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Network Parameters in Bitcoin Transactions: Event Analysis of Global Financial Downturns

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ABSTRACT

The paper examines how historical economic and geopolitical events influence the structure of the Bitcoin blockchain network through a directed network analysis of 980 mil. transactions. We construct a unique transaction-level dataset covering all Bitcoin transactions for the Cyprus banking crisis (2013), the Sanctions against Russia following the Crimean annexation (2014), and the Chinese stock market turbulence of 2015-2016. The findings suggest that events with a financial impact on individuals have led to heightened Bitcoin network activity and increased adoption of the cryptocurrency. The network parameters already change in the pre-event periods, observing the 20 days before the event, suggesting a certain degree of anticipation effect.

KEYWORDS: Bitcoin; Network Analysis; Financial Shocks; Illicit Financial Flows

JELCLASSIFICATION: C45, E44, C55

Parametre siete bitcoinových transakcií - analýza udalostí globálnych finančných poklesov

ABSTRAKT

Tento článok skúma, ako historické, ekonomické a geopolitické udalosti ovplyvňujú štruktúru siete Bitcoin blockchain prostredníctvom orientovanej analýzy 980 mil. transakcií. Konštruujeme unikátny súbor údajov na úrovni bitcoinových transakcií, ktorý v sebe obsahuje všetky transakcie týkajúce sa cyperskej bankovej krízy (2013), anexie Krymu (2014) a turbulencií na čínskom akciovom trhu v rokoch 2015 - 2016. Zistenia naznačujú, že udalosti s finančným dosahom na jednotlivcov viedli k zvýšenej aktivite siete bitcoinových transakcií a k zvýšenej miere prijatia tejto kryptomeny. Parametre siete sa menia už v obdobiach pred skúmanými udalosťami, sledovanými 20 dní pred udalosťou, čo naznačuje určitý stupeň prítomnosti efektu očakávania.

KĽÚČOVÉ SLOVÁ: bitcoin; sieťová analýza; finančné šoky; nelegitímne toky kapitálu

JEL KLASIFIKÁCIA: C45, E44, C55

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LAYOUT BY: Lucas Wiese - Florian Horky - Petr Koráb - Jarko Fidrmuc

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Introduction

Over the past two decades, the extreme growth in online activities has accelerated the adoption of new virtual reality features, revolutionizing how people interact and conduct business in the digital realm. This wave of creative destruction has included the unprecedented adoption of Blockchain-based technology, crypto-assets, and the so-called cryptocurrencies, which have created a new era of financial activities and transactions. These digital assets have gained immense traction in numerous areas, offering individuals and businesses an alternative means of buying, selling, and trading assets (Biais et al., 2023). At the heart of this digital revolution lies the Blockchain, a decentralized and distributed ledger technology that forms the foundation of cryptocurrencies. The Blockchain ensures the security and integrity of transactions by recording them transparently and immutably. Blockchain technology tries to create alternative intermediaries that are not directly related to banks and other financial institutions, thereby enabling peer-to-peer transactions on a global scale. So far, obtaining or analyzing data on these new illicit transactions has been extremely difficult.

Cryptocurrencies and blockchain applications have rapidly gained popularity due to their potential and publicly expected advantages (Iansiti & Lakhani, 2017). One possible benefit is the ability to facilitate cross-border transactions seamlessly. Traditional financial systems often involve complex processes and significant fees for international transfers. Cryptocurrencies, by contrast, potentially transcend geographical boundaries, enabling individuals and businesses to engage in instant and low-cost transactions across different countries. Moreover, Blockchain technology offers a potentially high level of trust and accountability previously unseen in traditional financial systems. While individual transactions can be conducted with anonymity, the Blockchain ensures that a comprehensive record of all transactions is stored and accessible to the public. This feature is a core element we will make use of in our presented research project. Despite the proliferation of a wide range of cryptocurrencies, surpassing the number of 1500 active ones (Liu & Tsyvinski, 2021), Bitcoin still stands out as the pioneer and most widely recognized cryptocurrency. With a market capitalization of several hundred billion EUR and new all-time highs in spring 2024, Bitcoin stands for a significant share of the overall cryptocurrency market, serving as a benchmark for other digital currencies (Hu et al., 2019). The cryptocurrency market's remarkable growth, its volatility, and its potential use cases, however, pose significant economic implications. The market's size and the magnitude of its fluctuations attract diverse participants, each with distinct motivations and objectives. On one hand, some investors view cryptocurrencies as a high-risk, high-return asset class providing the potential for large excess returns (Liu et al., 2022). These investors (individual and institutional) are drawn to the potential for substantial profits and are willing to tolerate the inherent volatility and uncertainty associated with cryptocurrencies (Baur et al., 2018). In conjunction with the rise of cryptocurrencies, the volume of illicit financial flows (IFFs) has steadily increased over the last decade, bringing about severe socio-economic consequences for countries affected. It is commonly believed that IFFs predominantly target low-income economies with insufficient quality institutions, low public trust, and underdeveloped financial markets (Ajayi and Ndikumana, 2014). However, although more limited due to third-party oversight, whenever possible, wealthy individuals and multinational companies residing in developed countries are involved in evading official accounts and transferring capital outside official oversight (Alstadsæter et al., 2019). The United Nations recently recognized the threat posed by the lack of information surrounding the IFFs problem by underscoring the importance of the reduction of IFFs as one of the priorities put forward in its 2030 Agenda. On the other hand, cryptocurrencies serve as a medium of exchange in various business models, serving legitimate and questionable illicit purposes. There is various research about the adoption of cryptocurrencies, specifically Bitcoin, in several scenarios, like illicit activities (Foley et al., 2019) but also on legal trades to avoid high cross-border fees charged by financial intermediaries (Böhme et al., 2015). This cross-border use case has been empirically investigated by von Luckner et al. (2022) recently and has been shown to be a relevant driver in crypto transactions. Foley et al. (2022) revealed several key factors influencing Bitcoin usage on a macroeconomic level. Tighter controls on money laundering and stricter capital flow restrictions have been associated with a reduction in Bitcoin activity, suggesting that regulatory measures can significantly impact cryptocurrency markets. Nevertheless, the increasing adoption of cryptocurrencies potentially leads to an environment where several currencies compete, with implications for monetary policy (Benigno, 2023). The lack of regulation is highly concerning and could lead to multiple undesired outcomes connected to the (mis)usage of several types of crypto assets. Illicit activities such as money laundering, tax evasion, and illegal transactions can be facilitated through the pseudonymous nature of cryptocurrencies, presenting challenges for regulatory authorities and law enforcement agencies (Foley et al., 2019). Although the EU has put in place the most sophisticated regulation regarding crypto assets in the world (MiCA), it is to be questioned whether this regulation really captures the real-world issues surrounding cryptocurrencies. Since the Russian invasion of Ukraine, the issue of sanctions evasion and illicit financial flows via the cryptocurrency networks is back at the forefront of interest. Indeed, first research shows a connection between Bitcoin and the War (Khalfaoui et al., 2023).

