r_{DXY}), and the cryptocurrency network characteristics. The other TVP-SV-VAR is constructed to investigate the time-varying relationships between gold returns (r_{GOLD}), the logarithm of Google Trend Index ($\ln GTU$), and the cryptocurrency network characteristics. All data were at a daily frequency and were confirmed to be stationary, as indicated by significant ADF test values shown in Table 1 and Table 2. For estimation, the model's lag order was set to one based on the Bayesian Information Criterion (BIC), with 10,000 MCMC samples drawn. The time-point analysis effectively captures the relationships between variables at specific moments with varying lags. In Section 4.5, we present the impulse response results over 15 lags (representing 15 trading days) during the Russia-Ukraine and Israel-Hamas wars. Additionally, Section 4.6 offers a detailed examination of the time-varying impulse response analyses for both conflicts. Given the present study's emphasis on the impact of war, time-point analysis is particularly suitable for accurately capturing these dynamic interactions.

4.5. Time point impulse response analysis

The results of the time-point impulse response analysis are presented in Figures 9, 10 and 11, and highlight the varying effects of the variables GPRD, DXY, OVX, Gold and GTU on the three key centrality measures (DC, BC and EC) and four global measures (assortativity, density, transitivity and MSP), in response to the two geopolitical events (shocks). For BC, $\ln GPRD$, $\ln OVX$, r_{DXY}, and $\ln GTU$ indicate a slight negative effects following the Russia-Ukraine and the Israel-Hamas conflicts, reducing the significance of intermediary nodes. Compared with the Russia-Ukraine war, the effects of $\ln GPRD$ and $\ln OVX$ are both more muted and short lived in response to the Israel-Hamas conflict, while the negative effects of r_{DXY} and $\ln GTU$ are stronger after the Israel-Hamas conflict. Additionally, r_{GOLD} significantly increases BC after the Israel-Hamas conflict starts, reflecting greater importance of intermediary nodes as gold's return rises.

Regarding DC and EC, the $\ln GPRD$ initially causes a positive effect on network connectivity following the Russia-Ukraine war, which then quickly diminished to zero. In contrast, r_{GOLD} exhibits a relatively persistent positive effect on DC and EC throughout this period. After the outbreak of the Israel-Hamas conflict, however, both $\ln GPRD$ and r_{GOLD} demonstrate short-term negative effects on network connectivity, except for the continued positive influence of r_{GOLD} on EC.The r_{DXY} triggers a sharp decline in both DC and EC following the Russia-Ukraine conflict, indicating a reduction in node connectivity associated with US dollar appreciation. In contrast, after the onset of the Israel-Hamas conflict, r_{DXY} produces a short-lived positive effect on network connectivity. During both conflicts, $\ln OVX$ and $\ln GTU$ temporarily enhanced DC and EC, although the impact of $\ln GTU$ is minimal. However, the impact of $\ln GTU$ is relatively limited, suggesting that crude oil volatility and public attention can temporarily boost overall network connectivity. Overall, $\ln GPRD$, r_{DXY}, and $\ln OVX$ exert stronger effects on DC and EC than r_{GOLD} and $\ln GTU$. Notably, $\ln OVX$ consistently increases network centrality during both conflicts, particularly strengthening node connectivity and intermediary roles in periods of heightened geopolitical uncertainty.

Figure 11 presents the time-point impulse response results of GPRD, DXY, OVX, Gold and GTU on the key global network metrics of assortativity, density, transitivity, and MSP, within the cryptocurrency network, in the context of two geopolitical events: the Russia-Ukraine conflict (red solid line) and the Israel war (green dashed line). These results demonstrate how these macroeconomic variables affect the network's structural characteristics during different geopolitical crises. The impulse response analysis reveals that geopolitical events like the Russia-Ukraine conflict and the Israel war have differing impacts on network assortativity and density in the cryptocurrency market.

For assortativity, $lnGPRD$ initially decreases homophily during the Russia-Ukraine conflict, but this effect quickly dissipates. During the Israel-Hamas war, the effect quickly shifts to a positive effect, and then plateaus at zero. Conversely, during the Russia-Ukraine conflict, r_{DXY} and $\ln OVX$ have brief positive impacts on assortativity, whereas during the Israel-Hamas war, they exert short-term negative effects, indicating a decrease in homophily. r_{GOLD} and $\ln GTU$ have a slight short-term positive impact on assortativity.

In terms of network density, transitivity and MSP, $\ln GPRD$ initially boosts density and transitivity while decreasing MSP during the Russia-Ukraine conflict, and then these effects quickly stagnated at zero. For the Israel-Hamas conflict, $\ln GPRD$ starts with negative impacts on density and transitivity, while exerting a positive effect on MSP, ultimately leveling off at zero. This shows that, following the Russia-Ukraine conflict, $\ln GPRD$ facilitates the connections between cryptocurrencies, whereas, after the Israel-Hamas conflict, it weakened the interconnections among cryptocurrencies. Conversely, following the Russia-Ukraine conflict, r_{DXY} reduced network density and transitivity in the short term, while increasing MSP. However, after the Israel-Hamas conflict, r_{DXY} enhanced density and transitivity, while decreasing MSP. These effects also quickly tended to zero. This suggests differing dynamics in network interconnectedness under each geopolitical event. Furthermore, both $\ln OVX$ and $\ln GTU$ raise density and transitivity, and reduce MSP, thereby promoting network interconnectivity during both conflicts. Among these, the impacts of the $\ln GTU$ are relatively mild. But the impacts of r_{GOLD} on network interconnectedness varies. Following the Russia-Ukraine conflict, r_{GOLD} increases the density and MSP, while decreasing transitivity. In contrast, after the Israel-Hamas conflict, r_{GOLD} has negative impacts on density, transitivity and MSP.

Overall, the results indicate that macroeconomic variables such as $\ln GPRD$, r_{DXY}, and $\ln OVX$ significantly affect the cryptocurrency network's structure, while the effects of r_{GOLD} and $\ln GTU$ are relatively minor. After both conflicts, $\ln OVX$ and $\ln GTU$ enhanced nodes' connectivity and influence, thereby strengthening the interconnectivity of cryptocurrency networks. The effects of $\ln GPRD$, r_{DXY}, and r_{GOLD}, however, vary depending on the geopolitical event. Following the Russia-Ukraine conflict, $\ln GPRD$ increases nodes' connectivity and influence, promoting connections between nodes in the network. In contrast, r_{DXY} decreases nodes' connectivity and influence, weakening connections between nodes. The effects are reversed after the Israel-Hamas conflict. Although the impact of r_{GOLD} on BC and DC was similar to that of $\ln GPRD$, its effects on network connectivity are inconsistent. These findings highlight the sensitivity of the cryptocurrency market to geopolitical and economic shocks.

4.6. Time-varying impulse response analysis

Time-varying impulse responses at different lags reveal how the relationships between variables evolve over time. Figure 12 displays the impulse response of $\ln GPRD$, r_{DXY}, $\ln OVX$, r_{GOLD} and $\ln GTU$ to network assortativity, density, transitivity and MSP. In the short term, $\ln GPRD$, r_{DXY}, $\ln OVX$, r_{GOLD} and $\ln GTU$ generally have positive effects on assortativity, suggesting that these variables impact the network up to one day ahead. With respect to density, transitivity, and MSP, $\ln GPRD$ generally leads to a short-term decrease in density and transitivity, except during extreme periods such as Q2-Q3 2020, Q1-Q3 2022, and Q1 2023, where $\ln GPRD$ has a positive effect. The MSP demonstrates the opposite effect. These

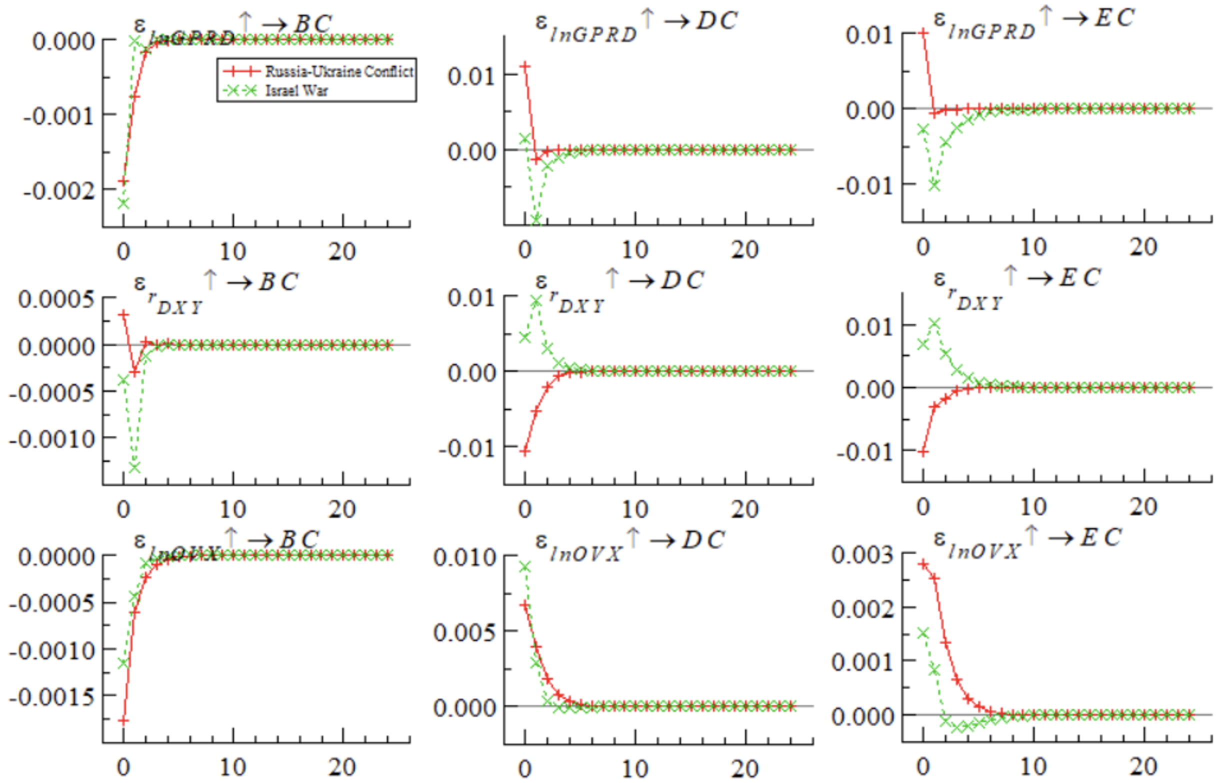

Figure 9: The timepoint impulse responses of GPRD, DXY, and OVX are examined with respect to three key centrality measures: betweenness centrality (BC), degree centrality (DC), and eigenvector centrality (EC).

