INTERNATIONAL TRADE AND CRYPTOCURRENCY MOVEMENTS:

A NETWORK ANALYSIS

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A Network Analysis

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DECLARATION OF ORIGINALITY

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ABSTRACT

International Trade and Cryptocurrency Movements: A Network Analysis

This thesis examines the intricate dynamics between international trade and cryptocurrency transactions, with a particular focus on Bitcoin. Employing an extensive dataset that includes the Direction of Trade Statistics for imports and exports, alongside the World Governance Indicators, this study explores the multifaceted relationships between global trade activities and cryptocurrency operations. The findings reveal that countries with substantial trade volumes are more likely to engage in significant cryptocurrency transactions, suggesting that cryptocurrencies are increasingly used to facilitate international trade. This research supports several hypotheses, including the positive correlation between trade volume and cryptocurrency activity, and the role of cryptocurrencies in enabling financial activities in countries facing capital account deficits. Conversely, the study also addresses hypotheses that were not supported, providing critical insights into the limitations of cryptocurrencies in contexts of political and economic instability. By analyzing the overlap and distinctions between cryptocurrency and traditional trade networks, this thesis contributes to a deeper understanding of the evolving landscape of digital finance and its implications for international trade and economic policy.

ÖZET

Uluslararası Ticaret ve Kripto Varlık Hareketleri: Network Analizi

Bu tez, özellikle Bitcoin üzerine odaklanarak, uluslararası ticaret ve kripto para işlemleri arasındaki karmaşık dinamikleri incelemektedir. İthalat ve ihracat için ticaret yönü İstatistiklerini içeren kapsamlı bir veri seti kullanılarak, küresel ticaret faaliyetleri ile kripto para operasyonları arasındaki çok yönlü ilişkiler araştırılmıştır. Bulgular, önemli ticaret hacimlerine sahip ülkelerin kripto para birimlerini artan bir şekilde kullandıklarını göstermektedir. Bu araştırma, ticaret hacmi ve kripto para aktivitesi arasında pozitif bir korelasyonu ve sermaye hesabı açıkları olan ülkelerde finansal faaliyetleri mümkün kılan kripto para birimlerinin rolünü ortaya koymaktadır. Öte yandan, çalışma desteklenmeyen hipotezleri de ele almakta ve kripto para birimlerinin politik ve ekonomik istikrarsızlık bağlamlarındaki sınırlılıklarına dair öncemli bulgular sunmaktadır. Bu tez, çeşitli jeopolitik bağlamlarda karşılaştırmalı analizler ve daha geniş ekonomik göstergeleri keşfetme yoluyla küresel ekonomik etkileşimlerde dijital para birimlerinin rolünü anlamamızı geliştirecek gelecek araştırmalar için yol göstermektedir.

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CHAPTER 1

INTRODUCTION

The advent of Bitcoin and its integration into economic systems presents a paradigm shift in how financial transactions can be conducted globally. As the first decentralized cryptocurrency, Bitcoin offers a unique mechanism for cross-border trade, potentially bypassing traditional banking systems and regulatory frameworks. This thesis explores the interrelation between Bitcoin transaction data and traditional economic metrics, such as Direction of Trade, Balance of Payment Statistics, and World Governance Indicators, to discern the underlying dynamics of this digital currency within the international trade context. cryptocurrencies like Bitcoin have not only challenged conventional monetary systems but have also shown potential as alternative vehicles in international trade settings. Their inherent properties, such as decentralization, ease of transfer, and relative anonymity, make them particularly appealing in scenarios where traditional financial systems are either too slow or encumbered by regulatory red tape. Several studies have highlighted the volatility of Bitcoin and its impact on financial markets and international trade. For instance, Garcia et al. (2014) discuss how the Bitcoin market responds to changes in sentiment and popularity, driven by social media and information searches, which in turn can influence economic activities (Garcia et al. 2014). Similarly, Ciaian et al. (2016) explore how various market forces, attractiveness indicators, and macro-financial developments can impact Bitcoin prices, suggesting a complex interplay that might affect its role in international trade (Ciaian, Rajcaniova, and Kancs 2016). Moreover, empirical research by Matta et al. (2015) on the predictive power of social media and search data on Bitcoin prices underscores the digital currency's sensitivity to public sentiment and its potential implications for trade transactions where currency values are pivotal (Matta, Lunesu, and Marchesi 2015).

The transformative potential of Bitcoin in international trade and finance is underscored by its capacity to act as a medium of exchange and a store of value, albeit with noted volatility. Kjærland et al. (2018) argue that despite the non-correlation of Bitcoin prices with traditional financial assets like gold and oil, its price is influenced by broader economic indicators, such as stock market returns, which could have implications for its use in trade (Kjærland et al. 2018). This thesis aims to provide a comprehensive analysis of Bitcoin's role within the broader economic landscape, particularly focusing on its integration into, and impact on, international trade dynamics. By leveraging quantitative data from traditional trade metrics and qualitative data from governance indicators, the study seeks to offer insights into how Bitcoin is reshaping financial transactions on a global scale and the potential economic implications of its widespread adoption. Within the thesis, several hypotheses will be tested to analyze the multifaceted relationship between Bitcoin and international trade dynamics. Our first hypothesis posits that countries with higher volumes of international trade may increasingly adopt Bitcoin as a flexible and efficient means of transaction, given its global accessibility and transfer ease. Countries with high volumes of international trade may require more flexible and efficient means of payment and financial transactions. cryptocurrencies, notably Bitcoin, with its global reach and ease of transfer, might be used increasingly in such countries to complement traditional trade financing methods. We use correlation and regression analyses to examine the relationship between the trade volumes (both the export and import metrics from the IMF Direction of Trade Dataset) and Bitcoin transaction volumes. Here, we control for factors such as economic size, World

Governance Indicators, and regulatory environment to isolate the effect of trade volume on Bitcoin usage. Second hypothesis explores the influence of political stability on Bitcoin transactions, suggesting that more stable political environments may foster greater economic activity, thereby increasing both the volume and value of Bitcoin transactions. For testing this hypothesis, we conduct a regression analysis where the dependent variable is the volume of Bitcoin transactions, and the independent variable is the political stability score. We also control for economic variables like GDP per capita and World Governance Indicators. Third, this research will assess the impact of geopolitical tensions, proposing that during such periods, Bitcoin may be sought as a safe haven, similar to gold, which could lead to an uptick in transaction volumes and prices. We employ a temporal analysis to examine periods of high geopolitical tension and corresponding changes in Bitcoin transaction volumes and prices, adjusting for global market trends. Fourth, the relationship between trade balance and Bitcoin usage will be examined, hypothesizing that countries with significant trade deficits might leverage Bitcoin to manage foreign currency reserves shortages or to facilitate more cost-effective cross-border transactions. We use regression analysis to explore the relationship between trade balance (exports minus imports) and Bitcoin transaction volumes, controlling for economic size.

Lastly, the study will explore how stringent trade regulations might correlate with increased Bitcoin transactions as businesses and individuals seek alternatives to circumvent restrictive trade practices. These hypotheses will be scrutinized through various data analyses, shedding light on Bitcoin’s potential role in modernizing and influencing global trade practices. Perform a correlation analysis to assess the relationship between capital control restrictions and the volume of Bitcoin transactions, adjusting for overall trade volume and economic openness. The thesis is structured as follows: The first section presents an extensive literature review that discusses the theoretical backdrop and case studies pivotal to the research question. This leads to the formulation of the conceptual framework. Building upon the literature, the paper advances by proposing ten informed hypotheses. Subsequent sections introduce the datasets, with an emphasis on Bitcoin transactions, Direction of Trade Statistics, Balance of Payments, and other relevant data sources, setting the stage for empirical analysis. In the following section, we conduct a robust examination of these hypotheses using analytical techniques. The concluding section summarizes the research findings, discusses their implications, acknowledges the study's limitations, and suggests directions for future research.

CHAPTER 2

LITERATURE REVIEW

The integration of Bitcoin and other cryptocurrencies into the global financial system, driven by the underlying blockchain technology, represents a significant shift in how economic transactions are conducted across borders. This literature review aims to dissect the vast body of scholarly work surrounding blockchain technologies, cryptocurrencies, and their intersection with international trade. It further explores how network analysis can enhance our understanding of the complexities inherent in these digital transactions. The review concludes with a synthesis of the findings and implications for both theory and practice. A methodological approach was adopted provide a comprehensive and transparent literature review was conducted to understand the interplay between the political-economic influences and transactions conducted via cryptocurrencies. Literature is reviewed under three main headings. First, we provide a comprehensive to blockchain as the underlying technology behind cryptocurrencies and examine the fundamentals of the state of the art. Second, we examine network analysis as a method for understanding cryptocurrency transactions and interpreting the data. Third, we review the intersection between cryptocurrencies and international trade through providing a review of the political economic and geopolitical aspect. Lastly, we analyze the gaps in literature and list our hypotheses based on the research.