In this study, we present a novel approach to parsing raw Bitcoin blockchain transaction data for economic research purposes. Utilizing raw blockchain transaction data, we have developed a specialized software environment to parse and analyze these data, addressing the gap in existing tools for economic analysis purposes. Our research demonstrates the potential of this parsing tool by conducting several event studies that investigate the behavior of Bitcoin transaction networks during specific periods of economic and political turmoil, namely the Cyprus banking crisis in 2013, the Crimean annexation in 2014, and the Shanghai stock market suspension in 2016. Specifically, this paper makes three major contributions to the literature: (1) it provides insight into a blockchain system at a very granular transaction-level data, helping to analyze previously unobserved patterns on a network structure. Previous research (Xu & Kinkyo, 2023; Aliu, 2023; Beckman et al., 2024) offers highly aggregated time series or small samples of Bitcoin transactions, which limits the depth of the analysis and useability of results. We provide (2) an architecture for consistently processing raw blockchain datasets for research purposes. Finally (3), the transaction-level analysis provides new insights into the global financial shock pass-through of the blockchain system.

The paper is structured as follows: the second section describes the construction of the dataset and proposes a new architecture data processing architecture. The third section explains the network model and the event analysis methodology. The consequent parts present the exploratory analysis of the network, including the time development of the network parameters, while the last section outlines new directions of the research with transaction-level blockchain data and concludes.

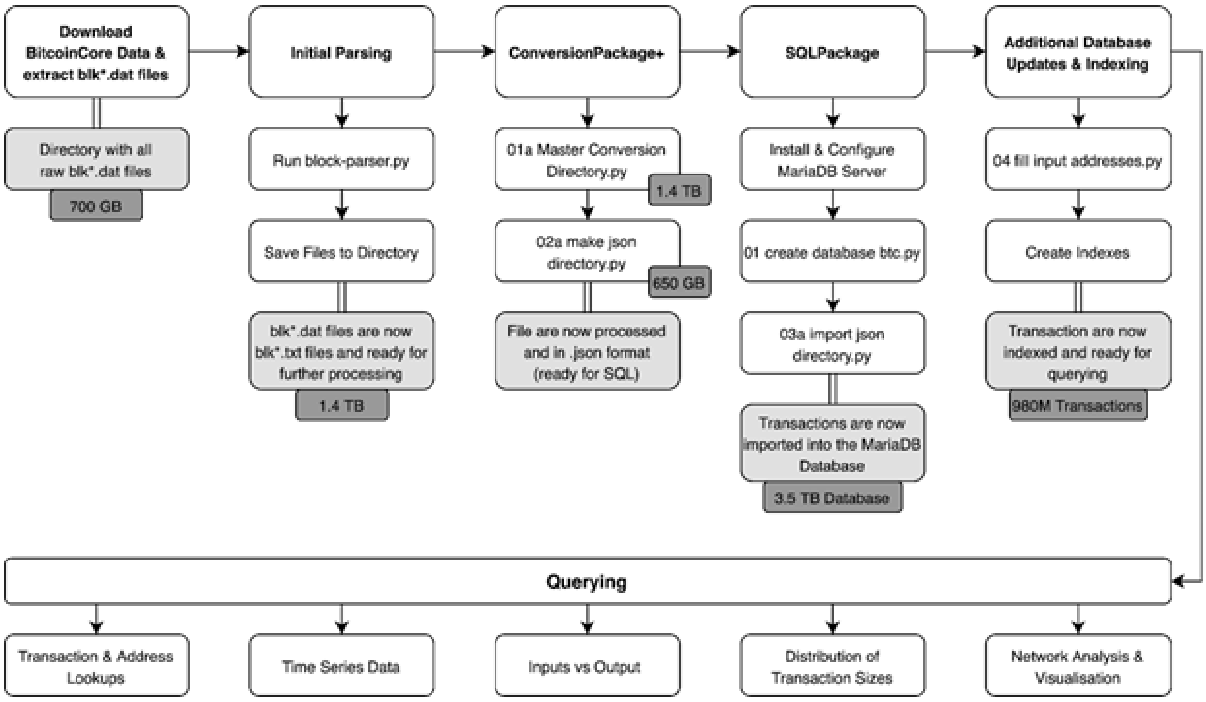
1 Architecture for Raw Blockchain Data Engineering

For scientific purposes, Bitcoin data could be used in raw, unprocessed format to preserve all transactional information, however, this is seldomly done. While there are several attempts in using transactional Bitcoin data in computer science and IT forensics (for instance McGinn et al., 2016; Meiklejohn et al., 2013; Kalodner et al., 2017), there are only single studies from an economic perspective (for instance: Cole et al., 2022) For the purpose of processing the raw data, we extracted Bitcoin Core data in blk*.dat files from the Bitcoin protocol API. We developed a processing architecture to process these blk*.dat files locally and store the transaction-level data in an SQL database. Finally, we created an automatic data pipeline to add newly mined blocks to the existing database in a Google Colab environment. This transformation offers numerous possibilities and applications, such as multilayer network analysis, time-series analysis, transaction lookups, network parameter calculations, clustering and heuristical identification strategies and visualizations. The raw Bitcoin blockchain data files were collected by running a full node on the Bitcoin network using the Bitcoin Core software. This approach ensures that all transactions and blocks meet the rules of the Bitcoin protocol. Although the software provides additional functionalities like mining support, our primary interest was acquiring the complete raw blk*.dat files. During the installation, we set a destination folder for the Bitcoin Core data directory, ensuring sufficient disk space for downloading all the data. The required space at the point of installation was 700 GB. Once the Bitcoin Core data was downloaded, we developed a robust architecture to process, clean, and store the files in an SQL database. This architecture is critical for several reasons. By using raw, unprocessed data, we ensure that all transaction details are retained, preserving data integrity essential for accurate and comprehensive economic research. Our architecture is designed to handle large volumes of data efficiently. The initial parsing stage uses a custom Python script, ”block-parser.py,” capable of reading raw data files from 2009 to 2024. This script processes the blk*.dat files and converts them to blk*.txt files, resulting in a directory size of approximately 1.4 TB.
With the files ready for further processing, the scripts in the ConversionPackage+ are executed. These scripts transform the data and generate JSON-formatted transaction objects, reducing the file size to 650 GB and preparing them for import into the SQL Server. This step is essential for optimizing storage and ensuring the data is in a usable format for analysis. As part of the SQLPackage, the MariaDB Server is configured, the database is created, and the transactions are imported. The database reaches a total size of 3.5 TB and requires additional updates and indexing. In the final step, the transactions are indexed, making all 980 million transactions available for querying. This comprehensive database management ensures that the data is easily accessible and queryable for various research applications. By creating and leveraging this detailed processing environment, we provide a robust tool for future economic research. This architecture addresses the gap in existing tools for economic analysis and offers a starting point for broader research on the implications of cryptocurrencies in the global financial system.

2 Methodology

To showcase the applicability of this dataset, we utilize the raw network data in a series of event studies. Event studies are a well-established research methodology in financial research, providing insights into how specific occurrences impact asset prices and market behavior (Fama et al., 1969; Watts, 1978) and also used recently for geopolitical events such as the Russian invasion

Figure 1: Architecture for Raw Blockchain Data Engineering



Notes: The figure presents an overview about the data handling process with the approximate data amounts

Source: Own representation

of Ukraine (Ahmed et al., 2022). These methodologies have also been adapted to the emerging field of cryptocurrency research (Marmora, 2022). By analyzing events of political and economic turmoil, i.e., the Cyprus banking crisis in 2013, the Crimean annexation in 2014, and the Shanghai stock market suspension in 2016, we simply show how these shocks transmit through the Bitcoin blockchain. This approach not only validates the robustness of our dataset but also extends the current literature by providing new insights into the behavior of the cryptocurrency network during these periods of stress.