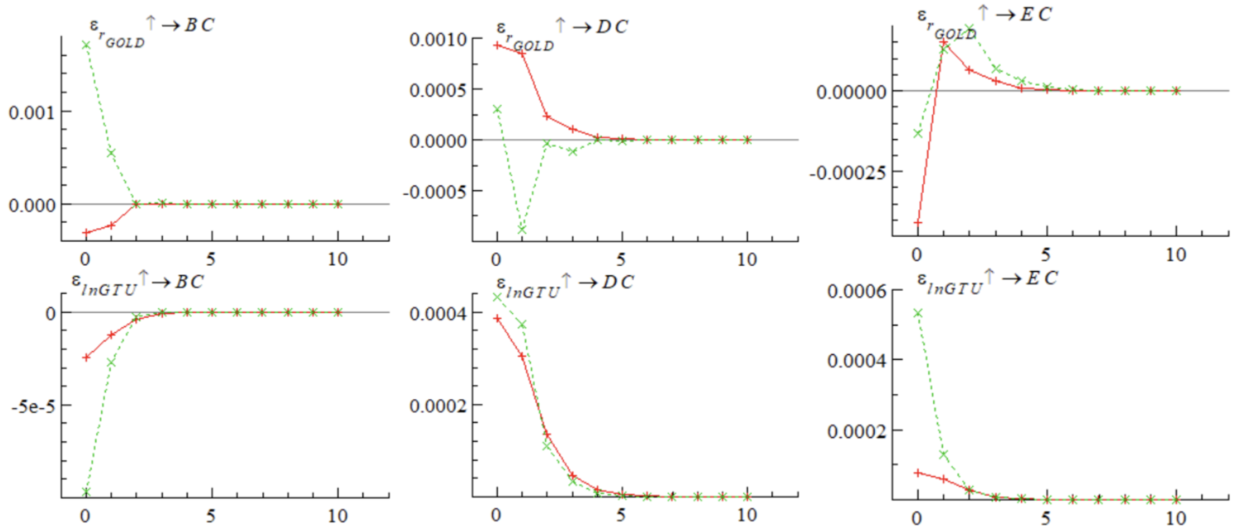

Figure 10: The timepoint impulse responses of GOLD and GTU are examined with respect to three key centrality measures: betweenness centrality (BC), degree centrality (DC), and eigenvector centrality (EC).

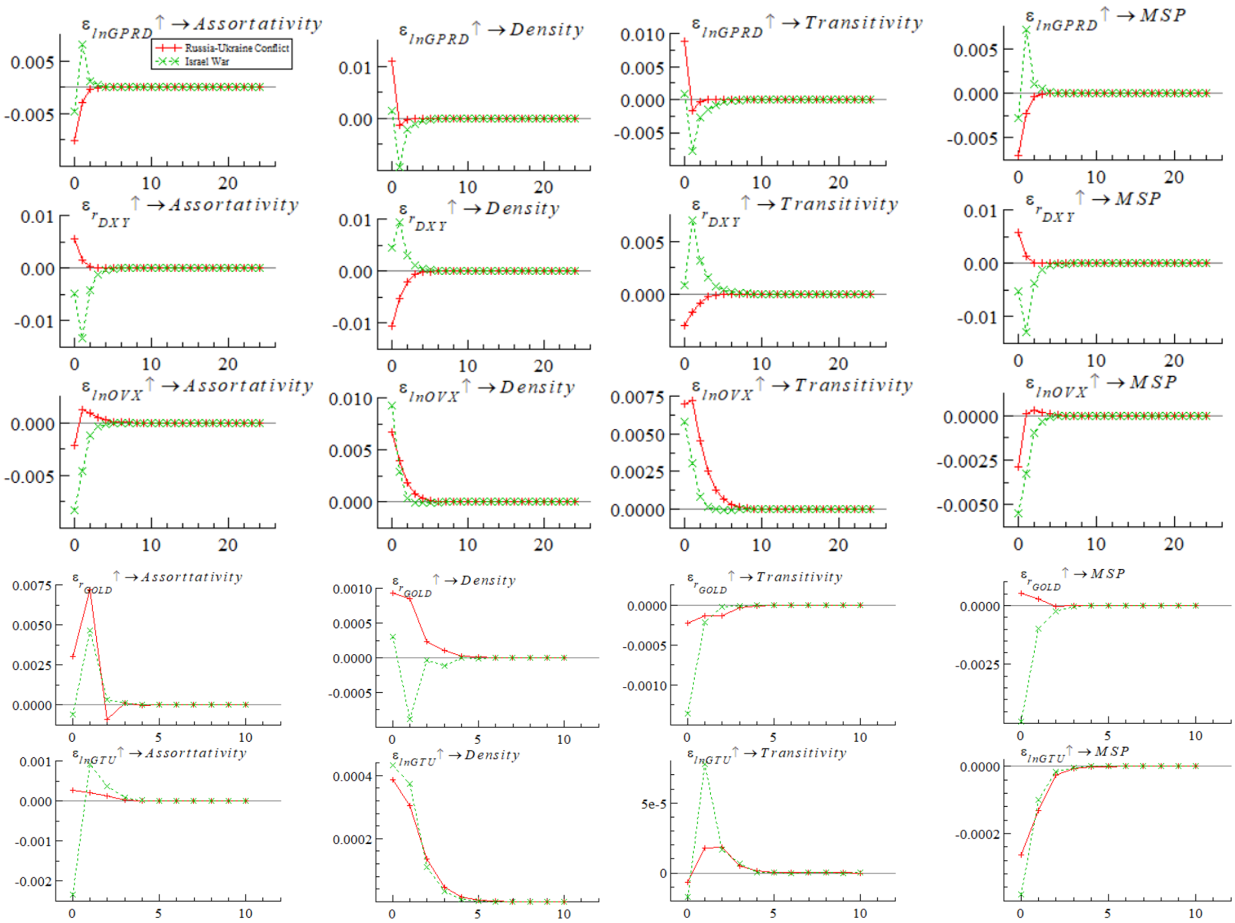

Figure 11: The timepoint impulse responses of GPRD, DXY, OVX, GOLD and GTU are examined with respect to four key global measures: Assortavity, Density, Transitivity and MSP.

extreme events likely correspond to the COVID-19 pandemic in 2020, the Russia-Ukraine war in February 2022, which are in line the results in Section 4.1 and suggests that $\ln GPRD$ is a significant driver of the interconnectedness in the cryptocurrency network. During these periods, capital inflows into the cryptocurrency market declined, and asset returns exhibited synchronous volatility. Before 2022, an increase in r_{DXY} generally led to higher network density, higher transitivity, and lower MSP. However, after 2022, an increase in the r_{DXY} generally resulted in a decrease in both density and transitivity, while MSP experienced an upward trend. In contrast, r_{GOLD} and $\ln GTU$ demonstrated an opposing effect. This shift coincides with the U.S. Federal Reserve's interest rate hikes beginning in March 2022, which led to the appreciation of the U.S. dollar and dollar-denominated assets. At the same time, the occurrence of the Russia-Ukraine conflict also increased geopolitical risks, leading to a rise in gold returns. As a result, more cryptocurrency assets were likely converted into dollar-denominated assets and gold, reducing the interconnectedness of the cryptocurrency network. Similarly, we observed that at the onset of the Russia-Ukraine war, the impact of the r_{DXY} was negative, suggesting that the r_{DXY} may also be an important driver of interconnectedness within the cryptocurrency network. The increase in $\ln GTU$ indicates that the growing market attention towards cryptocurrencies could enhance herding behavior, thereby strengthening the interconnectedness of the cryptocurrency market. Regarding the impact of $\ln OVX$ on density, an increase in $\ln OVX$ significantly intensifies network density and transitivity in both the short and medium term, while reducing MSP. This suggests that as crude oil volatility rises, the comovement of cryptocurrency returns increases, possibly due to the influx of hedging and speculative capital, and herding behavior, which strengthens interconnectedness within the cryptocurrency market.

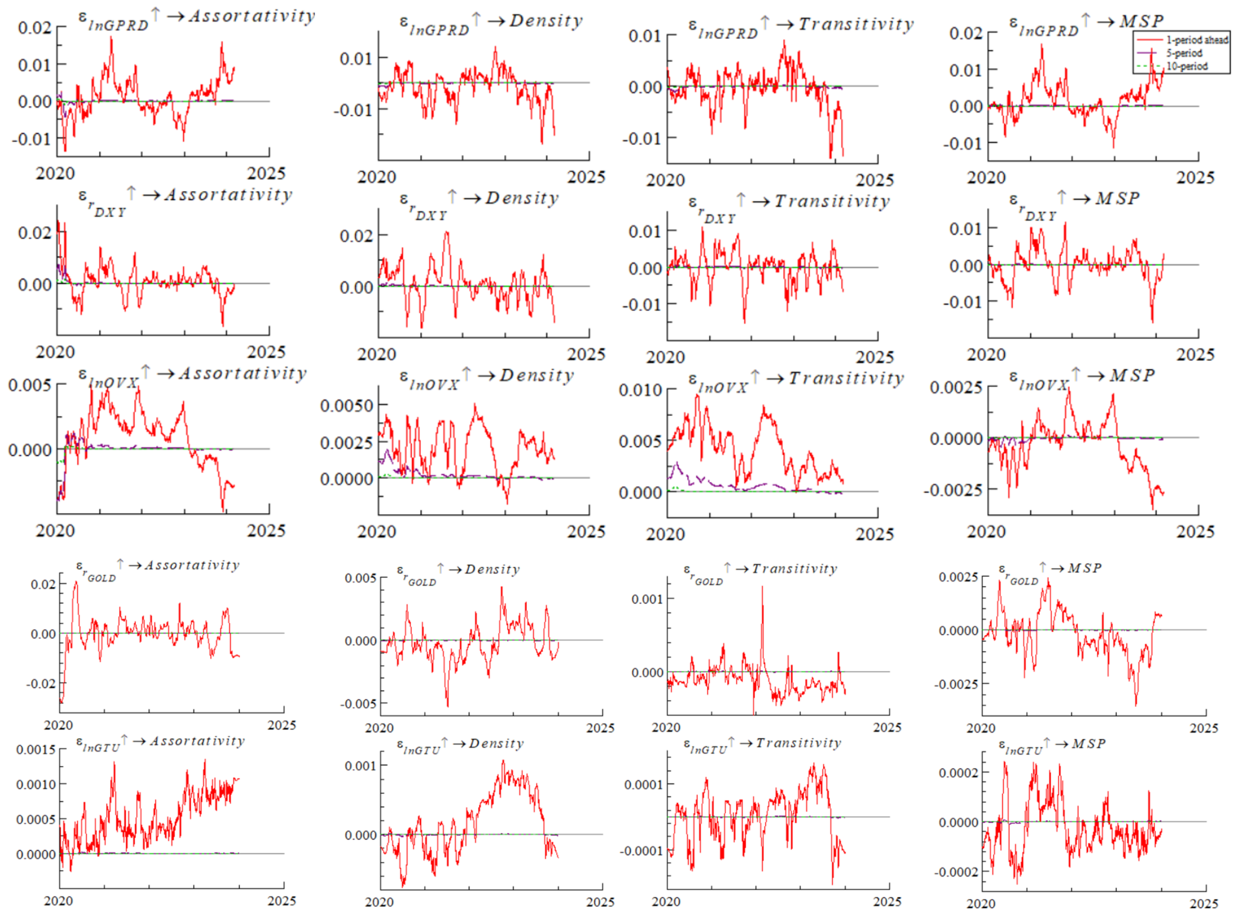

Figure 12: The time-varying response with different lags of Assortativity, Density, Transitivity and MSP.