During the literature review, we started with seminal articles on three main components of our research. More notably, seminal sources such as Bitcoin whitepaper (Nakamoto 2008), Statistical mechanics of complex networks (Albert and Barabási 2002), Finding and evaluating community structure in networks on network science (Newman and Girvan 2004), and Improving the efficiency and reliability of digital time-stamping (Bayer, Haber, and Stornetta 1993) were analyzed. Later, we expanded our research with related keywords on “cryptocurrencies,” “network analysis,” and “international trade,” published in refereed journals. Google Scholar and Boğaziçi University Library Catalogue were used as the main search tool. Main criteria for choosing articles were H-indexes, impact factors, Scimago journal scores, and the relevance with the research topic. Additional articles were defined using snowball method. In total, over 130 articles were reviewed as part of this literature review.

2.1 Blockchain and cryptocurrencies

The adoption of blockchain technology and cryptocurrencies has significant implications for traditional financial institutions and international trade. Therefore, before delving into the details of network analysis and exploring the interplay between international trade and cryptocurrencies, it is fundamental to provide an overview of cryptocurrencies and the underlying technology behind them. Therefore, under this section, we discuss the origins of blockchain technology, its key characteristics such as decentralization, immutability, and transparency, and how these features lend themselves to applications beyond mere currency transactions focusing on their implications for international trade and financial transactions. The literature on cryptocurrencies themselves, particularly Bitcoin, is reviewed in terms of their development, economic implications, market dynamics, and regulatory challenges. Seminal works by Nakamoto (2008) and subsequent analyses by scholars highlight the disruptive potential of these technologies in financial sectors.

2.1.1 The emergence of the state of the art

Barter systems from the early stages of human development enabled not only to exchange commodities but also to establish a trust bond between parties. Individuals engaging in face-to-face trade have the possibility to assess the value of goods to an extent and see what they are actually paying for. However, this auditing process has become outdated with increasing complexity of traded goods and increasing digitalization trends around the world (Sankar, Sindhu, and Sethumadhavan 2017), and various institutions and instruments had to be instated to deal with increasing difficulties in establishing trust. In addition to money and accounting systems; contracts, transactions, and records emerged as essential tools to govern assets and organizational boundaries. However, they have failed to keep up with the rapid transformation of technology (Iansiti and Lakhani 2017). There have been various issues with data management of public and private organizations such as maintaining the order of transactions and double-spending in finance (Casino, Dasaklis, and Patsakis 2019; Nakamoto 2008); fraud and data losses due to centralized data management, lack of traceability (Azzi, Chamoun, and Sokhn 2019a), an increase in counterfeit products (Casino et al. 2019) in supply chain management; and corruption, efficiency problems (Casino et al. 2019), and trust issues with centralized design of electronic systems in various governmental processes (Moura and Gomes 2017). Inefficiencies in international trade not only led to disadvantages in terms of cost, but also to detriments in establishment of trust between parties.

Defined in Harvard Business Review as “an open, distributed ledger that can record transactions between parties efficiently and in a verifiable and permanent way”, blockchain aims to provide a framework that can reconcile conflicting information and maintain the bond of trust between parties engaging in trade or operational relations (Iansiti and Lakhani 2017). In the light of this definition, blockchain can be considered as a digital record book for transactions that is not validated by a central authority. The true state of a shared ledger between any parties can be established thanks to blockchain even if the users are not verified by a third party (Catalini and Gans 2020). Blockchain was popularized in 2008 following the publication of the whitepaper of Bitcoin, a peer-to-peer payment technology that aims to solve the transaction order and double-spending problem (Chohan 2021; Nakamoto 2008). However, the fundamental technology that enabled the creation of Bitcoin and blockchain dates back to 1990s, when a new decentralized timestamping method was proposed by Bayer, Haber, and Stornetta to certify the document creation date in a way that can be observed by other parties. Cryptographic features of the technology could be used to reveal parts of a document to certify the authenticity in the event that the centralized authority is compromised (Bayer et al. 1993). One of the main characteristics of blockchain is being decentralized, and it is also referred to as the "distributed ledger technology (DLT)" (Ølnes, Ubacht, and Janssen 2017).

Even though there is a consensus on the large variety of application potential of blockchain in the literature (Azzi et al. 2019a; Casino et al. 2019), publications are divided about the impact of blockchain on digital services. Some articles refer to blockchain as a technology that will have a "radical" impact on all digital services (Casino et al. 2019). However, this has not been the case apart from the financial services, considering the limited amount of proven application examples since the emergence of the technology in 1993. It is more likely that the transformation to carry into practice gradually and steadily as the functional transitions proposed by the technology are expected to have fundamental impact on a wide range of services

(Catalini and Gans 2020; Iansiti and Lakhani 2017) both in terms of international business and governmental perspectives. Therefore, subjective and empirical research on the topic constitutes a great deal of importance for the future applications of the technology.

Blockchain technology brought serious innovation to the conventional business processes that require verification from third parties. The technology expected to provide the same level of certainty with the third-party verification methods while providing decentralization, transparency, robustness, auditability, and security (Casado-Vara et al. 2018; Casino et al. 2019). Some reviews in the literature categorizes the applications of blockchain directly as financial and non-financial since most notable application examples include cryptocurrencies (Casino et al. 2019; Ølnes et al. 2017). Even though blockchain is popularized as the technology behind Bitcoin, the applications are far from being limited to financial area. Therefore, in this section, we focus on the areas that are relevant and expected to have an impact on the international trade practices namely financial applications, governance and citizenship, data management, and supply chain management.

2.1.2 Operation

Even though there are different blockchain structures for different purposes, the operation of the system is based on a simple principle. We have discussed that the technology is developed upon the timestamping procedure (Szabo 1994) which provides transparency and decentralization for documents. In essence, modern blockchain applications consist of timestamped blocks that progresses in the form of a chain. Every new transaction is recorded at the end of the chain as a new block with each block including the hash of the previous (Ølnes et al. 2017; Queiroz, Telles, and Bonilla 2019). More complex blockchain applications and therefore transactions in a blockchain environment resemble a network rather than a chain. In this network environment, validating participants called ‘nodes’ or ‘miners’ that has the full copy of the blockchain data and must reach an agreement through completing different tasks to decide on whether transactions can and be recorded on the chain or not by ensuring the accuracy of the blockchain copies (Casino et al. 2019; Ølnes et al. 2017). This task prevents any corrupt branches and divergences, and usually involves solving the cryptographic hash that connects the new block to the previous {Citation}. It is essential that the majority of nodes in the blockchain network to validate the transaction before a new block is created to ensure the integrity of the system (Catalini and Gans 2020; Iansiti and Lakhani 2017; Queiroz et al. 2019). Every time a new block is added, the system synchronizes with other nodes (Ølnes et al. 2017). Therefore, this operation prevents retrospective change on previous blocks and results in an “immutable” or “tamper-proof” system (Azzi et al. 2019a).

There are various consensus mechanisms that can used on blockchain structures. The most common consensus mechanisms can be listed as proof-of-work (PoW), proof-of-stake (PoS), proof-of-activity (PoA), and proof-of-capacity (PoC) with proof-of-work (PoW) and proof-of-stake (PoS) being the most used consensus mechanisms (Casino et al. 2019). Proof-of-Work involves solving a difficult computational process similar to the mining of valuable minerals from the ground; therefore, nodes are often called “miners” (Azzi et al. 2019a; Casino et al. 2019). PoW is successful in ensuring the authentication and verifiability of the system but is often criticized for being an expensive and inefficient consensus method. Proof-of-Stake is another consensus mechanism that splits the nodes in accordance with their wealth; therefore, provides a fairer selection (Pilkington 2016) as opposed to PoW where the blocks are divided proportionately to the mining power (also called ‘hash rate’). PoS is a much more efficient system compared to PoW (Casino et al. 2019).