2.1 Directed Graph Estimation

To create a directed network graph of blockchain transactions, we define a blockchain network N of nodes and edges by $N = (V, E)$ where $V = \{v_1, v_2, \ldots, v_n\}$ represent blocks, and $E = \{(e_1, e_2) \mid e_1, e_2 \in E\}$ is a set of directed transactions in the network. In N, the nodes V represent unique Bitcoin addresses that can send or receive Bitcoin. Transactions in E are identified by a parameter representing the communication channel in a directed graph from sender node v_1 to receiver node v_2, derived from the previous block hash, showing which addresses have transacted with each other.

To understand the relationships and interactions between the nodes, several network parameters are used. The in-degree indicates the number of different addresses that have sent Bitcoin to a specific address. A higher in-degree suggests that the address receives transactions from many sources. The out-degree refers to the number of different addresses to which a particular address has sent Bitcoin, with a high out-degree implying that the address is distributing Bitcoin to numerous other addresses. The degree is the total number of connections (both incoming and outgoing) a node has, where a high degree indicates an address is very active in transactions.

Connected components represent individual groups of addresses, where each address is linked to at least one other address in the network through transactions. This parameter can be used to identify different clusters of addresses, showing coordinated activity. The clustering coefficient is a measure of the degree to which the addresses in the network tend to cluster together. It is calculated as:

$$\text{clustering coefficient} = \frac{1}{N} \sum_{i \in V(G)} \frac{|\Delta_i|}{k_i(k_i - 1)/2} \tag{1}$$

where: N are the nodes, Δ_i is the number of complete triangles and k_i is the degree of node i. Network density reflects the interconnectedness of the daily Bitcoin network, representing nodes $|N|$ and edges $|E|$. It is calculated as:

$$\text{density} = \frac{|E|}{|N|(|N| - 1)} \tag{2}$$

Self-loops are edges connecting an address to itself, occurring when a transaction is made from an address back to the same address where the sender and receiver are the same. Analyzing self-loops can help understand the flow of funds or identify behavioral patterns of individual addresses and network dynamics.

2.2 Event Analysis

The event analysis approach proposed by Fama et al. (1969) investigates the impact of the three global financial downturns, the Cyprus, Crimean, and Chinese crises, on the Bitcoin transactional network. While the approach is usually used for stock returns and other financial data, this paper applies it to the network variables: nodes, edges, average degree, clustering coefficient, density, connected components, and self-loops.

As part of this, a non-parametric test studies the effect of financial events. The Standardized Cross-Sectional Test (BMP Test) is robust against the way in which abnormal returns are distributed across the event window and, therefore, accounts for the volatility and serial correlation of the event (Boehmer et al., 1991). As previous studies have shown that parametric tests rely on distributional assumptions such as return normality, an additional non-parametric test will be carried out, as these assumptions are violated when using a daily time series (Ahmed et al., 2022). Studies have shown that non-parametric tests, such as the Wilcoxon statistic, are more applicable than other parametric tests (Barber and Lyon, 1996).

The event analysis includes both tests for robustness. The event windows for the analysis will range from 100 days before the event to 30 days after the event. This event window provides a sufficient period before the event to analyze the short-term effects of the shock the event may have caused. To calculate the abnormal market return around the event day, we follow Ahmed et al. (2022):

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \epsilon_{i,t} \tag{3}$$

where: $R_{i,t}$ is the logarithmic daily return of the network parameter i on day t, α_i is the intercept term estimated for the parameter i, representing the average return unexplained by existing market movements. β_i is the standard slope coefficient estimated for parameter i, representing how much the parameter's return moves in relation to a standard, $R_{M,t}$ is the return on day t, measured by an index, in our case, a network timeseries and $\epsilon_{i,t}$ represents the error term for parameter i on day t.

To measure the cumulative event effect on the network parameter over the event window, the Cumulative Abnormal Return (CAR) is calculated as:

$$\text{CAR}_i = \sum_{t=t_1}^{T} \text{AR}_{it} \tag{4}$$

where AR is the abnormal return calculated as $\text{AR}_{it} = R_{it} - (\alpha_i + \beta_i R_{M,t})$.

3 Results

This section offers event analyses of the financial downturns resulting in large financial flows across the globe. Since 06.03.2014, Russia has been subject to sanctions for the Crimea Annexation. We use this starting date for our event analysis as russian oligarchs are heavily invested in cryptocurrencies and might use the for snactions evasion or for obtaining additional liquidity (Khalfaoui et al., 2023). The US declared a national emergency and ordered sanctions, including travel bans and the freezing of U.S. assets, focusing on individuals who had asserted government authority in the Crimean region (U.S. Department of the Treasury, 2014). The annexation of Crimea has led to a cooling of political relations and the calling of mutual economic sanctions involving the European Union, the United States, and Russia. The sanctions involved asset freezing, travel visa restrictions, and economic sanctions against key Russians, focusing on individuals and institutions who had asserted government authority in the Crimean region. This led to significant economic consequences, such as the withdrawal of major American companies from the Russian market as well as the depreciation of the rubble. (Moagăr-Poladian and Drăgoi, 2015).

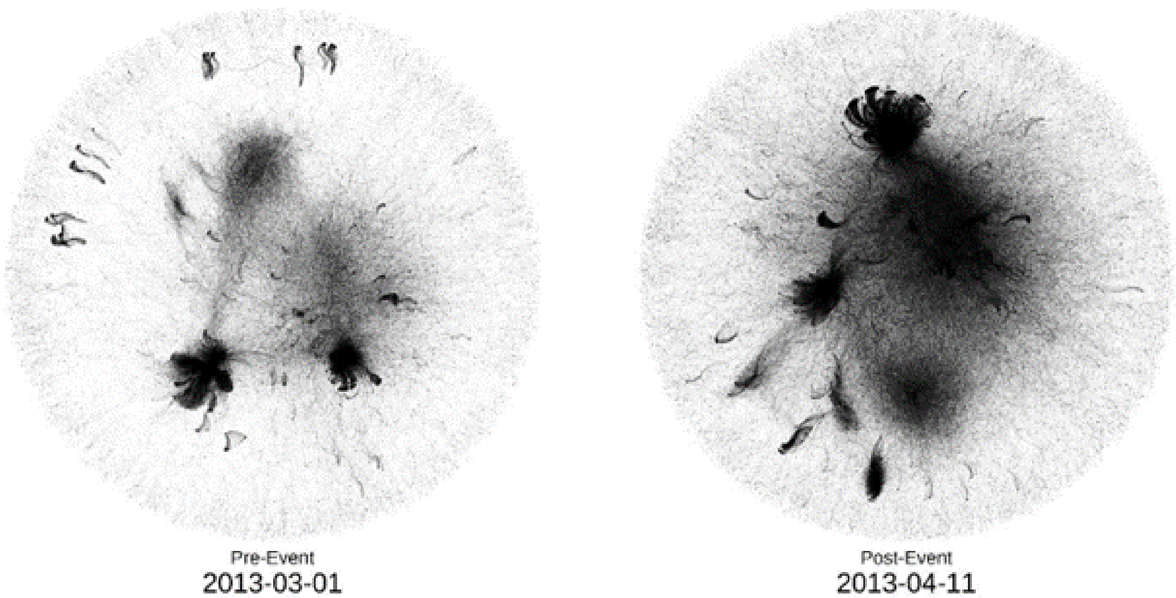
The Cyprus banking crisis was a significant chapter in the European debt crisis, peaking in early 2013. Through the banks' aggressive lending and expansion practices, Cyprian banks were heavily exposed to the Greek debt crisis, leading to Cypriot authorities closing all banks to prevent bank runs (Dixon, 2013). On 16.03.2013 the Eurogroup, European Central Bank, and International Monetary Fund announced a €10 billion bailout for Cyprus. This proposal sparked widespread outrage among Cypriots, international account holders, as well as observers and serves as our event date. On 18.03.2013, a public bank holiday was declared, and all banks were closed to prevent a bank run. While this closure was initially announced to last three days, it was extended several times. On 19.03.2013 the parliament unanimously rejected the bailout plan as an apparent response to the public protest over the proposed levy on deposits (Tagaris, 2013).