Figure 13 shows the time-varying impulse responses of $\ln GPRD$, r_{DXY}, $\ln OVX$, r_{GOLD} and $\ln GTU$ to BC, DC, and EC. $\ln GPRD$ is expected to positively affect BC, as rising geopolitical risk often triggers increased capital flows into the cryptocurrency market for hedging purposes. This increases the probability of digital assets being located on the shortest paths between other pairs. Both $\ln OVX$ and $\ln GTU$ have similar effects on BC. The heightened crude oil volatility introduces more uncertainty into the energy market, and the growing attention of investors towards crytocurrency assets prompt investors to use digital assets as hedging tools. However, during the sample period, the short-term (1-period ahead) responses of both $\varepsilon_{\ln GPRD\uparrow} \rightarrow BC$ and $\varepsilon_{\ln OVX\uparrow} \rightarrow BC$ are contrary to expectations. This deviation may be attributed to significant global events, such as the COVID-19 pandemic, the Russia-Ukraine conflict, and the Israel-Hamas war, which likely prompted investors to shift towards more diversified assets like crude oil, gold, and U.S. dollar assets. Consequently, the intermediary degree of cryptocurrency network nodes decrease. Similarly, increases in r_{DXY} and r_{GOLD} generally impacts BC negatively. The appreciations of the U.S. dollar and gold cause capital to flow out of cryptocurrencies and into dollar-denominated assets, stablecoins like USDT, or gold, which further reduce the intermediary degree of cryptocurrency network nodes.

Compared to BC, $\ln GPRD$, r_{DXY}, $\ln OVX$, r_{GOLD} and $\ln GTU$ have more positive effects on DC and EC, particularly after 2022. Specifically, after 2022, $\ln GPRD$ initially exerted a positive influence on DC and EC for about a year, before transitioning to a negative impact. Meanwhile, r_{GOLD} has negative influences on DC and EC for approximately six months, followed by a positive effect. $\ln GTU$ generally has positive influences on DC and EC. These findings align with the results of density, transitivity, and MSP, suggesting that network interconnectedness is initially affected by increasing geopolitical risks, and then further influenced by DXY, GOLD, and GTU. Additionally, $\ln OVX$ shows short-term and medium-term positive effects on DC and EC throughout the sample period, indicating that increased volatility in crude oil prices not only enhanced interconnectedness within cryptocurrency networks but also amplified the influence and connections of the nodes. Overall, $\ln GPRD$, r_{DXY}, $\ln OVX$, r_{GOLD} and $\ln GTU$ influence cryptocurrency network interconnectedness by affecting investors' diversification strategies between assets like cryptocurrency assets, US dollar-denominated assets, gold and crude oil.

4.7. Implications for Strategic Cryptocurrency Use in Conflict Zones

The findings of this study have significant real-world implications for strategic decisions involving cryptocurrencies in conflict zones like Ukraine and the Middle East. For actors in Ukraine, this research provides critical insights into how cryptocurrency market structures respond to geopolitical tensions, offering practical guidance for managing economic risks, optimizing fundraising efforts, and navigating sanctions.

Specifically, our results highlight the potential of Ethereum for effective fundraising during geopolitical conflicts. Ethereum's high interconnectedness during periods of geopolitical risk ensures stability and liquidity, making it an effective platform for receiving donations and converting them into other currencies. Its smart contract functionality supports complex fundraising mechanisms, providing transparency and automated fund management that appeal to donors seeking accountability. Additionally, Ethereum's decentralized finance (DeFi) capabilities allow for the creation of pooled funds or yield-generating strategies, increasing the value of donations and offering financial resilience during economic instability. These attributes likely contribute to Ukraine's preference for Ethereum in its fundraising efforts, providing stable and reliable channels for international support.

Moreover, the study finds that market interconnectedness often increases before conflicts escalate, as investors anticipate potential impacts. Ukrainian actors can use this insight to time their market entries or exits, securing investments during periods of stability or shifting capital into safer assets. The comparison of network dynamics between larger and smaller cryptocurrencies, particularly during the Russia-Ukraine conflict, further informs asset prioritization strategies. Understanding the "small world" structure of cryptocurrency networks, where major cryptocurrencies remain interconnected while smaller ones become isolated, provides valuable insights for managing investment risks.

Additionally, the study's analysis of macroeconomic factors, such as geopolitical risk, the U.S. Dollar Index, oil volatility and gold returns, as well as the Google Trend Index, offers a comprehensive framework for Ukrainian policymakers to forecast the impact of external economic shocks on cryptocurrency markets. The findings show that, alongside the significant roles of geopolitical risk, oil volatility, and the U.S. Dollar Index, gold returns provide further insight into safe haven behaviour and asset reallocation during periods of heightened uncertainty. Moreover, the inclusion of the Google Trend Index captures shifts in market attention and sentiment, further enhancing the ability to monitor and anticipate abrupt changes in market connectivity. This multidimensional understanding can guide regulatory adjustments to stabilize local markets and bolster the resilience of the digital economy in response to complex global events.

Finally, the research underscores the potential role of cryptocurrencies in evading sanctions. Ukrainian entities could leverage decentralized assets to maintain financial connectivity with global markets, using these insights to ensure that critical financial flows are preserved, even under restrictive economic and political conditions.

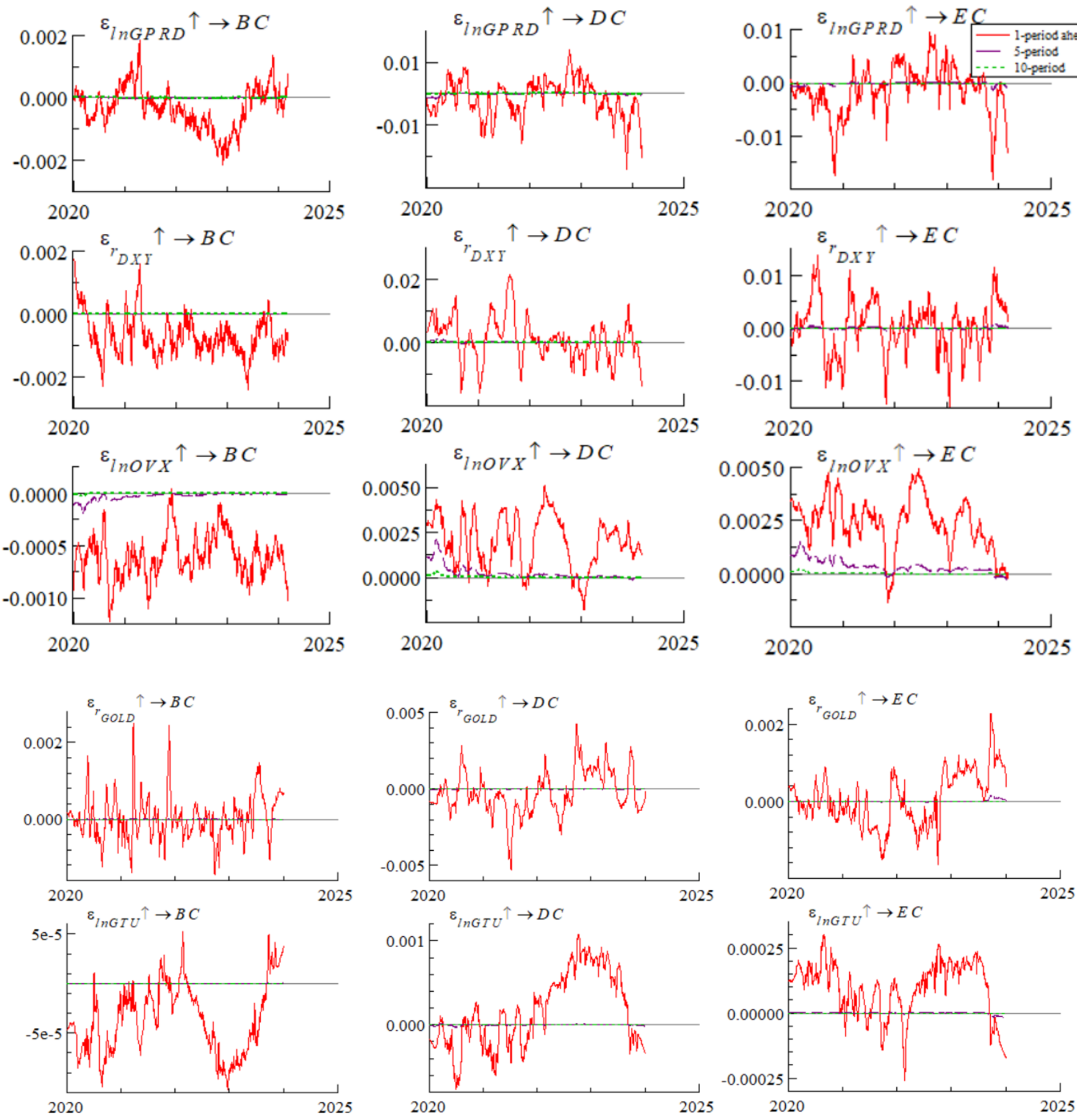

Figure 13: The time-varying response with different lags of BC, DC and EC.

5. Conclusion

In this paper, we analyse the evolution of the cryptocurrency market network structure during two recent military conflicts, the first year of the 2022 Russia-Ukraine war and the first six months of the 2023 Israel-Hamas war, and provide a comparison with a number of pre-war periods. Our analysis of the dynamic cryptocurrency network structure based on the correlation between cryptocurrency returns reveals both similarities and differences in the periods before and after the conflicts commence.

Our results show that before both wars officially start, the cryptocurrency network is highly connected, possibly due to investors factoring in information about tensions in anticipation of conflict, and moving investments over to the cryptocurrency market. After the wars break out, the network becomes significantly disconnected as evidenced by node and network level properties. On the one hand, after the outbreak of the Russia-Ukraine conflict, we observe a small world effect, where larger cryptocurrencies remain closely connected with each other, and smaller cryptocurrencies connect to few large cryptocurrencies. On the other hand, after the outbreak of the Israel-Hamas conflict, we observe larger cryptocurrenices becoming significantly more disconnected, which may be driving the overall disconnectivity, with the network not sustaining pre-war levels of interconnectedness. A slight difference with the Russia-Ukraine conflict, is that the network actually became highly interconnected for short period, immediately following the outbreak of war, becoming disconnected. This may be attributed to the significantly higher attention on the war compared with that associated with the Israel-Hamas conflict. The disconnected network structures following the wars suggests that the cryptocurrency market is able to absorb volatility shocks from the stock markets, and avoid the negative influence from geographical proximity to the war locations, due to their global and location-independent nature. The transitions between high and low connectedness may also correspond with changes between bullish and bearish market states.