Blockchain structures are categorized by several criteria in the literature. Firstly, according to the permission type, blockchains are categorized as public (permissionless), private (permissioned), and federated (permissioned) (Agbo, Mahmoud, and Eklund 2019; Azzi et al. 2019a; Casino et al. 2019). Public blockchain is an open ledger where all nodes can join the network as a user and participate in transactions without the need for a central authority. Both private and federated blockchains are permissioned; in other words, decision and validation mechanisms are handled by an organization (Chang, Iakovou, and Shi 2020). Admission to permissioned blockchains is usually regulated by a whitelist of nodes and users (Sankar et al., 2017). On the other hand, federated blockchains combine the security level of private blockchains while managing a partially decentralized design through the assignment of ‘leader nodes’ that can grant permission to others (Casino et al. 2019).

Secondly, according to the development of technology, Zhao et al. distinguishes the development of the technology in three generations. Blockchain 1.0 constitutes the foundation of the technology with allowing digital currency transactions. Blockchain 2.0 introduces Smart Contracts and blockchain-based applications to increase the capabilities of the system. And lastly, Blockchain 3.0 expands the application potential to a wider base including government, health, science, and IoT (Zhao, Fan, and Yan 2016). Furthermore, blockchain 3.0 also involves integration of the system with other IoT devices (Casado-Vara et al. 2018) and transportation technologies such as QR codes, RFID tags, various sensors, and autonomous vehicles (Queiroz et al. 2019).

Integration of smart contracts with blockchain 2.0 has been an important development and exponentially increased the application potential of blockchain into areas other than financial transactions (Casino et al. 2019; Christidis and Devetsikiotis 2016). Smart Contracts have been first defined by Szabo in 1994 as computerized transactions that automatically carry out the terms of a contract (Szabo 1994). Integration of smart contracts in blockchain allow users to translate contracts into embeddable code and record them in a blockchain environment without needing a central authority (Casino et al. 2019; Szabo 1994). Smart contracts have practically limitless application potential. They can be used for embedding all kinds of contracts, processes, or transactions (Iansiti and Lakhani 2017). Furthermore, such contracts can be executed even in the default of trust between parties by leveraging the validation and decentralization features provided by blockchain (Christidis and Devetsikiotis 2016). Therefore, smart contracts are considered as a potential candidate to replace various intermediaries such as lawyers, brokers, and even banks (Iansiti and Lakhani 2017). Smart contracts are further relevant for international trade practices in providing a variety of benefits such as responsiveness, lead-time reduction, and transaction-costs reduction (Christidis and Devetsikiotis 2016), which are further explained in the following sections of this research.

2.1.3 Financial applications of blockchain and cryptocurrencies

First and foremost, blockchain technology, with its decentralized and immutable ledger system, offers a novel solution to the challenges associated with cross-border transactions. Traditional methods of transferring funds across borders often involve multiple intermediaries, resulting in delays, high costs, and potential security vulnerabilities. In contrast, blockchain-powered transactions enable peer-to-peer transfers without the need for intermediaries, thereby reducing transaction costs and processing times (Narayanan et al. 2016). Bitcoin, as a decentralized digital currency operating on a blockchain network, exemplifies this disruptive potential by facilitating near-instantaneous and cost-effective cross-border transactions (Yermack 2015).

Blockchain operates in a way that transactions are recorded on blocks in an organized and immutable way (Azzi et al. 2019a; Queiroz et al. 2019). From a financial perspective, this design provides certain advantages compared to the centralized digital banking systems (Catalini and Gans 2020). For example, banks can cooperate under one blockchain to share customer transactions or users can benefit from the shared network without the consequences of lack of an authority such as increased market power and control over data (Catalini and Gans 2020). Furthermore, this approach facilitates auditing and provides lower barriers of entry for new service providers in decentralized finance and cryptocurrency asset industries especially for countries where established institutions are rare. While some institutions have embraced blockchain technology for its potential to streamline operations and reduce costs, others perceive cryptocurrencies as a threat to their business models (Gomber et al. 2018). The emergence of Bitcoin and other cryptocurrencies challenges the dominance of centralized financial systems, prompting regulators and policymakers to grapple with regulatory frameworks to govern their use and mitigate potential risks (Böhme et al. 2015).

Most reputable applications of blockchain in the financial area include, in general, most cryptocurrencies such as Bitcoin and Ethereum (Buterin 2013; Nakamoto 2008). Reduction in cost of verification, and lack of infrastructural costs are among the main features of cryptocurrencies (Casino et al. 2019; Catalini and

Gans 2020). Apart from being used as a medium of exchange, various other financial applications for blockchain have emerged such as prediction markets, securities, derivative contracts, loan management systems, financial auditing, foreign exchange, cross-border settlement, and securities settlement (Casino et al. 2019; Iansiti and Lakhani 2017). For example, Nasdaq is in collaboration with Chain.com to process and validate financial transactions , and R3 is reportedly exploring ways to establish a blockchain-based framework for the financial market along with Goldman Sachs and Barclays (Crosby et al. 2016). Numerous countries such as Bank of Canada is exploring a digital currency for interbank transfers called CAD-coin (Iansiti and Lakhani 2017). Furthermore, it is often argued that blockchain technology and cryptocurrencies have the potential to expand financial inclusion by providing access to financial services for underserved populations worldwide. Through decentralized finance (DeFi) applications built on blockchain platforms, individuals can access a wide range of financial services, including lending, borrowing, and asset management, without relying on traditional banking infrastructure (Catalini and Gans 2020).Bitcoin, as a borderless and censorship-resistant currency, empowers individuals in regions with limited access to traditional banking services to participate in the global economy(Kaur, Gupta, and Saxena 2021). Other blockchain-based financial applications can be listed as processing of commercial property and casualty claims, contingent convertible bonds, and rehypothecation (Casino et al. 2019). Such use cases also have implied cost saving in areas such as financial reporting and compliance since blockchain can provide a verifiable history of all transactions (Treat et al. 2017).

2.1.4 Other applications of blockchain and Bitcoin

Today, a huge amount of data is being generated and collected by both public and private organizations. IBM claims that approximately 90% of the data in the world as of 2017 has been created in the previous two years (IBM, 2017, as cited in Casino et al., 2019). Furthermore, data accessed by supply chains has been increased 50 times in the five-year period up to 2018 (Heutger and Kückelhaus 2016). While the surge in the creation of data is usually linked with growing world population and new technologies such as IoT (Casino et al. 2019), AI, and machine learning, blockchain applications are often praised for offering performance benefits (Chang, Chen, and Wu 2019) in terms of managing big data for businesses and governments. Complex organizations can potentially benefit from a decentralized data management systems to improve security, performance, and auditability .Furthermore, these implications are even more stated for e-commerce applications (Casino et al. 2019).

Health sector is another area that can benefit greatly from a decentralized data management approach. Electronic Health Records (EHR) contain valuable information regarding the medical records, and information about medical predictions, and treatment. EHR are currently managed by centralized data management systems that create issues related to single point of failure such as security, privacy, and accessibility (Agbo et al. 2019). As a technology that fundamentally address such potential problems with a decentralized approach, blockchain is referred in the literature as technology that can have a pivotal impact on healthcare management systems (Agbo et al. 2019; Casino et al. 2019). Such applications could provide public and easy verification, and immunity to tampering and system outages since there is no centralized owner that hackers can target (Agbo et al. 2019). Management of health records, online patient access as well as healthcare claims and preventing counterfeit medicine can be potentially achieved through blockchain applications (Agbo et al. 2019; Casino et al. 2019; Zhao et al. 2019). Furthermore, blockchain could support scientific research by providing evidence for credibility and selective publication and managing patient consent for trials (Agbo et al. 2019). However, it is often underlined in the literature that the interoperability of the system has not yet fully matured and there are limited application examples (Agbo et al. 2019; Casino et al. 2019).

Traceability and data management have posed various challenges for supply chains. The industries where these issues are most prominent are identified in the literature as healthcare, finance, food, and education citing the vulnerabilities of centralized data management systems such as vulnerability to fraud (Chang et al. 2020) and tampering (Abeyratne and Monfared 2016; Azzi et al. 2019a). Supply chain management arguably constitutes one of the most important application areas for blockchain in incorporating the crucial sourcing, production, and logistics functions for companies. Various devices such as RFID tags, wireless sensors, and QR codes have been implemented to improve monitoring, information sharing, and optimization in supply chain management (Queiroz et al. 2019); however, use of IoT technologies alone do not provide the required level of security since these devices can be manipulated or cloned. The combination of IoT with blockchain applications opens up new possibilities for supply chains. New developments in software support for low-power hardware to enable operation of blockchain on lighter devices such as wireless IoT sensors. Therefore, blockchain architecture is argued to have the potential to enhance IoT applications by reducing the deficiencies such as security and increasing their potential (Özyilmaz, Doğan, and Yurdakul 2018).In other words, a secure and interconnected network of IoT devices can be established in the form of an auditable data exchange (Casino et al. 2019) that enables scalability and efficiency with the use of blockchain technology.