The Chinese stock market turbulence of 2015-2016 marks a time of market panic. In June 2015, the stock market experienced a significant downturn, declining 30% in a few weeks, with half of all listed companies suspending trading to limit losses. This crisis was not isolated, and with China playing a significant role in the global economy, global financial markets were affected. (Bradsher and Tsang, 2016) This shook investor confidence since the Chinese market had been a symbol of robust growth since the recovery of the 2008 financial crisis. At the time of the turbulence, there was also a series of government interventions to attempt to stabilize the market, although these had limited success. In January 2016, the market experienced further sell-offs, which again led to trading halts (Shen and Sweeney, 2016). On 04.01.2016 the governement suspended trading on the Shanghai stock exchange after massive sell-offs which we use as our event date for the analysis.

3.1 Pre-post Network Analysis

The Cyprus banking crisis had a notable impact on Bitcoin's network structure. It shifted towards a slightly more unclustered structure and significantly increased network participation and interactions between addresses. Along with the slight but continued decline in clustering, a significant expansion of the network activity can be observed following the banking crisis. We can observe the significant changes in the network structure, specifically the increase in nodes when comparing a visualization of the pre-event daily network with a post-event daily network in Figure 2.

Figure 2: Network comparison of the Cyprus banking crisis



Notes: The figure shows the network of transactions at two days around the cyprus banking crisis. We can see increased transaction activity and distinct clustering behavior, when visually comparing the pre-crisis and the post crisis period. Visualizations only capture a moment in time.
Source: Own representation

The Crimean crisis impacted the structure of the Bitcoin transactional network. Already in the pre-event periods, observing the 20 days before the event, there seems to be a certain degree of anticipation. The nodes and edges indicate a slight yet sustained change in the network structure, but the observed changes are not as markable as those for the Cyprus banking crisis (Figure 3).

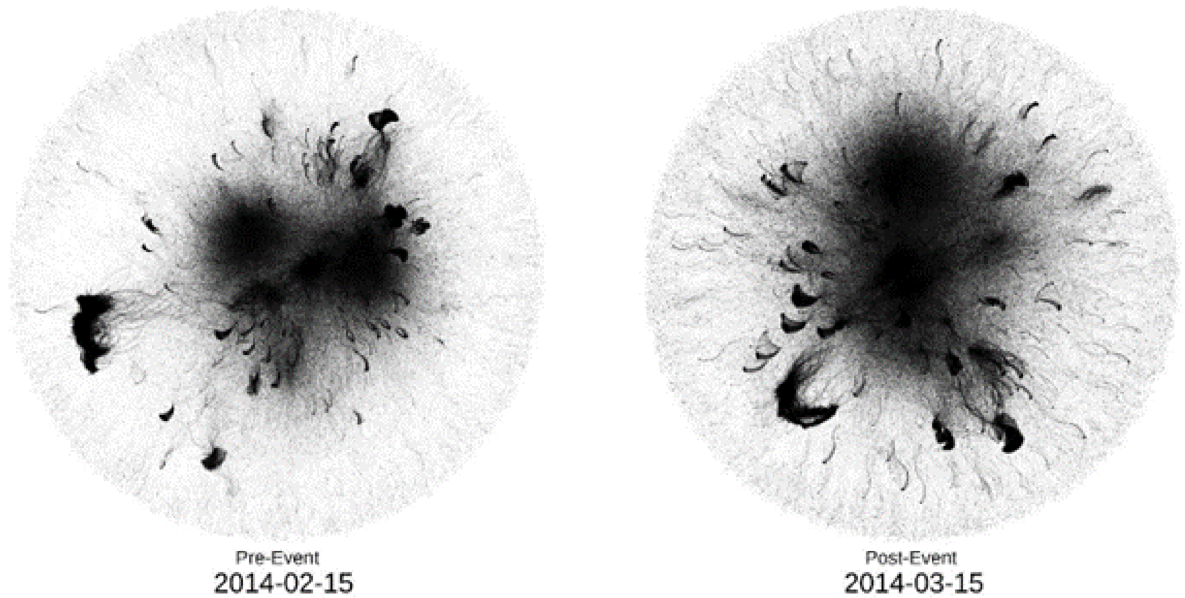
The Shanghai Stock Market suspension had a multilayered impact on the structure of the Bitcoin network, influencing connectivity and clustering but, most of all, leading to increased activity, more participants, and a sign of expansion in the post-event period. Figure 4 presents the pre-event and post-event daily transactional networks to show this change further.

The first visual exploratory analysis of the blockchain network indicates markable differences between the two sub-periods. The graphs show shifts in the network structure and the emergence of new clusters because of the events.

3.2 Network Returns During Financial Downturns

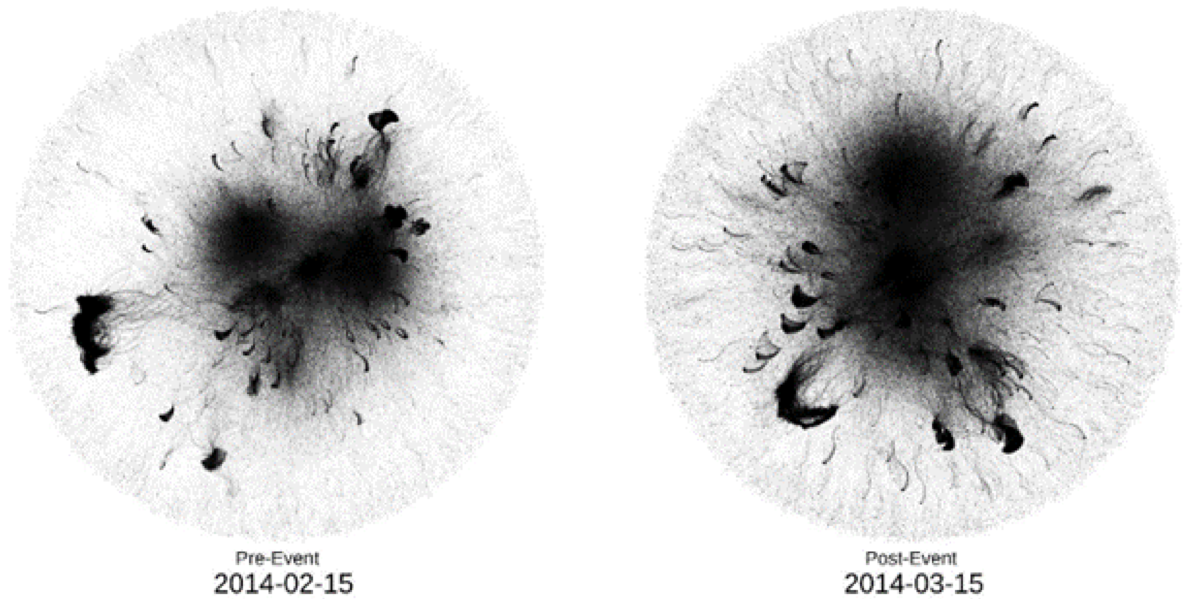
The visual exploration in the previous section indicates notable changes in the graph in the pre- and post-crisis windows. These shifts can be observed in the time-series perspective with the extracted network parameters in daily frequency.