Further analysis using the TVP-SV-VAR model examined the relationships between key economic variables, such as geopolitical risk, the U.S. Dollar Index, oil volatility and gold returns, as well as the Google Trend Index and cryptocurrency network characteristics. The results indicate that these macroeconomic variables significantly shape the cryptocurrency market network, with varying effects observed across the Russia-Ukraine and Israel-Hamas conflicts. Geopolitical risk exerts a more sustained positive influence on degree and eigenvector centralities during the Israel-Hamas conflict, emphasizing the increasing prominence of key cryptocurrencies as intermediaries under heightened geopolitical uncertainty. Conversely, the U.S. Dollar Index had a sharp negative effect on centrality measures immediately following the Russia-Ukraine conflict, reflecting reduced network connectivity and influence due to initial dollar appreciation; however, this impact stabilizes over time. Notably, oil volatility consistently enhances network centrality and density during both conflicts, suggesting increased crude oil market volatility promotes stronger node connectivity and greater intermediary roles, likely driven by hedging, speculative behavior, and market herding. Additionally, gold returns exhibit varying but significant influences on network centrality measures, initially negatively impacting node connectivity and intermediary roles following the Russia-Ukraine conflict before eventually transitioning to a sustained positive effect. During the Israel-Hamas conflict, rising gold returns notably increased the betweenness centrality, underscoring the heightened importance of intermediary nodes as market participants turned towards gold for its safe-haven properties. In contrast, the Google Trend Index consistently demonstrated a positive effect on network centralities, indicating that increased market attention and investor sentiment toward cryptocurrencies strengthens overall network interconnectedness, potentially due to amplified herding behaviors and speculative trading activities. Furthermore, the Israel-Hamas conflict induced more gradual yet persistent shifts in network assortativity and density, while the Russia-Ukraine conflict resulted in sharper, transient disruptions. The impulse response analysis also revealed evolving impacts of these economic variables on network assortativity and density over the observed periods. Although geopolitical risk generally increases network density in the short term, extreme events including the COVID-19 pandemic, the Russia-Ukraine war, and the Israel-Hamas conflict resulted in negative impacts due to declining capital inflows and market volatility. Additionally, the role of the U.S. Dollar Index shifted notably after 2022, correlating negatively with network density following the Federal Reserve's interest rate hikes. The consistently positive effect of oil volatility further underscores its role in enhancing network interconnectedness during periods of crisis. However, it is essential to recognize the differential impact that conflict specific regional variables may have on cryptocurrency networks. Chortane and Pandey (2022) found varying responses among global currencies to the Russia-Ukraine crisis, with certain European currencies depreciating against the USD, Pacific currencies appreciating significantly, and Middle East and African currencies showing limited responsiveness. The significant depreciation of the Russian ruble further highlights the nuanced currency-market interactions driven by geopolitical events. Hence, future research should consider incorporating other regional variables and currency dynamics to comprehensively assess their interactions with cryptocurrency market structures.

The results are important to further understand how significant global events such as military conflicts impact the network dynamics of the cryptocurrency market, and the relationship between economic indicators and the network structure of the cryptocurrency market. More specifically, these results are important for academics and investors in terms of understanding risk, diversification, and market efficiency, but also for policy makers in terms of timely interventions ensuring market stability, and possible regulatory or policy responses during geopolitical crises. Furthermore, from a legal perspective the results can assist in determining whether blockchain-based assets are being used to evade sanctions and facilitate cybercrime. As both conflicts remain ongoing, future work should focus on analysing later transitional periods after the war has been ongoing for an extended period, to determine whether changes to the network structure and the influence of economic variables are influenced by war-related events or other factors such as regulatory actions, sanctions, and cryptocurrency-specific events. In addition, a study into more complex network properties such as network motifs, which are "recurrent subgraph patterns whose occurring number is significantly higher than that in randomized networks" (Wu et al., 2021a), can provide further insights into the organizations within networks. Examining decentralised exchanges could also offer another perspective for assessing the use of cryptocurrencies to evade sanctions, given that funds from potentially illicit sources such as sanctioned entities and fraudulent activities may be traded on these platforms.

Appendix A.

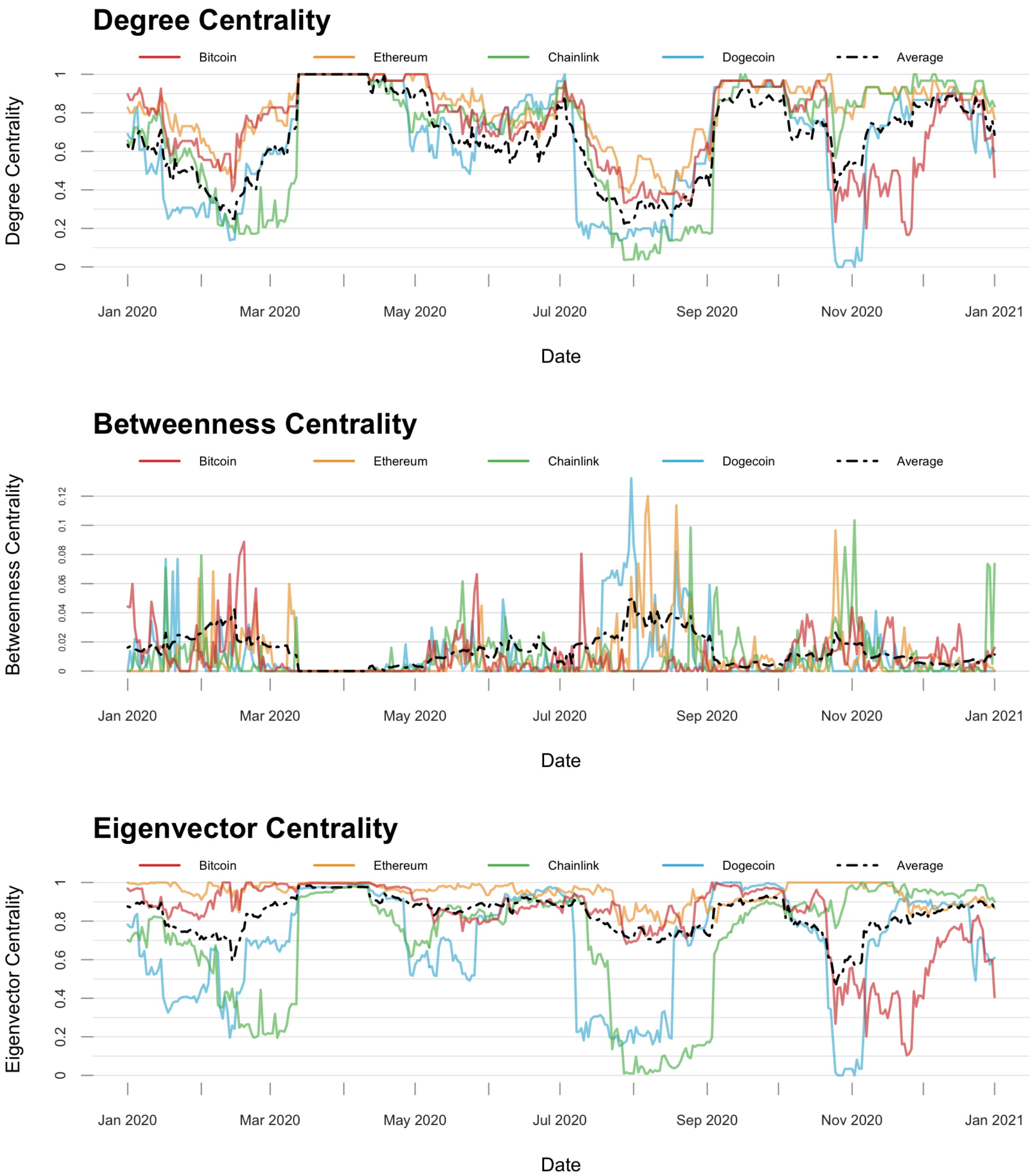

Figure A1: Plots of the (a) degree centrality (top); (b) betweenness centrality (middle); (c) eigenvector centrality (bottom), for the Russia-Ukraine conflict pre-war period 1 of January 2020 to January 2021.

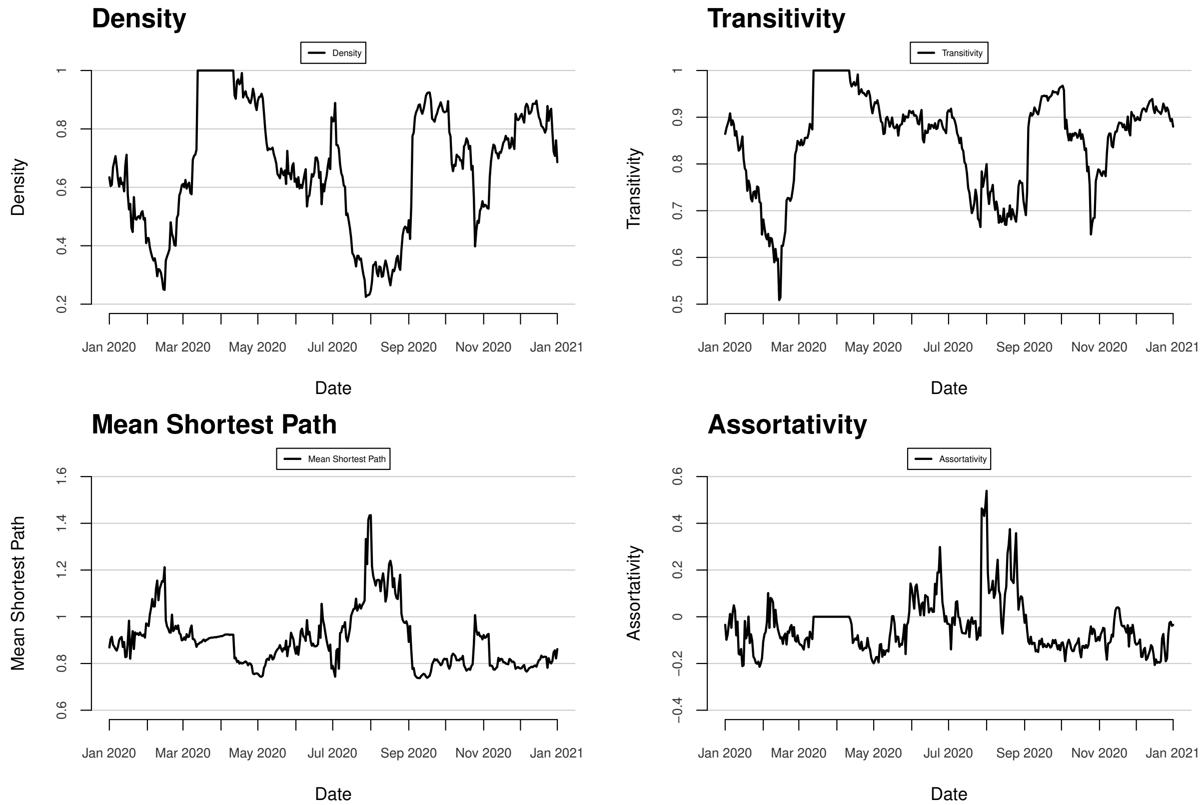

Figure A2: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Russia-Ukraine conflict pre-war period 1 of January 2020 to January 2021.