The application potential of blockchain is not limited to providing security to IoT systems. IBM defines potential breakthrough areas of the technology in supply chain management as visibility, optimization, and demand planning (IBM Corporation, 2016 as cited in Casino et al. 2019). More specifically, blockchain can be used to eliminating counterfeit products (Azzi et al. 2019a) decreasing paper load (Azzi et al. 2019a; Toyoda et al. 2017), ease of compliance (Azzi et al. 2019a), origin tracking (Casado-Vara et al., 2018), enabling direct transaction between buyers and sellers (Casino et al. 2019) providing a better information management, as a forecasting system for logistics providers (Chang et al. 2019; Miščević et al. 2018), reconciling conflicting information (Catalini and Gans 2020), and reduced insurance costs thanks to increased visibility (Queiroz et al. 2019). Furthermore, smart contracts built upon the blockchain ecosystem can be used to create self-executing supply contracts or automated cold chain management systems. For example, they can be programmed to automatically make the payment of a product or service as soon as the delivery information is added to the chain via the secure signature of the customer.

On the other hand, blockchain applications can be used to design more transparent and trustworthy supply networks (Queiroz et al. 2019). As another issue for global supply chain, highly demanded certifications such as organic, halal, kosher, or GMO-free can easily be replicated (Chang et al. 2020) resulting in an increase in counterfeit and fake products. In such cases, not only people’s health is affected but businesses suffer damage in terms of reputation and revenue as well (Azzi et al. 2019a; Chang et al. 2019; Toyoda et al. 2017). Therefore, origin and movement tracking for goods have emerged as important features for global supply chains to prevent counterfeit goods (Chang et al. 2020). In the light of these potential benefits, applications of blockchain technology in the supply chain have accelerated. For example, recent smart platform implementations based on blockchain technology enable the storage and sharing of the whole product lifecycle information; therefore, offer end-to-end authenticity protection through the ledger structure (Miščević et al. 2018). DHL has recently implemented a serialization tool that leverages blockchain as a tamper-proof mechanism specifically to combat counterfeit drugs . Furthermore, Walmart and IBM have conducted a pilot study for their recent blockchain-based tracking solution (Chang et al. 2020). During the study, twenty-three different lot codes and thousands of sliced mangoes were recorded over a 30-day period using a blockchain platform for tracking products “farm-to-fork”. The platform, in which two packing centers, sixteen farms, two import warehouses, three brokers, and one processing facility were involved, was able to trace a package of sliced mangoes in a U.S. store back to a Mexican orchard in just 2.2 seconds (Chang et al. 2020). Chang argues that the same procedure would take almost seven days without the blockchain integration. The pilot study by Walmart and IBM is an important demonstration of the capabilities of blockchain and provides an example for the real-world application.

In addition to the aforementioned application areas, blockchain has some other implementation possibilities that are indirectly related to international trade practices. Firstly, verification of intangible assets such as artworks and patents can be considered as an important field that blockchain is expected to have an impact (Kugler 2021). Decentralization of intangible assets can be conducted through a tokenization process on blockchains such as Ethereum {Citation}and resulting product is referred to as non-fungible tokens (NFT) (Kugler 2021). As the name suggests, the main difference between NFTs and cryptocurrencies is that while cryptocurrencies are considered as fungible assets while NFTs are non-fungible. In other words, while each cryptocurrency of the same type is designed to amount for an equal value, each NFT is unique in terms of proving the ownership rights of different assets (Kugler 2021). NFTs can be used as verification of PoO for real assets as well as the digital ones. To illustrate, imagine a digital piece of artwork that can be reproduced and shared unlimited times. NFTs make it possible to determine the original finished piece and its creator. Therefore, artists can receive the deserved credit and remuneration, if any (Kugler 2021). This process also creates a proof for intellectual property rights of the artwork. For example, Monegraph is a platform that help creators, publishers, and owners to earn a share from to royalties, advertising fees, streaming fees (Anon n.d.-b; Casino et al. 2019). Transfer of valuable assets through NFTs can be considered as one of the indirect effects of blockchain in international trade. In addition, tracking and verification of education records and certificates can also be maintained in a decentralized manner on blockchain based platforms.

Ultimately, the energy sector is often referred to as a benchmark example for blockchain integration (Casino et al. 2019; Ølnes et al. 2017) in terms of data and market management. Smart contract applications provided significant cost reduction, tracking, security, and visibility enhancements for the companies thanks to the decentralization of distribution in the energy industry (Queiroz et al. 2019). In addition to the previous examples where the blockchain provided cost reduction and better complexity management, the technology can provide various benefits specific to the energy industry such as facilitation of ownership information along energy grids and promotion of energy communities for prosumers to balance local supply and demand (Mengelkamp et al. 2018). These benefits can complement to the trust and transparency features of the energy market. Burger et al. (2016) and PricewaterhouseCoopers (2017) provide comprehensive review on the subject.

Another challenge with the application of blockchain is based on the identification of the users. As evidenced by various application examples, the literature is in favor of the identity verification and disintermediation features provided by blockchain. In a system based on blockchain, users can have either identifiable or anonymous keys according to the design of the system. However, many potential government applications require identification of the user (Ølnes, 2016). Therefore, the system does not provide an additional solution to digitalized services in terms of ensuring "the user who has the key is actually the one who should have the key" (Ølnes et al. 2017). Therefore, blockchain alone does not provide a solution to the identity verification problem that poses an issue for critical proposed purposes such as attestation of documents or voting. Furthermore, blockchain is claimed to provide the framework for a disintermediated structure where "the trust in the intermediary is replaced with trust in the underlying code and consensus rules" (Catalini and Gans 2020). However, especially in the case of private chains such as in government or corporate functions, a legislative process should still be in place where the policy makers can be accountable for the outcomes of their decisions (Ølnes et al. 2017). And, in other cases such as data management and supply chain applications, the underlying code and consensus rules must still be designed, operated, and maintained by an individual or organization (Ølnes et al. 2017). Therefore, centralization still exists.

Furthermore, GDPR practices present challenges in the implementation of blockchain-based data management systems (Agbo et al. 2019; Ølnes et al. 2017) especially for the applications that involve management of sensitive information such as healthcare and governance. The European law stipulates that the data must be processed in a way that users have the right to access, change, and remove the records (*Regulation EU 2016/679 of the European Parliament and of the Council of 27 April 2016*, 2016). However, the structure of blockchain is suited for permanent and unchangeable storage of data rather than easy modifications and deletions (Agbo et al. 2019; Ølnes et al. 2017). Therefore, blockchain should be adapted to comply not only with the requirements of the European Parliament (Agbo et al. 2019; Ølnes et al. 2017), but also with the local regulations.

Being a relatively new technology, there are still many uncertainties about the future of the blockchain. The fact that the system is still evolving presents additional challenges for the practical applications such as lack of ready-to-use solutions on the market (Longo et al. 2019), and issues such as latency, scalability, and energy consumption (Ølnes et al. 2017). We have previously discussed that the security of the system is achieved thanks to a design that requires each node having a full copy of the blockchain (Casino et al. 2019). However, this results in an exponential growth of data due to replicated information. Therefore, distributed solutions for blockchain are more difficult to scale compared to conventional centralized applications (Ølnes et al. 2017). For reference, the size of the bitcoin blockchain already reached 375.46 gigabytes as of January 9, 2022 (Statista n.d.). Growing size of the chain as well as increasing number of nodes also contribute to the increasing energy consumption of blockchain (Ølnes, 2016). Especially for a technology aiming to replace the social and economic structures, scalability and energy consumption are identified as important issues. Therefore, some new approaches have been proposed by various new blockchain projects such as Solarcoin (Casino et al. 2019) that promotes the use of renewable energy sources to power blockchain and Mina Protocol which aims to address scalability issue by building a fixed size blockchain (Anon n.d.-a). On the other hand, transaction speeds of most cryptocurrencies are still lower compared to established systems such as VISA, which can process up to thousands of transactions per second (Casino et al. 2019). Last but not least, exploiting the value of cryptocurrencies for money laundering has been a problem for permissionless blockchains. Even though, the number of shady transactions has been declined in recent last years (Tasca, Liu, & Hayes, 2016, as cited in Ølnes et al. 2017), this can be an important issue that complicate the highly anticipated regulations and widespread use.