Figure 3: Network comparison of the Crimean annexion



Notes: The figure shows the network of transactions at two days around the crimean annexion.
Source: Own representation

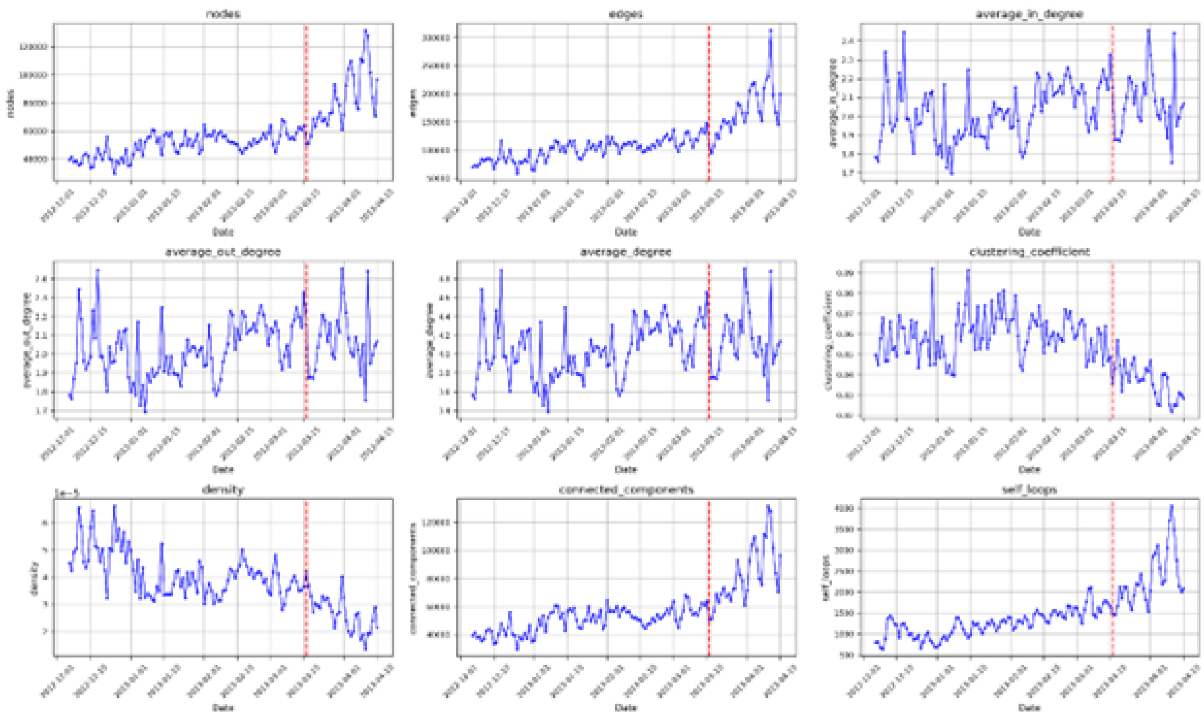
Figure 4: Network comparison of the Shanghai stock market suspension



Notes: The figure shows the network of transactions at two days around the Shanghai stock market suspension.
Source: Own representation

The number of active addresses in the network prior to the announcement of the Cyprus bailout was relatively stable, as indicated by the development of the nodes (Figure **??**). Directly after the proposal, we can see a steady increase and strong fluctuation in node volumes. It indicates the network expansion, possibly due to the uncertainty in the traditional banking sector. Edges were relatively stable before the event and increased significantly in the 30 days after the proposal, which implies a growing interaction in the network. The increase in both the nodes and edges is an indicator that network activity increased following the event, most likely through more people transferring, exchanging, and moving funds through the network.

Figure 5: Network Statistics Surrounding the Cyprus Banking Crisis



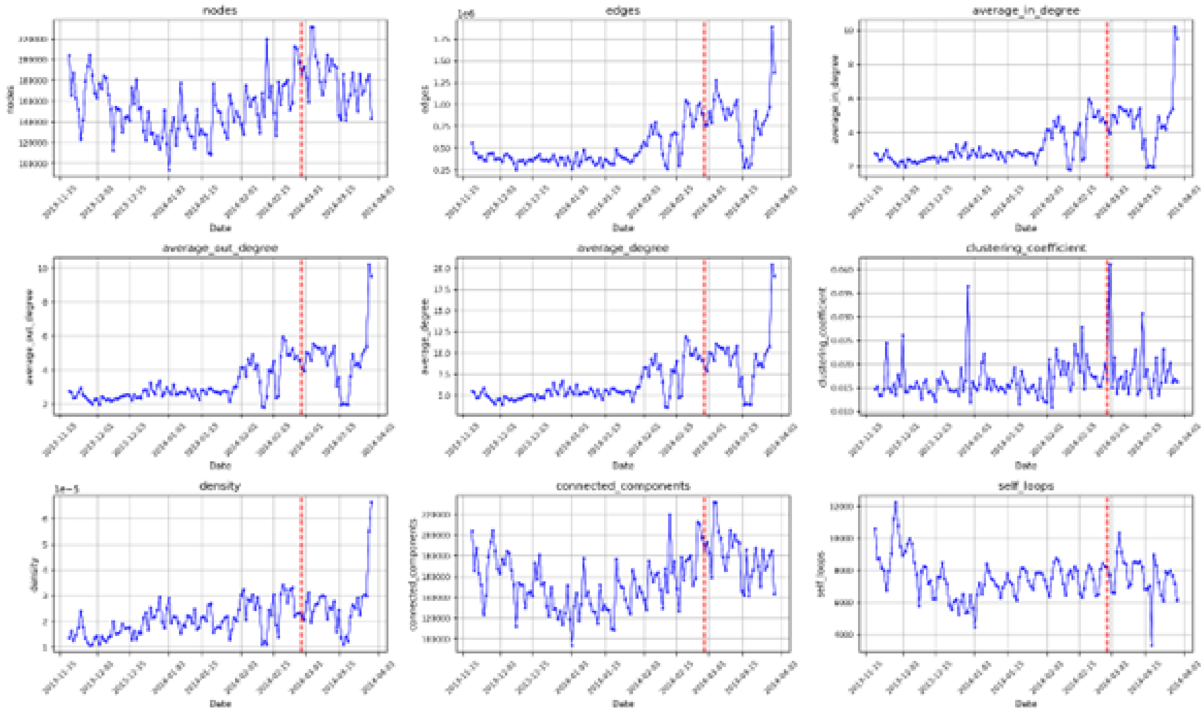
Notes: The red line marks the EU's bailout proposal.
Source: Own representation

The changes observed for the Crimean annexation are not as predominantly observed as for the Cyprus banking crisis . Before the Crimean annexation of 15.02.2014, the node volume was 147,945, decreasing by 1% by 15.03. to 146,017. This minimal decrease in the number of nodes indicates a slight reduction in the number of entities active in the network. However, there was a significant decrease in the number of interactions between the addresses, suggested by the decline in edges by 22% from 667,245 to 519,923 by 15.04. In Figure 3, this can be seen through clusters dispersing, with nodes spreading through the network as they are no longer connected. The slight changes in the clustering coefficient suggest that the overall network structure in terms of clustering remained relatively stable throughout the event period.

The timeframe considered for analyzing the Chinese Stock market crisis begins on 26.09.2015, 100 days before the major sell-off that led to the trading suspension on 04.01.2016. The 30-day window after the event ends on 03.02.2016. In Figure **??**, we can see the nodes increasing by 91% on 01.02.2016, showing that there were significantly more active addresses after the event. The edges parameter also increased by 58%, which signals extensive interactions between individual addresses.