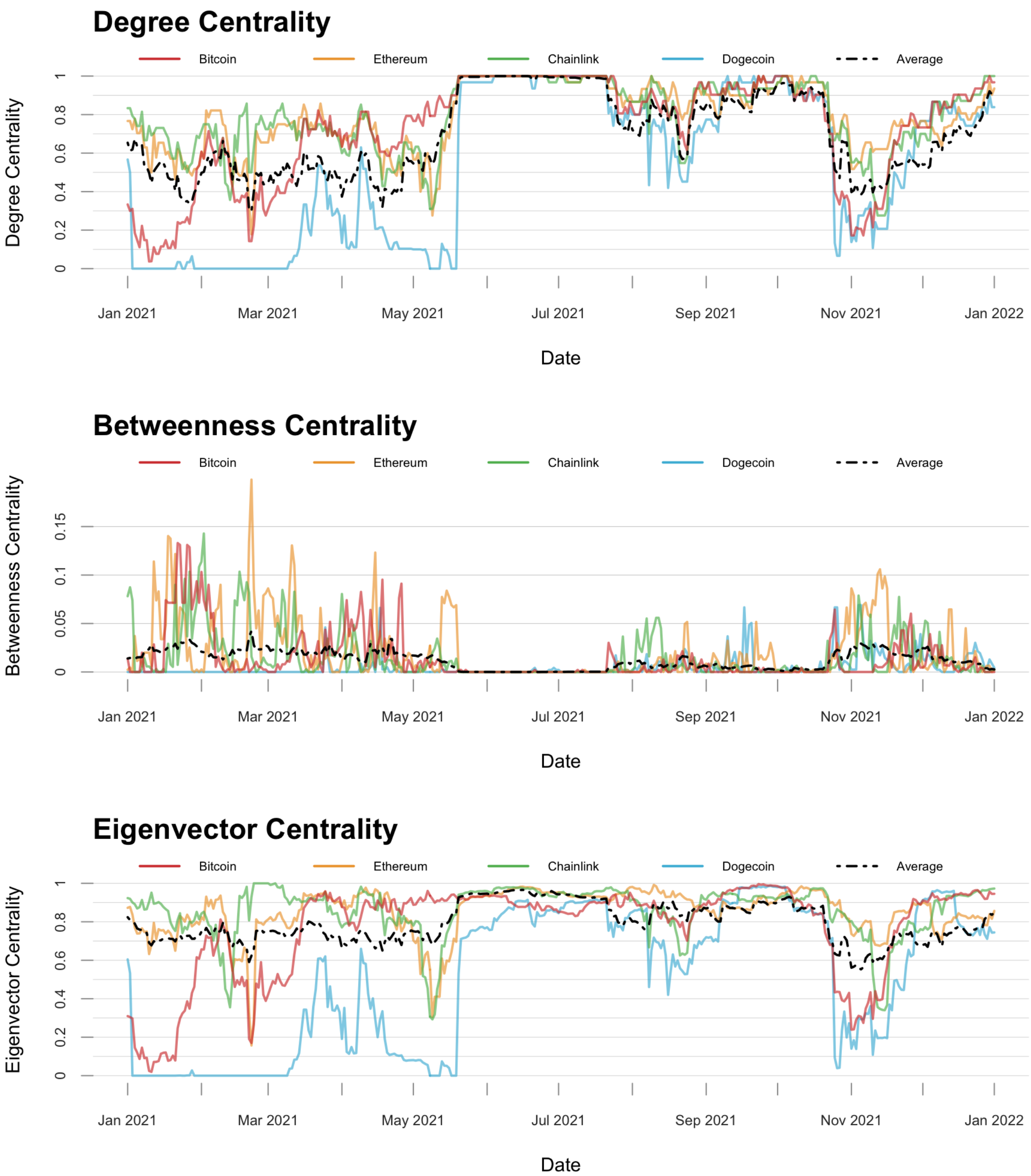

Figure A3: Plots of the (a) degree centrality (top); (b) betweenness centrality (middle); (c) eigenvector centrality (bottom), for the Russia-Ukraine conflict pre-war period 2 of January 2021 to January 2022.

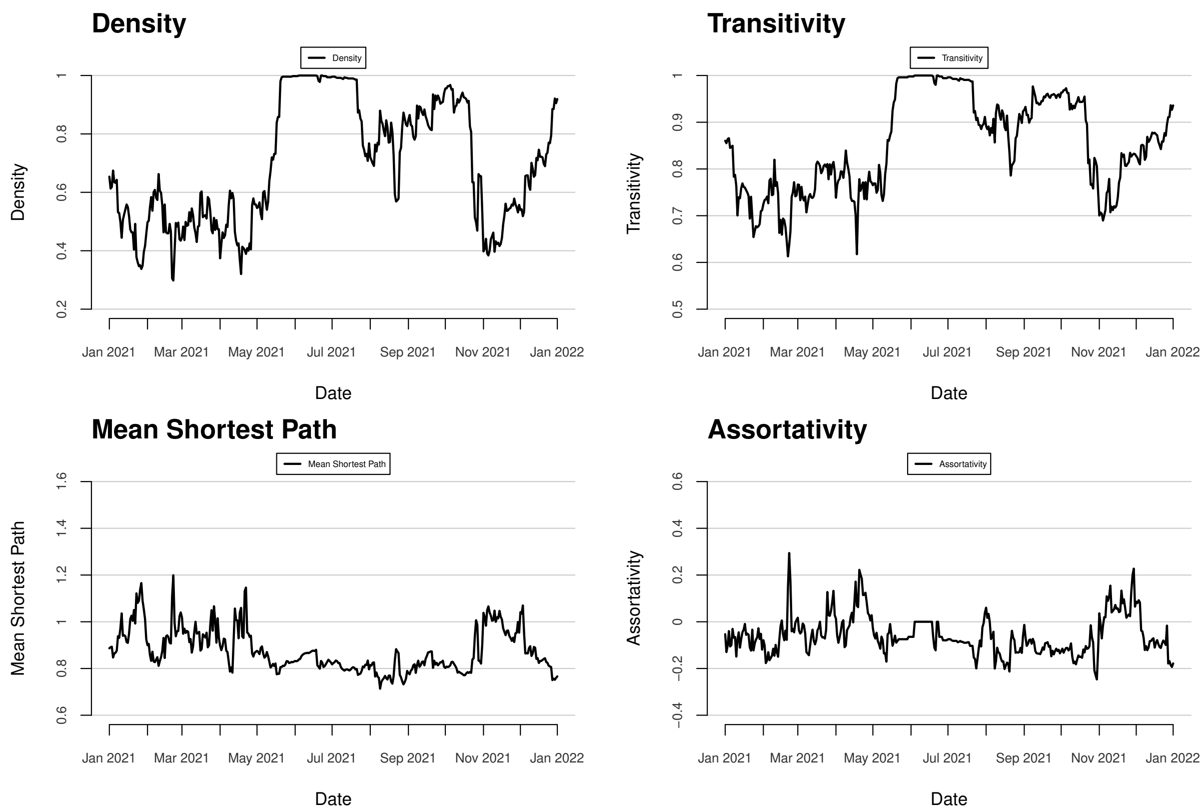

Figure A4: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Russia-Ukraine conflict pre-war period 2 of January 2021 to January 2022.

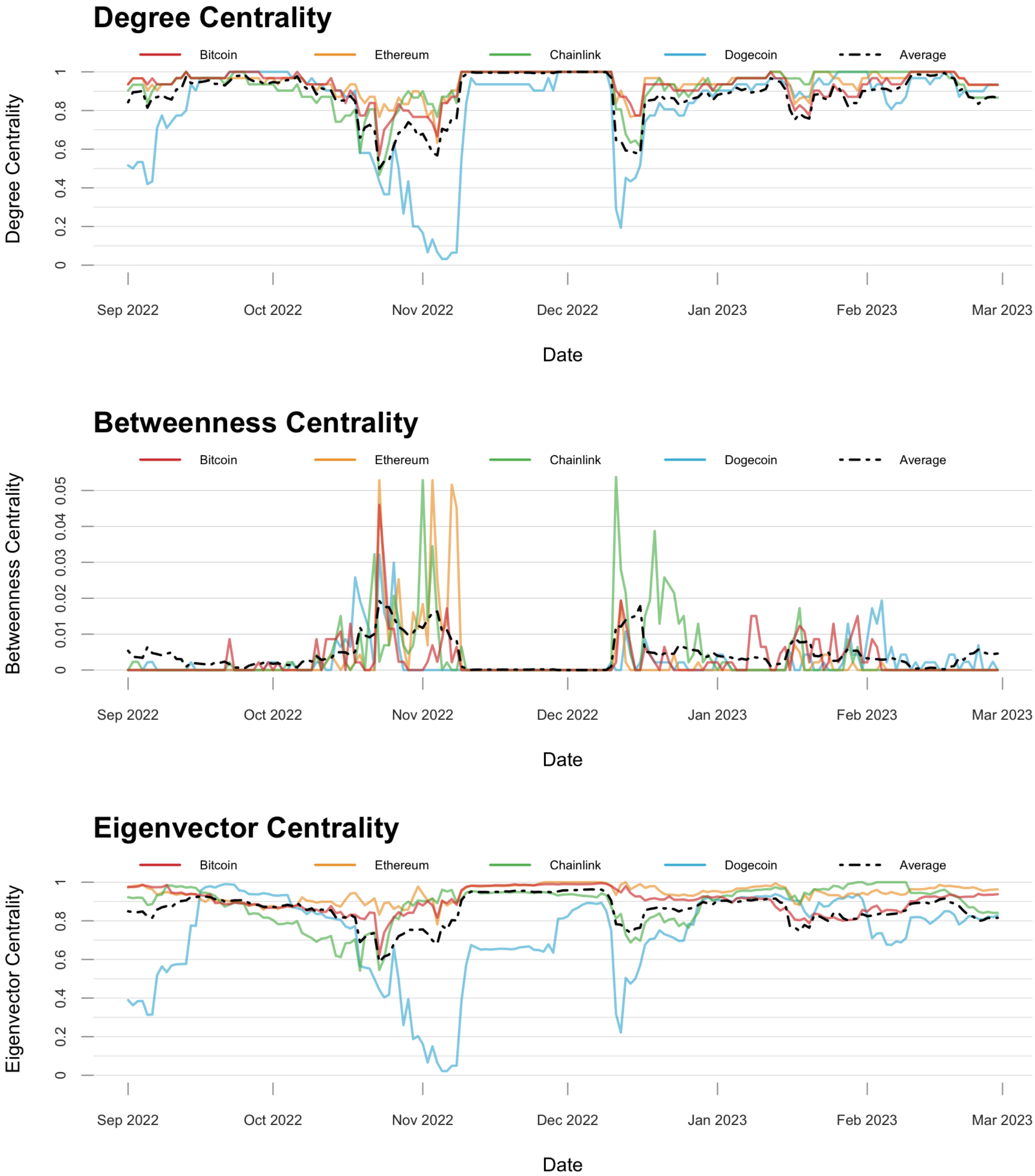

Figure A5: Plots of the (a) degree centrality (top); (b) betweenness centrality (middle); (c) eigenvector centrality (bottom), for the Israel-Hamas conflict pre-war period 1 of Sep 2022 to March 2023.