For example, once a blockchain-based system is established, it is impossible to change the recorded information on the network. Retrospective changes can only be made by means of hard forks, which simply means moving the entire database to a new one every time a change is made.

Another difficulty is in separating the benefits that blockchain implementation alone provides with the effects of other operational processes. Longo addresses this issue with an experimental study on a simulated supply chain environment to explore the economic and operational benefits of the system. The simulation compares two possible scenarios in which one of the management systems does not provide information share between SC parties and the other provides real-time information sharing with a blockchain-based supply management system. The simulation is developed solely for the purpose of the research using UnicalCoin blockchain developed by University of Calabria and takes place in a 60-day period. The research concludes that a blockchain-based supply chain management system achieves better results in terms of operational aspects such as providing a better service level through improved forecasting and communication, origin tracking, and integrity verification service; however, it fails to achieve a significant profit advantage (information sharing with blockchain: 49.904.198,21€, vs. no information share: 49.873.559,77€), because the higher inventory costs offset the gains from increased sales. It is worth noting that raw supply chain data is not stored on the chain and the information is processed by a third party SCM software before being stored on blockchain environment. Therefore, transaction costs are expected to be at negligible levels for the simulation; however, they might go up in a real-life situation where there are not limited number of SC parties and the amount of data would be much higher compared to the simulation (Longo et al. 2019). The study is beneficial in terms of providing an insight into cost perspective of blockchain applications in SC; however, it does not provide a direct comparison for the results of blockchain-based information sharing with centralized software solutions. Furthermore, the simulation fails to achieve a significant cost advantage in spite of the exclusions such as the cost of initial investment and the increasing transaction cost due to limitless number of supply chain parties.

2.1.5 Challenges

Blockchain technology and cryptocurrencies have started a new era of innovation in the financial sector, offering transformative solutions to longstanding challenges in international trade and financial transactions. By enhancing transparency, security, and efficiency, blockchain technology holds promise for fostering financial inclusion, mitigating counterparty risk, and revolutionizing supply chain management. However, the widespread adoption of blockchain technology and cryptocurrencies requires collaboration among stakeholders, including regulators, policymakers, and industry participants, to address regulatory concerns and foster responsible innovation in the global financial ecosystem. The literature seems to agree on the potential benefits of the system. As explained in the previous section, blockchain and cryptocurrencies promise many advantages for various industries and notably for international trade. However, such benefits are not achieved without consequences. Especially cryptocurrencies with fixed supply and permissionless design such as Bitcoin are exposed to illegal activity (Catalini and Gans 2020). Along with price instability, these limitations hinder the potential of cryptocurrencies (Catalini and Gans 2020).

Despite the growing interest in blockchain technology and cryptocurrencies, there remains a significant gap in empirical analysis and research on their real-world impact and limitations. As Ølnes (2016) argues, much of the existing research focuses on the benefits and potential applications of blockchain and cryptocurrencies, overlooking their limitations and drawbacks. Moreover, the lack of empirical studies analyzing actual blockchain implementations hinders our understanding of the practical challenges and operational implications of adopting blockchain technology in various industries (Ølnes et al. 2017). Due to the anonymous nature of cryptocurrencies, there are only a limited number of ways to track the geographical transfers of cryptocurrencies. The most common data collection method for cryptocurrencies is presented by Foley et al., and it involves obtaining 'user-level' data by extracting a full record of bitcoin transactions from the public blockchain. This approach includes unique transaction hash, the transaction amount, the fee, the sender and recipient addresses, the timestamp, and the block number (Foley, Karlsen, and Putniņš 2019). However, this method does not capture the geographical direction of transactions for countries. Therefore, is not suitable for a geographical comparison with other data sources. Other popular methods used for analyzing cryptocurrency transactions is proposed by Du et Al, which involves creating an index based on Google Search trends to capture the Bitcoin adoption speed (Du, Jia, and Zhu 2021). There are also other research papers and datasets based on surveys including the Global Cryptocurrency Adoption Data by Triple-A and Cryptocurrency Adoption Among Consumers report by Statista. These researches focus on understanding cryptocurrency adoption trends however, neither of the approaches provide the directed movement information required for a direct comparison between trade statistics (Statista 2021; Triple-A 2023).

2.2 Network analysis

Network analysis provides a powerful tool to examine complex systems characterized by interconnected nodes and edges. It has its roots in graph theory, which deals with the mathematical properties of graphs, which are representations of networks consisting of nodes (vertices) and edges (connections) (Newman 2018). As discussed previously, complex blockchain applications readily resemble a network system rather than a chain. Therefore, in the context of international trade and cryptocurrency movements, the methodology provided by Network Science offers a framework to understand the interconnectedness of the cryptocurrency market with traditional financial systems and provides a quantitative method to assess the impact of cryptocurrencies on international trade.

The objective of employing network analysis in the study is twofold. First, we seek to provide a holistic understanding of financial transactions by capturing the interactions between different nodes. Second, we aim to uncover the underlying reasons driving the evolution of these transactions over time. By identifying structural properties such as centrality, connectivity, and clustering, we aim to gain insights into the resilience, and overall connectivity of international trade and cryptocurrency networks. Moreover, by integrating quantitative data with qualitative indicators such as governance metrics, network analysis facilitates a nuanced understanding of the political-economic and geopolitical forces shaping these phenomena. In this section, we aim to provide a comprehensive overview of network analysis methods. We begin with the history of this methodology. Then, we delve into the fundamentals of network analysis, the core concepts, theory, metrics, and algorithms in its application. Furthermore, we explore various network analysis methods employed in this study such as graph theory, backbone extraction, and clustering.

2.2.1 The history of network analysis

The roots of network analysis can be traced back to diverse disciplines such as sociology, mathematics, and computer science. While the term "network analysis" gained prominence in the latter half of the 20th century, it actually dates back much further. Early sociologists like Georg Simmel and Émile Durkheim explored social structures as networks of interconnected individuals and groups, laying the groundwork for later developments in the field (Wasserman and Faust 1994). However, it was in the realm of mathematics and graph theory where the formalization of network analysis began to take shape. Euler's solution to the Seven Bridges of Königsberg problem in the 18th century marked a seminal moment in graph theory, providing a framework for analyzing networks in terms of nodes and edges. Before Euler intervened, this was simply a puzzle which involved creating a walk path that crosses each bridge in the city of Königsberg once. Euler approached this problem not by attempting to walk the route himself or by drawing maps, but by abstracting the problem into what we now recognize as a graph, a set of vertices (in this case, the landmasses) connected by edges (the bridges). In 1736, Euler proved mathematically that no such walk was possible and, in doing so, laid the groundwork for graph theory. Euler's method was revolutionary because it shifted the focus from the physical problem to an abstract representation that could be analyzed mathematically. This laid the foundation for subsequent mathematical developments that underpin modern network analysis (Newman 2018).

Throughout the 20th century, advancements in fields such as computer science and telecommunications further accelerated the evolution of network analysis. With the rise of digital technologies, researchers gained access to vast amounts of data, facilitating the application of network analysis techniques to a wide array of domains, including social networks, transportation systems, and biological networks (Barabási 2013). The field of Network Science has been significantly shaped by seminal papers such as those by Watts & Strogatz, Barabási & Albert, and Girvan & Newman, which introduced the concepts of small-world networks, scale-free networks, and the community structure of complex networks, respectively (Molontay and Nagy 2019). These foundational works have laid the groundwork for the interdisciplinary field of network science, which has since seen significant advancements in the study of multilayer networks (Artime et al. 2022) and the application of network science to a wide range of natural and technological systems. In the context of international trade and finance, the application of network analysis gained traction in recent decades as globalization intensified economic interdependencies among nations. Researchers began to explore trade networks as complex systems characterized by interconnected flows of goods, services, and capital (Fagiolo, Reyes, and Schiavo 2009). This paved the way for the integration of network analysis with traditional economic models, offering new insights into the dynamics of global trade patterns.