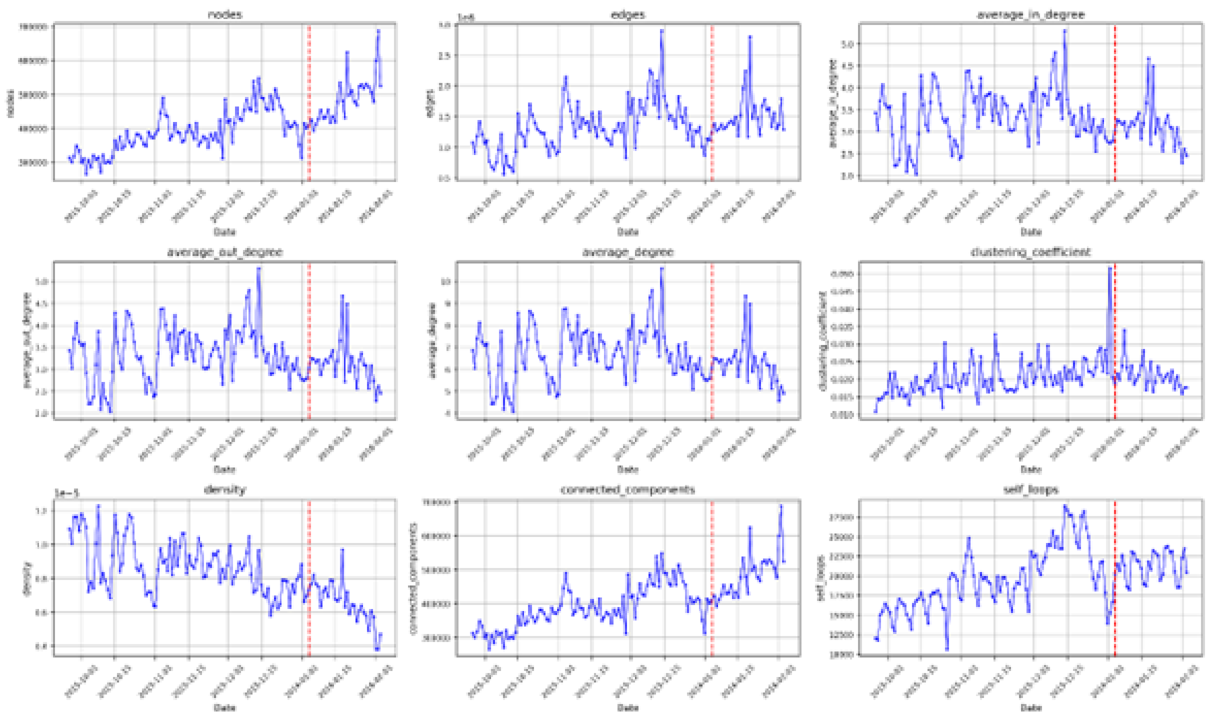
The effect can be seen in the visualization through the darker colors, showing more overlap of nodes and edges and significantly more activity. With the average degree of the network decreasing by 18%, despite the increase in the nodes and edges, we can see that even though the network grew larger, the average connectivity of each address decreased, which indicates a more dispersed network.

Figure 6: Network Statistics Surrounding the Crimean Annexation



Notes: The red line marks the day when the sanctions against russia were imposed.
Source: Own representation.

Figure 7: Network Statistics Surrounding the Shanghai Stock Market Suspension



Notes: The red line marks the trading suspension.
Source: Own representation.

3.3 Cumulative Event Effects on Network Parameters

To statistically test the findings from the exploratory analyses from the previous sections, we run CAR on several pre-, around-, and post-event windows for the four network parameters: average degree, clustering coefficient, edges, and nodes.

The event analysis for the Cyprus Banking crisis shows changes in the various Bitcoin network parameters (Table 1). Regarding network connectivity, we can observe only slight changes in the CAR with values of 0.99 and 0.65 in the [-15, 0] and [-15, 0] windows, analyzing the days prior to the event. This suggests slightly higher than usual interconnectedness of the network addresses leading up to the crisis. With values fluctuating around the event and returning to normal, we can observe a further slight abnormality with a CAR of 0.52 in the [0, 20] window post-event. According to the statistical tests, the values directly surrounding the event are not significant.

Table 1: Cumulative Abnormal Return (CAR) for Cyprus Banking Crisis

Event	Network Parameter	Window	Window Type	CAR	BMP	Wilcoxon p-value
Cyprus	average degree	[-20, 0]	pre-event	0.99	16.87	0***
Cyprus	average degree	[-15, 0]	pre-event	0.65	11.01	0***
Cyprus	average degree	[-3, 3]	around-event	0.12	2.06	0.81
Cyprus	average degree	[-5, 5]	around-event	0.25	4.31	0.28
Cyprus	average degree	[0, 15]	post-event	0.33	5.71	0.21
Cyprus	average degree	[0, 20]	post-event	0.52	8.75	0.07*
Cyprus	clustering coefficient	[-20, 0]	pre-event	-0.06	-5.58	0.32
Cyprus	clustering coefficient	[-15, 0]	pre-event	-0.09	-8.41	0.06*
Cyprus	clustering coefficient	[-3, 3]	around-event	-0.07	-6.85	0.05**
Cyprus	clustering coefficient	[-5, 5]	around-event	-0.12	-11.54	0.01**
Cyprus	clustering coefficient	[0, 15]	post-event	-0.25	-23.02	0***
Cyprus	clustering coefficient	[0, 20]	post-event	-0.36	-32.69	0***
Cyprus	edges	[-20, 0]	pre-event	4.54	25.05	0***
Cyprus	edges	[-15, 0]	pre-event	3.35	18.31	0***
Cyprus	edges	[-3, 3]	around-event	1.38	7.37	0.03**
Cyprus	edges	[-5, 5]	around-event	2.37	12.77	0***
Cyprus	edges	[0, 15]	post-event	5.1	25.09	0***
Cyprus	edges	[0, 20]	post-event	8.29	38.34	0***
Cyprus	nodes	[-20, 0]	pre-event	3.3	19.09	0***
Cyprus	nodes	[-15, 0]	pre-event	2.54	14.66	0***
Cyprus	nodes	[-3, 3]	around-event	1.23	7.06	0.02**
Cyprus	nodes	[-5, 5]	around-event	2.06	11.77	0***
Cyprus	nodes	[0, 15]	post-event	4.68	24.93	0***
Cyprus	nodes	[0, 20]	post-event	7.64	38.28	0***

The event analysis for the Crimean annexation considers several event windows before 16.3.2013, around the date and post-event, to help understand the event's impact over several analyzed timeframes (Table 2). We can already see a significant CAR in the pre-event windows of 5.74 and 5.99 in the average degree. Around the event, the CAR decreases to 2.81 and 4.77 in the [-3, 3] and [-5, 5] windows, suggesting a reduction in the average degree during the event. However, these values are still significantly higher than typical levels, as indicated by the BMP values. Post-event, the CAR increases again, reaching 6.51 and 5.16 for the [0, 15] and [0, 20] windows, suggesting a further increase in the connections per node after the event, also with very significant BMP values.