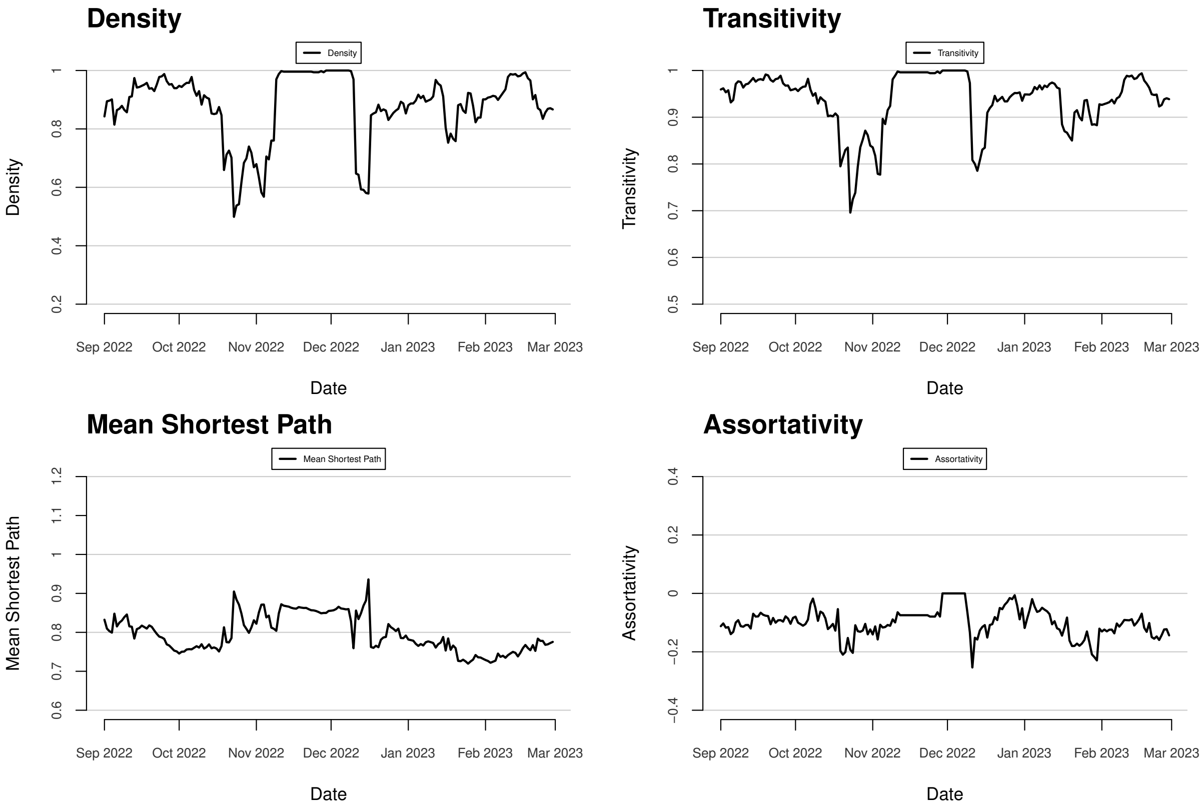

Figure A6: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Israel-Hamas conflict pre-war period 1 of Sep 2022 to March 2023.

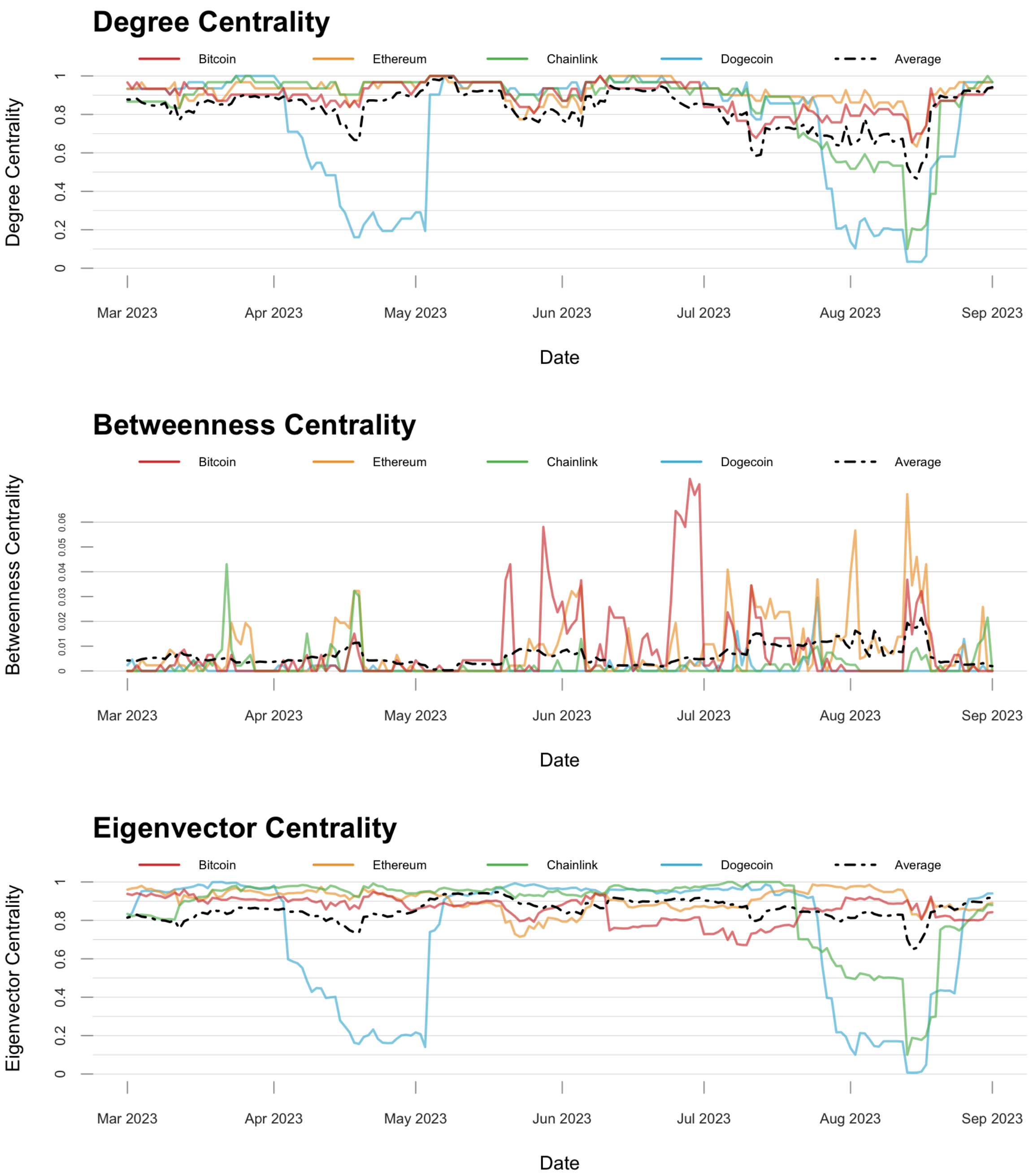

Figure A7: Plots of the (a) degree centrality (top); (b) betweenness centrality (middle); (c) eigenvector centrality (bottom), for the Israel-Hamas conflict pre-war period 2 of March 2023 to January 2024.

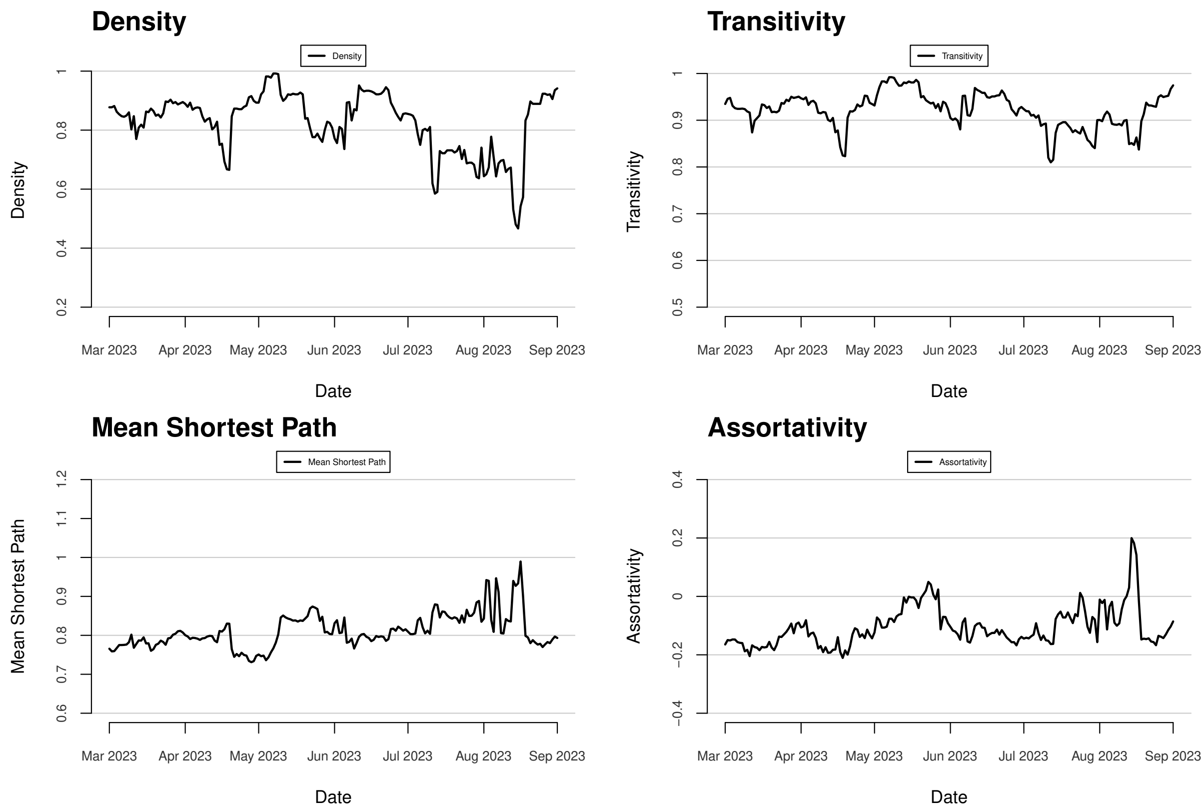

Figure A8: Plots of the (a) density (top left); (b) transitivity (top right); (c) mean shortest path (bottom left); (d) assortativity (bottom right), for the Israel-Hamas conflict pre-war period 2 of March 2023 to January 2024.

Appendix B.

B.1 Small-World Index

We follow the methodology proposed by Humphries and Gurney (2008) for computing a quantitative small-world index for a network, which takes into account the level of clustering and the mean shortest path length. For a network G with n nodes and m edges, the index is defined as

$$S^{\Delta} = \frac{\gamma_g^{\Delta}}{\lambda_g},$$

where

$$\gamma_g^{\Delta} = \frac{C_g^{\Delta}}{C_{rand}^{\Delta}}$$

and

$$\lambda_g = \frac{L_g}{L_{rand}},$$

where L_g denotes the mean shortest path length of G and C_g^{Δ} its clustering coefficient (based on transitivity), and L_{rand} and C_{rand}^{Δ} denote the corresponding quantities for a corresponding Erdös–Rényi random graph. As noted in Humphries and Gurney (2008), a network is classed as being a small-world network if $S^{\Delta} > 1$, which follows from the categorical definition of a small-world network implying that $\lambda_g \geq 1$ and $\gamma_g^{\Delta} >> 1$. To compute L_{rand} and C_{rand}^{Δ}, we generate 100 random graphs and take the average of the 100 mean shortest path lengths and clustering coefficients, respectively.

B.2 Core-Periphery Index

We follow the methodology of Borgatti and Everett (1999) for fitting a core-periphery model (optimal pattern matrix) to a given network using degree centrality, and computing a core-periphery index, ρ, based on the maximal correlation of the adjacency matrix with the optimal pattern matrix. As noted by Borgatti and Everett (1999), for undirected graphs the value ρ is defined as the Pearson correlation coefficient applied to the upper half of the adjacency matrices. It follows that "a structure is a core-periphery structure to the extent that ρ is large" (Borgatti and Everett, 1999), in other words as ρ tends to 1, the network structure tends towards a strong core-periphery topology.

Acknowledgments

We are grateful to the editor and the reviewers for their constructive feedback and comments which greatly improved the paper.

Declaration of interest

Declarations of interest: none

Funding sources

Jeffrey Chu is supported by the Beijing Natural Science Foundation (No. IS23126). Stephen Chan is supported by the American University of Sharjah [FRG23]. Yuanyuan Zhang is supported by the University of Manchester Internationalisation: Global Scholars Fund 2023-2024.