2.2.2 Network analysis approaches

At its core, network analysis seeks to uncover the underlying structure and dynamics of complex systems represented as networks. A network consists of nodes, which represent entities such as countries, companies, or individuals, and edges, which denote the relationships or interactions between these entities (Newman 2018). In the context of cryptocurrency and financial transactions, nodes could either represent individual addresses or an aggregation of addresses such as cryptocurrency exchanges, countries, or regions. On the other hand, edges represent transactions between these addresses. Networks can be categorized based on multiple criteria. One such aspect is the directionality of edges, which can be either directed or undirected. In a directed network, edges have a specific direction, indicating that the relationship between two nodes is asymmetric. For example, in a network representing email communication, the edges would be directed from the sender to the recipient, reflecting the one-way nature of email communication. In contrast, in an undirected network, edges do not have a specific direction, indicating that the relationship between two nodes is symmetric. For example, in a network representing friendship between individuals, the edges would be undirected, as the relationship of friendship is typically mutual (Newman 2018). In addition to the basic structure of nodes and edges, networks can also incorporate weight values, which represent the strength or intensity of the relationship between two nodes. Weights can be used to represent various aspects of the relationship between nodes, depending on the context of the network. For example, in a network representing the flow of funds through cryptocurrency assets, the weight of an edge could represent the value of cryptocurrency transferred between two addresses (Barabási 2013). The significance of weights and directions in our analysis is paramount for understanding the flow of funds, identifying patterns of capital transactions, and detecting potentially illicit activities.

Network analysis encompasses a diverse array of methods and techniques tailored to different research questions and data types. To simplify complex networks and make them more manageable for analysis, the first step of network analysis involves a process called backbone extraction. In essence, backbone extraction reduces the size of network while preserving key topological and spatial features. On the other hand, the methods for analyzing a network can be divided into multiple categories. One commonly used approach is descriptive network analysis, which focuses on characterizing the structural properties of networks and identifying meaningful patterns or anomalies (Carrington, Scott, and Wasserman 2005). Descriptive techniques include visualization methods such as node-link diagrams and matrix representations, as well as statistical measures such as degree distributions and network motifs. In addition to descriptive analysis, network researchers employ inferential techniques to test hypotheses and make predictions about network behavior. These methods leverage statistical models and machine learning algorithms to infer underlying processes driving network dynamics, such as information diffusion, collaboration dynamics, or trade patterns (Butts 2008).

2.2.3 Backbone extraction methods

Backbone extraction methods are crucial in simplifying and clarifying complex networks by retaining only the most significant connections. This process helps discovering the underlying structures and patterns that might be obscured in a fully connected network (Yassin et al. 2023). For instance, in the context of transportation or communication networks, backbone extraction can reveal the most crucial routes or channels that sustain the majority of traffic or information flow, which could be analogous to identifying key trade routes or transaction paths in economic networks. This is a crucial process in analyzing complex networks such as trade data and is particularly important in the context of cryptocurrencies as they often contain noise and irrelevant details. This process of removing irrelevant edges from a network is often referred to as 'Pruning' in literature (Coscia and Neffke 2017).

Numerous Backboning methods are available for analyzing complex networks, each offering distinct advantages and suited to specific applications. The most commonly employed methods include:

- Doubly Stochastic
- Naive Threshold
- Disparity Filter
- High Salience Skeleton
- Maximum Spanning Tree
- Noise-Corrected

Yassin et al. (2023) categorize these methods into three primary types: Statistical, Structural, and Hybrid. Statistical methods assess the importance of network edges by conducting hypothesis testing based on empirical distributions or a null model. In simpler terms, hypothesis testing allows for comparing the actual data (from the empirical distribution) to what we would expect if the connections were random (from the null model). If the actual data shows a connection is much stronger or weaker than the random model predicts that connection is considered important or significant. Therefore, hypothesis testing allows testing if the observed connections in the network happen just by chance or if they are statistically significant. This helps in understanding which connections really matter in the network. In contrast, Structural methods focus on the network's topology to identify a backbone that exhibits certain topological characteristics. Hybrid methods combine these approaches by first calculating scores for edges or nodes based on topological data, then applying statistical tests to these scores. Backboning methods can also be differentiated by their pruning techniques. Some methods allow users to manually set the pruning level using an alpha value (significance level) or a threshold value. Others employ automated pruning strategies or use preset values to eliminate edges. An additional crucial consideration in selecting a Backboning method is its compatibility with the network type; certain methods are designed specifically for weighted and directed networks, while others are more appropriate for unweighted and undirected networks (Yassin et al. 2023). In that sense, it is important to highlight that not all backbone extraction methods fit all network types. A comprehensive list of backbone extraction methods evaluated as part of this research is detailed in Appendix A: List of Backbone Extraction Methods.

2.2.4 Descriptive analysis metrics

Descriptive analysis is used for observing the structural properties of networks, providing an assessment of network data. This approach focuses on summarizing the network’s attributes without making causal inferences. Descriptive analysis involves the initial examination of data to summarize its main characteristics often using visualization and tables or various network analysis methods. For instance, in patent citation networks, descriptive analysis can reveal the most influential patents or the main clusters within the innovation landscape, providing insights into how innovations spread through industries and across geographical boundaries (Barabási 2013).

Table 1 provides an overview of the most common and key descriptive analysis metrics commonly used in network science. These metrics, such as Average Weighted Degree, Diameter, Radius, Average Path Length, and Density, are essential for understanding the structural characteristics and connectivity patterns within a network. To be more specific, Average Weighted Degree calculates the average strength of connectivity across all nodes in the network, taking into account either individual edges or the sum of all edge weights. Therefore, a higher average weighted degree would suggest more intensive economic interaction among the nodes involved. For example, in a financial network, nodes with a high Average Weighted Degree might represent institutions that have significant influence due to their strong connections with other nodes (Newman 2010). In the case of Bitcoin, this would imply not just frequent transactions, but transactions of significant value. This may correlate with heightened activity in traditional trade, as businesses and individuals that engage heavily in cryptocurrency might also participate actively in the conventional economy.

The diameter of a network calculates the longest of all the shortest paths between any two nodes and demonstrates the maximum distance between any two points in the network. In the context of a financial transaction network, a large network diameter might indicate that capital flows through many intermediaries before reaching its destination. Similarly, it also indicates the reach of a country's transactions. A higher diameter involving a particular country suggests that its transactions are not only numerous but also spread across a wide range of trading partners or across extensive geographical distances. This extensive reach is expected to correlate with higher overall transaction volumes.

Table 1. Descriptive Analysis Metrics in Network Science

Descriptive Analysis Metrics		
Variable Name	Description	Source
Avg_Wdeg	Average Weighted Degree - This metric calculates the average strength of connectivity across all nodes in the network, taking into account either individual edges or the sum of all edge weights. It is useful for understanding the importance of nodes based on their connectivity strength. For example, in a financial network, nodes with a high average weighted degree might represent institutions that have significant influence due to their strong connections with other nodes.	(Newman 2010)
Diameter	The diameter of a network is the maximum shortest path length between any pair of nodes. It provides a measure of how far apart the most distant nodes are in the network. In the context of financial transactions, a large network diameter might indicate that capital can flow through many intermediaries before reaching its destination.	(Brandes 2001)
Radius	The radius of a network is the minimum eccentricity (the maximum distance from that node to all other nodes in the network. Essentially, it measures how far a node is from the farthest other nodes in terms of shortest paths) of any node in the network. It provides a measure of the network's "center," indicating how quickly information or capital can spread from a central node to other nodes in the network.	
Avg_Path_Len	Average Path Length - This metric calculates the average shortest path length between all pairs of nodes in the network. It provides a measure of how efficiently information or capital can flow through the network.	
Density	Graph density is the ratio of the number of edges in the network to the total number of possible edges. It provides a measure of how interconnected or 'dense' the nodes are in the network.	(Estrada 2011)

2.2.5 Centrality analysis metrics

Centrality in a network measures the relative importance of a node within the network's structure. It is not only about the number of connections a node has but can also consider a node's position and influence in facilitating or controlling the flow of information or resources through the network (Barabási 2013). The application and relevance of centrality measures can vary significantly across different types of networks. For instance, in social networks, betweenness and degree centralities are often crucial for identifying influencers or key spreaders of information. In contrast, in transportation or communication networks, closeness and Eigenvector centralities can be more relevant for identifying crucial nodes that minimize travel times or enhance communication efficiency. As can be seen in Table 2, we provided a summary of the key centrality analysis metrics used in network science, which are crucial for assessing the significance and influence of nodes within a network. Metrics like Weighted In-Degree, Betweenness Centrality, and PageRank provide insights into the roles of nodes as connectors, influencers, or authorities within the network, thereby helping to understand the network's hierarchical structure and the flow of influence or information.