Table 2: Cumulative Abnormal Return (CAR) for the Crimean Annexation

Event	Network Parameter	Window	Window Type	CAR	BMP	Wilcoxon p-value
Crimea	average degree	[-20, 0]	pre-event	5.99	29.72	0.00***
Crimea	average degree	[-15, 0]	pre-event	5.73	27.95	0.00***
Crimea	average degree	[-3, 3]	around-event	2.81	12.12	0.02**
Crimea	average degree	[-5, 5]	around-event	4.77	20.66	0.00***
Crimea	average degree	[0, 15]	post-event	6.51	25.89	0.00***
Crimea	average degree	[0, 20]	post-event	5.16	20.88	0.00***
Crimea	clustering coefficient	[-20, 0]	pre-event	0.05	13.34	0.00***
Crimea	clustering coefficient	[-15, 0]	pre-event	0.04	10.42	0.02**
Crimea	clustering coefficient	[-3, 3]	around-event	0.03	7.05	0.30
Crimea	clustering coefficient	[-5, 5]	around-event	0.03	6.33	0.58
Crimea	clustering coefficient	[0, 15]	post-event	0.04	9.11	0.46
Crimea	clustering coefficient	[0, 20]	post-event	0.04	8.3	0.68
Crimea	edges	[-20, 0]	pre-event	9.58	34.78	0.00***
Crimea	edges	[-15, 0]	pre-event	9.18	32.88	0.00***
Crimea	edges	[-3, 3]	around-event	4.91	14.94	0.02**
Crimea	edges	[-5, 5]	around-event	8.09	24.52	0.00***
Crimea	edges	[0, 15]	post-event	11.12	29.83	0.00***
Crimea	edges	[0, 20]	post-event	9.5	25.84	0.00***
Crimea	nodes	[-20, 0]	pre-event	2.75	16.91	0.00***
Crimea	nodes	[-15, 0]	pre-event	2.62	16.76	0.00***
Crimea	nodes	[-3, 3]	around-event	1.68	10.09	0.02**
Crimea	nodes	[-5, 5]	around-event	2.61	15.48	0.00***
Crimea	nodes	[0, 15]	post-event	3.6	20.77	0.00***
Crimea	nodes	[0, 20]	post-event	3.65	20.77	0.00***

Pre-event, the clustering coefficient parameter has a minimally negative CAR of -0.09 and 0.06. A negative value would suggest a decline in the tendency of nodes to cluster together before the event. The window [-15, 0] shows a significant value according to both the BMP and Wilcoxon significance. The negative trend continues slightly around the event period in the windows [-3, 3] and [-5, 5] with a CAR of -0.07 and -0.12. Post-event, we can see a more pronounced decline in clustering, with CAR values of -0.25 and -0.36 and very significant BMP values, suggesting a decrease in the addresses clustering together due to the event.

We can observe more noticeable changes in the edges parameter, with CAR values of 3.35 and 4.54 before the event. The edges CAR remains positive, but smaller, in the windows around the event, suggesting a slight reduction increase around the days of the event. We can also observe significant BMP values during this, indicating confidence in these results. Post-event, the edges' CAR values significantly increase to 5.10 in the [0, 15] and 8.29 in the [0, 20] window. Significantly high BMP values suggest a significant increase in the number of edges; the number of interactions between addresses tends to increase as time progresses.

We can also observe an increase in the number of active addresses through the nodes parameter through the event. Pre-event, the CAR was 2.54 and 3.3, indicating an increase in the number of nodes before the event. The statistical tests are also highly significant throughout the period. In the windows around the event, we can see the increase continuing but at a reduced pace, with CAR values of 1.23 and 2.06. Post-event, however, shows a greater increase with a CAR of 4.68 and 7.64, indicating a significant growth in the number of active addresses after the occurrence of the event. The BMP values are also highly significant, underscoring the robustness of the increase.

Overall, the Cyprus banking crisis had a notable impact on Bitcoin's network structure, with a shift towards a slightly more unclustered structure and a significant increase in network participation and interactions between addresses. Along with the slight but continued decline in clustering, a significant expansion of the network activity can be observed following the banking crisis.

Observing the average degree parameter for the Chinese Stock Exchange event, the pre-event windows show a negative CAR with values of -1.45 and -1.37, indicating a significant decrease in the average number of connections per node (Table 3). The significant BMP of -8.84* further supports this decline, suggesting an already notable decline in network connectivity in the immediate time leading up to the event. Around the event, the negative trend coincides with CAR values of -0.61 and -0.9, suggesting a further but slower decrease in the average degree during the event. This decline slows, with CAR values of -0.28 and -0.39 post-event. While still negative, the BMP values are less significant, suggesting a less pronounced decline post-event.

The clustering coefficient shows positive CAR values of 0.09 and 0.08 pre-event, indicating a slightly increased tendency of nodes clustering before the event. Around the event, the CAR values decrease to 0.03 and 0.06 but remain positive. Post-event, we can further observe a stabilization of the clustering coefficient with a CAR value of 0.03 and 0.02 in the [0, 15] and [0, 20] windows. Important to note is the decreased significance of the BMP values, which suggests these changes are less robust compared to the pre-event values.

The CAR values are relatively mixed in the pre-event windows when observing the edges. A positive value of 0.95 can be observed in the [-20, 0] window, alongside a negative value of -0.18 in the [-15, 0] window. Both the lack of consistency and the significance in the BMP suggest an unstable trend in the edges parameter pre-event. Around the event, we can observe negative CAR values of -0.5 and -0.57, indicating a more clear decrease in the number of interactions between the addresses. Post-event, the observed positive CAR values of 1.72 and 2.93 indicate a relatively strong increase, with significant BMP values supporting these findings.

In the nodes parameter, the positive CAR values of 2.59 and 1.38 in the pre-event windows suggest an already increased number of active addresses in the network before the event, also with highly significant BMP values. Around the event, the CAR values dropped to 0.19 and 0.44, indicating a slowdown in the increase rate of the number of nodes. The BMP values were, however, not significant, suggesting less confidence in these changes. Post-event, however, we can observe a strong increase again with CAR values of 2.02 and 3.36 in the [0, 15] and [0, 20] windows. This is further supported by highly significant BMP values creating robustness in these findings.

Overall, these changes show a significant expansion of the network in size but a decrease in interconnectedness, suggesting a shift in the network dynamic with more participants but significantly less integration and interactions among these.

Table 3: Cumulative Abnormal Return (CAR) for the Chinese Stock Market Suspension

Event	Network Parameter	Window	Window Type	CAR	BMP	Wilcoxon p-value
Shanghai	average degree	[-20, 0]	pre-event	-1.45	-8.84	0***
Shanghai	average degree	[-15, 0]	pre-event	-1.37	-8.36	0***
Shanghai	average degree	[-3, 3]	around-event	-0.61	-3.76	0.02**
Shanghai	average degree	[-5, 5]	around-event	-0.9	-5.54	0***
Shanghai	average degree	[0, 15]	post-event	-0.28	-1.75	0.1
Shanghai	average degree	[0, 20]	post-event	-0.39	-2.46	0.08*
Shanghai	clustering coefficient	[-20, 0]	pre-event	0.09	19.72	0***
Shanghai	clustering coefficient	[-15, 0]	pre-event	0.08	17.44	0***
Shanghai	clustering coefficient	[-3, 3]	around-event	0.03	6.55	0.3
Shanghai	clustering coefficient	[-5, 5]	around-event	0.06	11.94	0.02**
Shanghai	clustering coefficient	[0, 15]	post-event	0.03	5.42	0.21
Shanghai	clustering coefficient	[0, 20]	post-event	0.02	4.72	0.45
Shanghai	edges	[-20, 0]	pre-event	0.95	2.85	0.29
Shanghai	edges	[-15, 0]	pre-event	-0.18	-0.68	0.78
Shanghai	edges	[-3, 3]	around-event	-0.5	-1.66	0.38
Shanghai	edges	[-5, 5]	around-event	-0.57	-1.88	0.58
Shanghai	edges	[0, 15]	post-event	1.72	5.96	0.01**
Shanghai	edges	[0, 20]	post-event	2.93	10.03	0***
Shanghai	nodes	[-20, 0]	pre-event	2.59	16.24	0***
Shanghai	nodes	[-15, 0]	pre-event	1.38	8.52	0.02**
Shanghai	nodes	[-3, 3]	around-event	0.19	1.22	0.3
Shanghai	nodes	[-5, 5]	around-event	0.44	2.85	0.21
Shanghai	nodes	[0, 15]	post-event	2.02	13.02	0***
Shanghai	nodes	[0, 20]	post-event	3.36	21.19	0***