References

Ahmed, S., Hasan, M.M. and Kamal, M.R., 2022. Russia–Ukraine crisis: The effects on the European stock market. European Financial Management, Online Version, https://doi.org/10.1111/eufm.12386.

Alarabiya News, 2024. Gaza medics say Israeli forces raided Al-Amal Hospital in Khan Younis. Available at: https://english.alarabiya.net/News/middle-east/2024/02/09/Gaza-medics-say-Israeli-forces-raid-Al-Amal-Hospital-in-Khan-Younis

Albert, A. and Barabasi, A.-L., 2002. Statistical mechanics of complex networks. Reviews of Modern Physics, 74, pp. 47-97.

Ari, A.P., Siwu, J., Sambur, M.S. and Kawulur, S.K., 2023. The return response on gold and crude oil during global geopolitical issues. The Contrarian: Finance, Accounting, and Business Research, 2(1), pp.12-17.

Arnaboldi, V., Passarella, A., Conti, M. and Dunbar, R.I.M., 2015. Chapter 2 - Human Social Networks. In (eds) Arnaboldi, V., Passarella, A., Conti, M. and Dunbar, R.I.M., Computer Science Reviews and Trends, Online Social Networks, Elsevier, pp. 9-35.

Aslanidis, N., Bariviera, A.F., & López, Ó.G., 2022. The link between cryptocurrencies and Google Trends attention. Finance Research Letters, 47, 102654.

Ballis, A. and Drakos, K., 2020. Testing for herding in the cryptocurrency market. Finance Research Letters, 33, 101210.

Batrancea, L.M., Akgüller, Ö., Balcı, M.A. and Nichita, A., 2024. Financial network communities and methodological insights: a case study for Borsa Istanbul Sustainability Index. Humanities and Social Sciences Communications, 11, pp. 1-27.

BBC, 2023. Available at: https://www.bbc.com/news/world-middle-east-67614911

Bedowska-Sójka, B., Demir, E. and Zaremba, A., 2022. Hedging Geopolitical Risks with Different Asset Classes: A Focus on the Russian Invasion of Ukraine. Finance Research Letters, 50, 103192.

Bhattacharjee, A., Sidana, N., Goel, R., Shukre, A. and Singh, T., 2025. Cross-border ripples: investigating stock market responses to Israel-Hamas conflict in trading partner nations using event study method. Journal of Economic Studies, 52(4), pp.803-823.

Boginski, V., Butenko, S. and Pardalos, P.M., 2005. Statistical analysis of financial networks. Computational Statistics & Data Analysis, 48, pp. 431-443.

Boufatech, T. and Saadaoui, Z., 2021. The time-varying responses of financial intermediation and inflation to oil supply and demand shocks in the U.S.: evidence from Bayesian TVP-SVAR-SV approach. Energy Economics, 102, 105535.

Boungou, W. and Yatié, A., 2022. The impact of the Ukraine–Russia war on world stock market returns. Economics Letters, 215, 110516.

Bouri, E., Gupta, R. and Rouband, D., 2019. Herding behaviour in cryptocurrencies. Finance Research Letters, 29, pp. 216-221.

Borgatti, S.P. and Everett, M.G., 1999. Models of corerperiphery structures. Social Networks, 21, pp. 375-395.

Brigatti, E., Rocha Grecco, V., Hernández, A.R. and Bertella, M.A., 2023. Inferring interactions in multispecies communities: The cryptocurrency market case. Plos one, 18, e0291130.

Britannica, 2024. Hamas-Palestinian Conflict, Gaza, Militancy. Available at: https://www.britannica.com/topic/Hamas/Conflict-with-Israel

Buccheri, G., Marmi, S. and Mantegna, R.N., 2013. Evolution of correlation structure of industrial indices of US equity markets. Physical Review E - Statistical, Nonlinear, and Soft Matter Physics, 88, 012806.

Caferra, R. and Vidal-Tomás, D., 2021. Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. Finance Research Letters, 43, 101954.

Caldara, D. and Iacoviello, M., 2022. Measuring Geopolitical Risk. American Economic Review, 112, pp. 1194-1225.

Castelnuovo, E. and Tran, T.D., 2017. Google It Up! A Google Trends-based Uncertainty index for the United States and Australia. Economics Letters, 161, pp. 149-153.

Chan, J.C., Eisenstat, E. and Strachan, R.W., 2020. Reducing the state space dimension in a large TVP-VAR. Journal of Econometrics, 218(1), pp.105-118.

Chen, Y., Chiu, J., Chung, H. and Lien, D., 2024. Bitcoin market connectedness across political uncertainty. International Review of Economics & Finance, 96, 103623.

Chortane, S.G. and Pandey, D.K., 2022. Does the Russia-Ukraine war lead to currency asymmetries? A US dollar tale. The Journal of Economic Asymmetries, 26, p.e00265.

Choudhry, T., 2010. World War II events and the Dow Jones industrial index. Journal of Banking and Finance, 34, pp. 1022-1031.

City A.M., 2022. London Stock Exchange's FTSE 100 plunges by more than 200 points as Ukraine war heats up rapidly. Available at: https://www.cityam.com/breaking-london-stock-exchange-plunges-by-more-than-200-points-as-ukraine-war-heats-up-rapidly.

Clauset, A., Moore, C., Newman, M.E.J., 2008. Hierarchical structure and the prediction of missing links in networks. Nature 453, pp. 98–101.

CNN, 2024. January 1, 2024, Israel-Hamas War. Available at: https://edition.cnn.com/middleeast/live-news/israel-hamas-war-gaza-news-01-01-24/index.html

Csermely, P., London, A., Wu, L.-Y. and Uzzi, B. 2013. Structure and dynamics of core/periphery networks. Journal of Complex Networks, 1, pp. 93-123.

Cui, J. and Maghyereh, A., 2024a. Higher-order moment risk spillovers across various financial and commodity markets: Insights from the Israeli–Palestinian conflict. Finance Research Letters, 59, 104832.

Cui, J. and Maghyereh, A., 2024b. Unveiling interconnectedness: Exploring higher-order moments among energy, precious metals, industrial metals, and agricultural commodities in the context of geopolitical risks and systemic stress. Journal of Commodity Markets, 33, 100380.

Diaconaşu, D.E., Mehdian, S.M. and Stoica, O., 2022. The reaction of financial markets to Russia's invasion of Ukraine: evidence from gold, oil, bitcoin, and major stock markets. Applied Economics Letters.

Elliptic, 2023a. Crypto in Conflict - How the role of cryptoassets has evolved in the Russia-Ukrainian War. Available at: https://www.elliptic.co/resources/crypto-in-conflict.

Elliptic, 2023b. Setting the record straight on crypto crowdfunding by Hamas. Available at: https://www.elliptic.co/blog/setting-the-record-straight-on-crypto-crowdfunding-by-hamas

Enilov, M. and Mishra, T., 2023. Gold and the herd of Cryptos: Saving oil in blurry times. Energy Economics, 122, 106690.

Fernandes, L.H.S, Bouri, E., Silva, J.W.L., Bejan, L. and de Araujo, F.H.A., 2022. The resilience of cryptocurrency market efficiency to COVID-19 shock. Physica A: Statistical Mechanics and its Applications, 607, 128218.

Foroutan, P. and Lahmiri, S., 2024. Connectedness of cryptocurrency markets to crude oil and gold: an analysis of the effect of COVID-19 pandemic. Financial Innovation, 10(1), p.68.

Gaio, L.E., Stefanelli, N.O., Júnior, T.P., Bonacim, C.A.G. and Gatsios, R.F., 2022. The impact of the Russia-Ukraine conflict on market efficiency: Evidence for the developed stock market. Finance Research Letters, 50, 103302.

Gambarelli, L., Marchi, G. and Muzzioli, S., 2023. Hedging effectiveness of cryptocurrencies in the European stock market. Journal of International Financial Markets, Institutions and Money, 84, 101757.

Goldman, D. and Toh, M., 2023. Dow climbs nearly 200 points as investors brush off worries about rising oil prices. CNN Business. Available at: https://edition.cnn.com/2023/10/08/investing/global-markets-israel-hamas-hnk-intl/index.html

Goodell, J.W., Yadav, M.P., Ruan, J., Abedin, M.Z. and Malhotra, N., 2023. Traditional assets, digital assets and renewable energy: Investigating connectedness during COVID-19 and the Russia-Ukraine war. Finance Research Letters, 58, 104323.

Gupta, N., Singh, A. and Cherifi, H. 2016. Centrality measures for networks with community structure. Physica A: Statistical Mechanics and its Applications, 452, pp. 46-59.

Hamouda, F., Yousaf, I. and Naeem, M.A., 2024. Exploring the dynamics of equity and cryptocurrency markets: fresh evidence from the Russia–Ukraine war. Computational Economics, Available at: https://doi.org/10.1007/s10614-024-10573-w.

Heiberger, R.H., 2014. Stock network stability in times of crisis. Physica A: Statistical Mechanics and its Applications, 393, pp. 376-381.

Huang, Y. and Chen, F., 2021. Community structure and systemic risk of bank correlation networks based on the US financial crisis in 2008. Algorithms, 14, 162.

Hudson, R. and Urquhart, A., 2015. War and stock markets: The effect of World War Two on the British stock market. International Review of Financial Analysis, 40, pp. 166-177.

Hudson, R. and Urquhart, A., 2022. Naval disasters, world war two and the British stock market. Research in International Business and Finance, 59, 101556.

Hu, G., Liu, S., Wu, G., Hu, P., Li, R. and Chen, L., 2023. Economic policy uncertainty, geopolitical risks, and the heterogeneity of commodity price fluctuations in China —— an empirical study based on TVP-SV-VAR model. Resources Policy, 85(A), 104009.

Humphries, M.D. and Gurney, K., 2008. Network 'Small-World-Ness': A Quantitative Method for Determining Canonical Network Equivalence. Plos One, 3, e0002051.

Hurd, T.R., Gleeson, J.P. and Melnik, S., 2017. A framework for analyzing contagion in assortative banking networks. PloS one, 12(2), p.e0170579.

iFinD, 2024. Available at: https://www.51ifind.com

Investing.com, 2024a. CBOE Crude Oil Volatility Historical Price Data. Available at: https://uk.investing.com/indices/cboe-crude-oil-volatility-historical-data

Investing.com, 2024b. US Dollar Index Historical Price Data. Available at: https://uk.investing.com/indices/usdollar-historical-data

Investing.com. (2025). Gold (GCQ5). Investing.com. Available at: https://www.investing.com/commodities/gold-historical-data

Isogai, T., 2016. Building a dynamic correlation network for fat-tailed financial asset returns. Applied Network Science, 1(1), p.7.

Izzeldin, M., Muradoğlu, Y.G., Pappas, V., Petropoulou, A. and Sivaprased, S., 2023. The impact of the Russian-Ukrainian war on global financial markets. International Review of Financial Analysis, 87, 102598.

Jackson Jr, R.J. and Mitts, J., 2023. Trading on terror?. Available at SSRN 4652027.

Kakinaka, S. and Umeno, K., 2022. Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: An asymmetric multifractal analysis approach. Finance Research Letters, 46, 102319.

Kauê Dal'Maso Peron, T., da Fontoura Costa, L. and Rodrigues, F.A., 2012. The structure and resilience of financial market networks. Chaos: An Interdisciplinary Journal of Nonlinear Science, 22(1).