Degree Centrality is the simplest form of centrality, determined by counting the number of links incident upon a node, that is, the number of ties that a node has (Newman 2001). In directed networks, this measure can further be divided into in-degree and out-degree centralities, which refer to the number of incoming and outgoing connections, respectively. Closeness Centrality, meanwhile, reflects how close a node is to all other nodes in the network. It is calculated as the reciprocal of the sum of the shortest path distances from a node to all other nodes. Nodes with lower total distances to all other nodes score higher, suggesting shorter paths to access all other nodes in the network. Betweenness Centrality corresponds to the number of times a node becomes a ‘bridge’ on the shortest path between two other nodes, highlighting nodes that control the flow between other nodes within the network (Newman 2001). On the other hand, Eigenvector Centrality considers both the quantity and the quality of direct connections.

Table 2. Centrality Analysis Metrics in Network Science

Centrality Analysis Metrics		
Variable Name	Description	Source
WinDeg	The weighted in-degree of a node is the sum of weights of all incoming edges to that node. It reflects how much influence or importance other nodes (with their associated weights) have on the focal node.	(Newman 2001)
WoutDeg	The weighted-out degree of a node is calculated by summing up the weights of all its outgoing edges (i.e., connections pointing away from the node). It reflects the total strength of a node's interactions with other nodes.	
Wdeg	For a given node, the Weighted Degree is calculated as the sum of the weights assigned to its direct connections. These weights represent the strength of the ties between nodes. In other words, it reflects how influential a node is based on the intensity of its connections.	
Eccent	The Eccentricity of a node refers to the maximum distance from that node to all other nodes in the network. It is calculated as the reciprocal of the sum of the shortest path distances from a node to all other nodes. Essentially, it measures how far a node is from the farthest other nodes in terms of shortest paths.	(Hage and Harary 1995)
CloseC	Closeness Centrality measures the proximity of a node to all other nodes within the network, emphasizing the average distance to other nodes. In contrast, Eccentricity considers the longest distance to any node.	
HarmoC	Harmonic centrality offers an alternative approach to calculating average distances. Instead of summing the distances of a node to all other nodes (as in closeness centrality), harmonic centrality sums the inverse of those distances. This allows to deal with infinite values.	(Marchiori and Latora 2000)
BtwnC	Betweenness centrality is a used to assess the importance of nodes within a network. Specifically, it quantifies the degree to which nodes act as bridges or intermediaries between other nodes.	(Freeman 1977)
PRScore	PageRank measures the importance of each node (or vertex) within a graph. The underlying assumption is that important nodes are those that have many incoming connections from other important nodes. While PageRank was initially designed for web pages, it can be applied to any type of network. It works best for networks with directed edges (where nodes have specific directions of influence). In our case, in a trade network, influential countries would have higher PageRank values.	(Page et al. 1999)
EigenC	Eigenvector centrality measures the relative significance of a node within a connected network by assigning scores to each node. This measure is based on the principle that connections to nodes with higher scores have a greater impact on a node's overall centrality than connections to nodes with lower scores.	(Bonacich 1972)
Auth	The authority value is a concept used in link analysis algorithms. Specifically, it's part of the HITS algorithm (Hyperlink-Induced Topic Search), also known as "hubs and authorities." Authorities represent nodes that are linked by many different hubs. Authority value is computed as the sum of the scaled hub values that point to that page.	(Kleinberg 1999)
Hub	The Hub value is the other metric as part of the HITS algorithm. The underlying assumption is that certain nodes act as hubs—large directories that point to other nodes. A hub value is the sum of the scaled authority values of the nodes it points to.	

A node connected to many well-connected nodes will score higher in eigenvector centrality, indicating its strategic placement within the network. With the increasing analysis of dynamic networks, temporal centrality metrics have gained importance. These metrics, such as temporal degree centrality and temporal closeness centrality, consider the timing of interactions and the evolution of network topology over time, making them crucial for understanding dynamic networks (Bonacich 1972).

In addition to the traditional centrality measures previously discussed, specialized metrics like hub and authority scores and PageRank have been developed to address specific aspects of network structures, particularly in the context of web navigation and information retrieval. The concepts of hub and authority were introduced by Kleinberg as a part of the HITS algorithm (Hyperlink-Induced Topic Search) (Kleinberg 1999). In this framework, a 'good' Hub is a node that points to many other nodes, and a 'good' Authority is a node that is pointed at by many hubs. This distinction is particularly useful in networks where the typical role of nodes can be divided into two categories: those that provide information and those that reference information. For example, in a web context, hub pages might link to several high-quality content pages, while authority pages might be the target of links from multiple hub pages. The calculation of Hub and Authority scores is iterative and mutually reinforcing. This method of assigning centrality captures the essence of node influence in a more nuanced way than merely counting connections or shortest paths (Kleinberg 1999). On the other hand, PageRank is another centrality measure originally designed by Larry Page and Sergey Brin, to rank web pages in search engine results (Page et al. 1999). The PageRank of a page is based on the number and quality of links to it, assuming that more important websites are likely to receive more links from other websites. This metric uses a similar iterative approach to the Hub and Authority scores but integrates the entire network's structure into the calculation. PageRank extends the idea of Eigenvector centrality by not only considering the number of connections (or links) each node has but also the "strength" or "quality" of these connections. A link from a highly ranked page on the network contributes more to the page's score than a link from a lower-ranked one. This centrality measure is robust in highlighting nodes (or pages) that form the backbone of the network's connectivity structure, thereby identifying the most influential nodes within complex networks. Hub and Authority provide insights into the quality of information distribution and reference within networks, while PageRank has been instrumental in revolutionizing search technologies by providing a reliable method to gauge the importance of web pages. The use of these metrics is not confined to web analysis; they are also applicable in other types of networks like citation networks, where articles (nodes) that are frequently cited (linked) by other influential articles gain higher importance. In the context of cryptocurrencies and international trade, countries that are central in either network are likely exhibit strong economic integration and influence. Therefore, it is expected for these countries to rank higher in terms of centrality and provide a positive correlation.

One of the primary challenges in centrality analysis is the interpretation and application of these metrics across different types of networks. Each network's unique structure and dynamics can affect the applicability and interpretation of centrality measures. Furthermore, the growing size and complexity of networks require more computationally efficient methods to calculate centrality metrics at scale. Additionally, the emergence of big data and complex networked systems is driving the development of new centrality measures that can better capture the nuances of dynamic and large-scale networks.

2.2.6 Community detection metrics

Community detection algorithms aim to partition the network into cohesive groups or communities based on patterns of connectivity. The aim of community detection is to identify clusters or groups within a network where nodes are more densely connected to each other than to the rest of the network (Newman 2010). Understanding community structures in networks provides insights that can be applied across various fields. In epidemiology, it can help in tracking the spread of diseases through communities. In social networks, it aids in identifying influential groups or in understanding patterns of information dissemination. In economic networks, such as those involved in international trade and cryptocurrency movements, community detection can reveal how clusters of transactions evolve in response to changes in policy or economic conditions. For example, this can uncover trading blocs in international trade or clusters of closely linked countries in cryptocurrency networks. Under Table 3, we provided an outline of the community detection metrics used in network science to identify and analyze clusters within complex networks. The table also highlights the methodological advancements in community detection, such as the development of the Leiden algorithm to address the limitations of earlier methods like Louvain.

Community detection methods can broadly be categorized into several types, each with its own approach and application context. Modularity optimization is one of the most widely used methods, which seeks to maximize the density of connections within communities compared to between communities (Newman

2006). Spectral clustering uses the Eigenvalues of the network to find an optimal partition of the network (Von Luxburg 2007). Another method is clustering based on density, which aims to identify densely connected groups of nodes. This often involves metrics like conductance, which assesses the quality of a partition based on the number of edges that cut between groups (Andersen, Chung, and Lang 2006).