4 Conclusion

The present study develops a framework for using raw Bitcoin blockchain data. Moreover, it employs the dataset to create transactional networks around three major geopolitical events: the Cyprus banking crisis, the Crimean annexation, and the Shanghai stock market suspension. Based on the daily network statistics, we employ an event study to calculate abnormal network changes around these events. This helps to understand how selected geopolitical episodes of turmoil transmit through the Bitcoin blockchain. In the event analysis of the annexation of Crimea by the Russian Federation in 2014, a strong anticipatory increase in Bitcoin activity could be observed. Due to the nature of this inherently political disaster, there has been previous intensive news coverage, leading to smaller changes in the network structure after the breakout of the conflict. As far as the Cypriot financial crisis of 2012-2013 occurred soon after the introduction of the Bitcoin cryptocurrency, with a significantly lower degree of anticipation, we could find more significant changes. Combined with the media's introduction of Bitcoin as an alternative asset along with the crisis directly impacting the financial wealth of individuals, the heightened activity can be explained as a cause of the event. The Chinese stock market turbulence, with the suspension of the stock market in January 2016, a more complex response of the Bitcoin transactional networks was observed, with both negative and positive relative changes in the individual network parameters. With the event being in a time during which Bitcoin was already more established, the already high network activity was further observed to be increasing as a result.

The observed impacts on the Bitcoin network during these events, particularly significant in the Cyprus and Shanghai events, highlight the substantial influence of geopolitical and economic crises on the network. These findings align with existing literature showing how large geopolitical events, sanctions, and financial market disruptions can drive significant changes in Bitcoin activity, often as individuals seek alternative assets. However, we are able to provide a more detailed insight based on our transactional networks.

Policy implications from these findings suggest that during times of financial instability, there may be an increase in the use of cryptocurrencies as individuals seek to mitigate risks associated with traditional financial systems and move financial assets through unregulated channels, leading to significant illicit financial flows. This highlights the need for regulatory authorities to monitor cryptocurrency markets closely during such periods, as the heightened activity might also indicate potential shifts in illicit financial flows and preferences for holding Bitcoin. The current descriptive analysis of the blockchain network provides valuable insights but does not yet offer clearly generalizable policy-relevant conclusions. However, the detailed data processing architecture developed in this study opens numerous avenues for deeper micro-level analyses. Future research can further explore how different actors of the Bitcoin blockchain system interact with macroeconomic and geopolitical events. Research can potentially be extended to illicit flows, financial agents, but also the recent inflationary environment.

References

[1] Ahmed, S., Hasan, M. M., & Kamal, M. R. (2023). Russia–Ukraine crisis: The effects on the European stock market. *European Financial Management*, *29*(4), 1078-1118.

[2] Ajayi, S. I., & Ndikumana, L. (Eds.). (2014). Capital flight from Africa: Causes, effects, and policy issues. OUP Oxford.

[3] Aliu, F. (2024). Do infectious diseases explain Bitcoin price fluctuations? *Journal of International Financial Markets, Institutions and Money*, *92*(4).

[4] Alstadsæter, A., Johannesen, N., & Zucman, G. (2019). Tax evasion and inequality. *American Economic Review*, *109*(6), 2073-2103.

[5] Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, *54*, 177-189.

[6] Beckmann, S., Geldner, T., & Wüstenfeld, J. (2024). The relevance of media sentiment for small and large scale bitcoin investors. *Journal of International Financial Markets, Institutions and Money*, *92*(4).

[7] Benigno, P. (2023). Monetary policy in a world of cryptocurrencies. *Journal of the European Economic Association*, *21*(4), 1363-1396.

[8] Biais, B., Capponi, A., Cong, L. W., Gaur, V., & Giesecke, K. (2023). Advances in blockchain and crypto economics. *Management Science*, *69*(11), 6417-6426.

[9] Cole, B. M., Dyhrberg, A. H., Foley, S., & Svec, J. (2022). Can Bitcoin be Trusted? Quantifying the economic value of blockchain transactions. *Journal of International Financial Markets, Institutions and Money*, *79*, 101577.

[10] Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, *10*(1), 1–21.

[11] Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies*, *32*(5), 1798-1853.

[12] Foley, S., Frijns, B., Garel, A., & Roh, T. Y. (2022). Who buys Bitcoin? The cultural determinants of Bitcoin activity. *International Review of Financial Analysis*, *84*, 102385.

[13] Hu, A. S., Parlour, C. A., & Rajan, U. (2019). Cryptocurrencies: Stylized facts on a new investible instrument. *Financial Management*, *48*(4), 1049-1068.

[14] Iansiti, M., & Lakhani, K. R. (2017). The truth about blockchain. *Harvard Business Review*, *95*(1), 118-127.

[15] Kalodner, H., Möser, M., Lee, K., Goldfeder, S., Plattner, M., Chator, A., & Narayanan, A. (2020). BlockSci: Design and applications of a blockchain analysis platform. In 29th USENIX Security Symposium (USENIX Security 20) (pp. 2721-2738).

[16] Khalfaoui, R., Gozgor, G., & Goodell, J. W. (2023). Impact of Russia-Ukraine war attention on cryptocurrency: Evidence from quantile dependence analysis. *Finance Research Letters*, *52*, 103365.

[17] Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, *34*(6), 2689-2727.

[18] Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), 1133-1177.

[19] Marmora, P. (2022). Does monetary policy fuel bitcoin demand? Event-study evidence from emerging markets. *Journal of International Financial Markets, Institutions and Money*, *77*, 101489.

[20] McGinn, D., Birch, D., Akroyd, D., Molina-Solana, M., Guo, Y., & Knottenbelt, W. J. (2016). Visu-

alizing dynamic bitcoin transaction patterns. *Big Data*, *4*(2), 109-119.

[21] Meiklejohn, S., Pomarole, M., Jordan, G., Levchenko, K., McCoy, D., Voelker, G. M., & Savage, S. (2013, October). A fistful of bitcoins: characterizing payments among men with no names. In Proceedings of the 2013 conference on Internet measurement conference (pp. 127-140).

[22] von Luckner, C. G., Reinhart, C. M., & Rogoff, K. (2023). Decrypting new age international capital flows. *Journal of Monetary Economics*, *138*, 104-122.

[23] Watts, R. L. (1978). Systematic 'abnormal' returns after quarterly earnings announcements. *Journal of Financial Economics*, *6*(2-3), 127-150.

[24] Xu, L., T. (2023). Hedging effectiveness of bitcoin and gold: Evidence from G7 stock markets. *Journal of International Financial Markets, Institutions and Money*, *85*(6).