Khalfaoui, R., Gozgor, G. and Goodell, J.W., 2023. Impact of Russia-Ukraine war attention on cryptocurrency: Evidence from quantile dependence analysis. Finance Research Letters, 52, 103365.

Khan, S. and Rehman, M.Z., 2023. The impact of the Israel-Palestine conflict on the GCC-Israel and the leading global stock market indices. Available at SSRN 4658577.

Kitanovski, D., Mirchev, M., Chorbev, I. and Mishkovski, I., 2022. Cryptocurrency portfolio diversification using network community detection. In: 2022 30th Telecommunications Forum (TELFOR), pp. 1-4, IEEE.

Kumar, S., Patel, R., Iqbal, N. and Gubareva, M., 2023. Interconnectivity among cryptocurrencies, NFTs, and DeFi: Evidence from the Russia-Ukraine conflict. The North American Journal of Economics and Finance, 68, 101983.

Koch, S. and Dimpfl, T., 2023. Attention and retail investor herding in cryptocurrency markets. Finance Research Letters, 51, 103474.

Lin, Z.-L., Ouyang, W.-P. and Yu, Q.-R., 2024. Risk spillover effects of the Israel–Hamas War on global financial and commodity markets: A time–frequency and network analysis. Finance Research Letters, 66, 105618.

Liu, Z. and Bambi, H., 2005. Epidemic spreading in community networks. Europhysics Letters, 72, pp. 315–321.

Lubik, T.A. and Matthes, C., 2015. Time-varying parameter vector autoregressions: Specification, estimation, and an application. Economic Quarterly.

Markose, S., Giansante, S. and Shaghaghi, A.R., 2012. 'Too interconnected to fail'financial network of US CDS market: Topological fragility and systemic risk. Journal of Economic Behavior & Organization, 83(3), pp.627-646.

Martins, A.M., 2024. Global Equity, Commodities and Bond Market Response to Israel-Hamas War. Finance Research Letters, p.105900.

Mchirgui, D., Digheem, M.A.S. and Adwela, F.S., 2025. Connectedness between Bitcoin, Gold, Gold-Backed Cryptocurrencies and Energy Commodities during the COVID-19 Pandemic and the Russia-Ukraine Conflict. International Journal of Energy Economics and Policy, 15(3), pp.411-425.

Mensi, W., El Khoury, R., Ali, S.R.M., Vo, X.V. and Kang, S.H., 2023. Quantile dependencies and connectedness between the gold and cryptocurrency markets: Effects of the COVID-19 crisis. Research in International Business and Finance, 65, p.101929.

Mgadmi, N., Sadraoui, T., Alkaabi, W. and Abidi, A., 2023. T he interconnectedness of stock indices and cryptocurrencies during the Russia-Ukraine war. Journal of Economic Criminology, 2, 100039.

Mnif, E., Jarboui, A. and Mouakhar, K., 2020. How the cryptocurrency market has performed during COVID 19? A multifractal analysis. Finance Research Letters, 36, 101647.

Moghadam, H.E., Mohammadi, T., Kashani, M.F., Shakeri, A., 2019. Complex networks analysis in Iran stock market: The application of centrality. Physica A: Statistical Mechanics and its Applications, 531, 121800.

Mohamed, A., 2022. Safe flight to which haven when Russia invades Ukraine? A 48-hour story. Economics Letters, 216, 110558.

Mondragón, R.J., 2020. Estimating degree–degree correlation and network cores from the connectivity of high–degree nodes in complex networks. Scientific reports, 10(1), p.5668.

Montasser, G.E, Charfeddine, L. and Benhamed, A., 2022. COVID-19, cryptocurrencies bubbles and digital market efficiency: sensitivity and similarity analysis. Finance Research Letters, 46, 102362.

Morningstar, 2022. S&P 500 logs first correction in 2 years as Russia-Ukraine conflict escalates. Here's what history says happens next to U.S. stock-market benchmark. Available at: https://www.morningstar.com/news/marketwatch/2022022389/sp-500-logs-first-correction-in-2-years-as- russia-ukraine-conflict-escalates-heres-what-history-says-happens-next-to-us-stock-market-benchmark

Naeem, M.A., Bouri, E., Peng, Z., Shahzad, S.J.H. and Vo, X.V., 2021. Asymmetric efficiency of cryptocurrencies during COVID19. Physica A: Statistical Mechanics and its Applications, 565, 125562.

Newman, M.E.J., 2003. Mixing patterns in networks. Arxiv: arXiv:cond-mat/0209450 [cond-mat.stat-mech].

Newman, M.E.J., 2010. Networks - An Introduction. Oxford University Press.

Newman, M.E.J. and Watts, D.J., 1999. Renormalization group analysis of the small-world network model. Physics Letters A, 263, pp. 341-346.

Nicolle, E., 2023. Assessing Crypto's Role in Illicit Financing. Bloomberg. Available at: https://www.bloomberg.com/news/newsletters/2023-10-12/what-is-crypto-s-role-in-israel-hamas-war

Nishikawa, T., Motter, A.E., Lai, Y.-C. and Hoppensteadt, F.C., 2002. Smallest small-world network. Physical Review E, 66, 046139.

Nobi, A., Maeng, S. E., Ha, G. G., and Lee, J. W., 2014. Effects of global financial crisis on network structure in a local stock market. Physica A: Statistical Mechanics and Its Applications, 407, pp. 135-143.

Orman, K., Labatut, V., Cherifi, H., 2013. An Empirical Study of the Relation between Community Structure and Transitivity. In: Menezes, R., Evsukoff, A., González, M. (eds) Complex Networks. Studies in Computational Intelligence, vol 424. Springer, Berlin, Heidelberg.

Papana, A., Kyrtsou, C., Kugiumtzis, D. and Diks, C., 2017. Financial networks based on Granger causality: A case study. Physica A: Statistical Mechanics and its Applications, 482, pp.65-73.

Pastor-Satorras, R., Rubi, M., Diaz-Guilera, A., Barabási, A.-L., Ravasz, E., Oltvai, Z., 2003. Hierarchical Organization of Modularity in Complex Networks. In: Statistical Mechanics of Complex Networks, vol. 625, pp. 46–65. Springer, Heidelberg.

Patel, R., Kumar, S., Bouri, E. and Iqbal, N., 2023. Spillovers between green and dirty cryptocurrencies and socially responsible investments around the war in Ukraine. Inteernational Review of Economics & and Finance, 87, pp. 143-162.

Primiceri, G.E., 2005. Time Varying Structural Vector Autoregressions and Monetary Policy. The Review of Economic Studies, 72, pp. 821-852.

Raddant, M. and Kenett, D.Y., 2021. Interconnectedness in the global financial market. Journal of International Money and Finance, 110, 102280.

Reuters, 2022. Cryptocurrencies in a Time of War. Available at: https://www.reuters.com/technology/cryptocurrencies-time-war-2022-03-04/.

Rodrigues, F.A., 2019. Network Centrality: An Introduction. In: Macau, E. (eds) A Mathematical Modeling Approach from Nonlinear Dynamics to Complex Systems. Nonlinear Systems and Complexity, vol 22. Springer, Cham.

Santorsola, M., Caferra, R. and Morone, A., 2022. The financial repercussions of military escalation. Physica A: Statistical Mechanics and its Applications, 603, 127791.

Stosic, D., Stosic, D., Ludermir, T.B. and Stosic, T., 2018. Collective behavior of cryptocurrency price changes. Physica A:

Statistical Mechanics and its Applications, 507, pp. 499-509.
Susana, D., Kavisanmathi, J.K. and Sreejith, S., 2020. Does Herding Behaviour Among Traders Increase During Covid 19 Pandemic? Evidence from the Cryptocurrency Market. In: Sharma, S.K., Dwivedi, Y.K., Metri, B., Rana, N.P. (eds) Re-imagining Diffusion and Adoption of Information Technology and Systems: A Continuing Conversation. TDIT 2020. IFIP Advances in Information and Communication Technology, vol 617. Springer, Cham.
Tajaddini, R. and Gholipour, H.F., 2023. Trade dependence and stock market reaction to the Russia-Ukraine war. International Review of Finance, Online Version, https://doi.org/10.1111/irfi.12414.
Torri, G. and Giacometti, R., 2023. Financial contagion in banking networks with community structure. Communications in Nonlinear Science and Numerical Simulation, 117, p.106924.
TRM Insights, 2023. In Wake of Attack on Israel, Understanding How Hamas Uses Crypto. TRM Labs. Available at: https://www.trmlabs.com/post/in-wake-of-attack-on-israel-understanding-how-hamas-uses-crypto
Tse, C.K., Liu, J. and Lau, F.C.M, 2010. A network perspective of the stock market. Journal of Empirical Finance, 17, pp. 659-667.
Umar, Z., Polat, O., Choi, S.-Y. and Teplova, T., 2022. Dynamic connectedness between non-fungible tokens, decentralized finance, and conventional financial assets in a time-frequency framework. Pacific-Basin Finance Journal, 76, 101876.
Vidal-Tomás, D., 2019. Herding in the cryptocurrency market: CSSD and CSAD approaches. Finance Research Letters, 30, pp. 181-186.
Vidal-Tomás, D., 2021. Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis. Finance Research Letters, 43, 101981.
Wang, G.J. and Xie, C., 2015. Correlation structure and dynamics of international real estate securities markets: A network perspective. Physica A: Statistical Mechanics and its Applications, 424, pp. 176-193.
Wang, G.J., Xie, C. and Chen, S., 2017. Multiscale correlation networks analysis of the US stock market: a wavelet analysis. Journal of Economic Interaction and Coordination, 12, pp.561-594.
Wang, H., Huang, W.-B. and Bu, Y., 2025. The attention inequality of scientists: A core-periphery structure perspective. Information Processing & Management, 62, 104170.
Wasserman, S. and Faust, K., 1994. Social Network Analysis: Methods and Applications. Cambridge University Press.
Watts, D., 1999. Networks, Dynamics, and the Small-World Phenomenon. American Journal of Sociology, 105, pp. 493-527.
Wu, J., Liu, J., Zhao, Y. and Zheng, Z., 2021. Analysis of cryptocurrency transactions from a network perspective: An overview. Journal of Network and Computer Applications, 190, p.103139.
Wu, S.X., Wu, Z., Chen, S., Li, G. and Zhang, S., 2021. Community detection in blockchain social networks. Journal of Communications and Information Networks, 6, pp.59-71.
Yao, J., Ma, C. and He, W.P., 2014. Investor herding behaviour of Chinese stock market. International Review of Economics & Finance, 29, pp. 12-29.
Yarovaya, L., Matkovsky, R. and Jalan, A., 2021. The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. Journal of International Financial Markets, Institutions and Money, 75, 101321.
Yousaf, I. and Yarovaya, L., 2022a. Herding behavior in conventional cryptocurrency market, non-fungible tokens, and DeFi assets. Finance Research Letters, 50, 103299.
Yousaf, I., Patel, R. and Yarovaya, L., 2022b. The reaction of G20+ stock markets to the Russia-Ukraine conflict "black-swan" event: Evidence from event study approach. Journal of Behavioral and Experimental Finance, 35, 100723.
Yousaf, I., Riaz, Y. and Goodell, J.W., 2023. Energy cryptocurrencies: Assessing connectedness with other asset classes. Finance Research Letters, 52, 103389.
Zheng, T., Ye, S. and Hong, Y., 2023. Fast estimation of a large TVP-VAR model with score-driven volatilities. Journal of Economic Dynamics and Control, 157, p.104762.