Table 3. Community Detection Metrics in Network Science

Community Detection Metrics		
Variable Name	Description	Source
Inf_Commun	Statistical Inference approach assigns a group to each country based on statistical inference of assortative community structures, which is a methodology for identifying and analyzing communities within complex network. In essence, in a network, nodes tend to connect with others who are similar to them. Assortative communities are groups of nodes that exhibit this tendency. The resulting value represents the number of communities detected by Statistical Inference for the three main datasets (DOTe, DOTi, BTC) per year.	(Blondel et al. 2008; Lambiotte, Delvenne, and Barahona 2014)
Resolution	Refers to the resolution value set when running the modularity module.	
Modularity	Modularity assesses the strength of a network's division into communities. It compares the actual number of edges within these communities to the expected number if the edges were randomly distributed.	(Brandes 2001)
Modul_Res	This is a variant of modularity that incorporates the resolution parameter. It allows for the detection of communities at different scales within the network.	
Modul_Commun	The Number of Communities value represents the number of clusters detected within the network. It provides a measure of the network's community structure.	
Desc_Len	Description length is a measure of the complexity of a network. It quantifies the amount of information needed to describe the network's structure, often in the context of model selection.	(Peixoto 2019; Zhang and Peixoto 2020).
Louvain	The Louvain method for community detection is an efficient algorithm used to identify non-overlapping communities within large-scale networks. However, it has a flaw: Louvain algorithm can group nodes into clusters even if they have no link with others in the same clusters.	(Blondel et al. 2008)
Leiden	The Leiden algorithm was developed to address the flaw of Louvain algorithm. It guarantees to find well-connected clusters and does so more efficiently than the Louvain algorithm.	(Traag, Waltman, and van Eck 2019)

Community detection, while critical for many fields, is challenging due to the diverse nature of networks and the different scales at which these structures can exist. The community detection problem is inherently ill-posed for several reasons.

First, the definition of what constitutes a community is not universally agreed upon, leading to different methods and results depending on the chosen definition (Fortunato 2010). Additionally, the resolution at which a community is identified can vary, which introduces scale dependency issues. Moreover, there are numerous algorithms that can be used for community detection, which often produces inconsistent results, and the results can be sensitive to the initial conditions of the algorithm. In "Discovering communities of community discovery," Coscia analyzes the similarity of outcomes among different algorithms and provides a tool for selecting algorithms that best meet their specific needs (Coscia 2019). This research in itself is an example of the complexities and ambiguities in defining and detecting communities making this field an ongoing area of research.

2.2.7 Dynamic analysis methods

Dynamic network analysis (DNA) is a methodological framework that focuses on the study of networks that evolve over time. These networks can represent various types of relationships and interactions, such as trade exchanges, financial transactions, or social interactions, which change as actors come and go, and as relationships strengthen or weaken (Holme and Saramäki 2012; Snijders 2005). This can reveal temporal trends, patterns of change, and the impact of external events on network dynamics. In the context of international trade and cryptocurrency movements, dynamic analysis can shed light on shifting trade relationships and the influence of geopolitical factors on transaction patterns. Network visualization with various tools such as Python, R, or Gephi are among the most common approaches for dynamic analysis. These tools allow researchers to visually explore and analyze complex networks, making it easier to identify patterns and structures within the data. In the context of cryptocurrency transaction networks, these tools can be used to visualize the flow of funds between different countries.

2.2.8 Statistical modeling

Statistical modeling serves as a mathematical method designed to describe, analyze, and make predictions from data patterns and trends. This involves constructing mathematical models that embody the relationships between different variables, aiding researchers, analysts, and scientists in decision-making processes based on systematic data analysis (Newman 2010). Statistical models are essentially tools that encapsulate and quantify real-world processes into structured data sets. These models are employed to estimate the relationships among various variables, often with the aim of prediction or to understand underlying structures. These models can range from simple linear regression models used for predicting quantitative outcomes based on predictor variables to more complex hierarchical models that take into account various layers of data grouping (Wasserman and Faust 1994). Among the myriads of statistical modeling techniques applicable to network analysis, each addresses different dimensions of networks, from predicting node behavior to understanding the dynamics within the network. Regression models, for instance, include linear regression, which predicts a quantitative response, and logistic regression, which is commonly used for predicting binary outcomes, such as the presence or absence of a connection between two nodes (Newman 2010).

In conclusion, as network analysis continues to evolve, its application in studying the interplay between international trade and cryptocurrency movements offers promising prospects. This methodology not only helps in identifying key transaction nodes and flow patterns but also aids in predicting future trends based on historical data. The ongoing development of more sophisticated analytical tools and techniques will undoubtedly expand the potential of network analysis in economic and financial research.

2.3 International trade

International trade has always been a part of the world history. Evolving and developing through the time, the landscape changed from the self-sufficient economic approaches of the 16th century to today's complex global supply chains. The volume of international trade has quadrupled since 1960s and become a more prominent factor in the world economy with the increased globalization (Krugman, Melitz, and Marc 2012). As the variety of products and services subject to international trade increases, international trade relations and ways of trade also become more and more complex. Similarly, the progression of trade theories and their practical applications mirrors changes in economic, political, and technological environments. Trade is vital for economic growth. It helps spread technology, increases competition, and improves efficiency, which collectively lead to better living standards (Baldwin and Martin, 1999). On the other hand, the wave of globalization has heightened the impact of trade, reduced trade barriers and weaving together financial markets more tightly than ever. This has made it easier to trade across borders, though it comes with its own set of challenges (Sachs 2020).

In this section, we take a look at the broad subject of international trade, tracing its historical roots, examining foundational theories, discussing the contemporary issues, which is fundamental in understanding and explaining the changes in the cryptocurrency trade. We also provide a detailed outline of the major events starting from the advent of cryptocurrencies. The years between 2015 and

2021 saw significant upheaval in the trade world, with major economies clashing over trade policies, a trend towards protectionism, and an economic slump triggered by the COVID-19 pandemic. These events have put the international trade system to the test, leading to a reevaluation of economic ties and agreements. Through this exploration, we seek to better understand how international trade contributes to economic development and global connectivity, and how it can explain shifts and trends related to cryptocurrency transactions.

2.3.1 Historical roots of international trade and economic theories

The history of international trade dates back to ancient times when early civilizations engaged in bartering goods and services across borders. This early exchange laid the foundation for more structured trade routes like the Silk Road, which connected the Far East with Europe and the Middle East, facilitating not just the trade of goods but also the exchange of culture, technology, and ideas (Acemoglu and Robinson 2012). The Age of Discovery in the fifteenth century marked a significant expansion of global trade networks, driven by European explorations that established new trade routes to the Americas and around the Cape of Good Hope. These new links brought about profound exchanges during the Columbian Exchange, introducing new crops and animals across continents, which reshaped agricultural practices worldwide (Acemoglu and Robinson 2012). The globalization of trade accelerated significantly post-World War II, with advances in technology and communication, coupled with a reduction in trade barriers. This era saw the establishment of key international institutions like the World Bank and the International Monetary Fund during the Bretton Woods Conference, which were instrumental in promoting free trade and economic cooperation. In recent decades, the shift towards a more integrated world economy has been characterized by the rise of bilateral trade agreements and significant increases in trade volumes (Sachs 2020).

2.3.2 A brief overview of economic theories

Mercantilism emerged as one of the early economic theories practiced from the 16th to the 18th centuries. It posits that national wealth and strength were best enhanced by maximizing exports and minimizing imports. Under this doctrine, nations sought to accumulate precious metals, typically gold and silver, by achieving a trade surplus with other nations. Mercantilism was often supported by imperial powers that used military might to enforce trade policies that favored the mother country, suppressing the economies of their colonies (Heckscher 2013). The theory of absolute advantage, introduced by Adam Smith, marked a fundamental shift from mercantilism. Smith argued that a country should specialize in producing and exporting goods in which it has an absolute advantage—that is, the ability to produce more of a good, using the same number of resources, than what other countries could produce. This specialization would lead to greater efficiency and economic wealth globally, contrasting sharply with the zero-sum game envisioned by mercantilists (Smith 1937). Building on Smith's insights, David Ricardo introduced the theory of comparative advantage. Competitive Advantage suggests that a country benefits by specializing in producing and exporting goods in which it has a relative efficiency advantage. This means that even if one country is less efficient in producing all goods compared to another country, there is still a basis for beneficial trade if they specialize according to their relative efficiencies. This principle forms the cornerstone of modern international trade theory and supports the case for free trade (Porter 2011). The Heckscher-Ohlin model (H-O model) extends the concept of comparative advantage by focusing on the different factor endowments of countries. This model predicts that countries will export goods that utilize their abundant factors intensively and import goods that utilize their scarce factors. For example, a country with abundant capital would be inclined to export capital-heavy products and import labor-heavy products if labor is scarce (Leamer and others 1995). In the late 20th century, the New Trade Theory emerged, introduced by economists such as Paul Krugman. This theory explains the phenomena of economies of scale and network effects, which were not adequately addressed by traditional theories. It suggests that through the specialization and production of certain goods, countries can achieve economies of scale, which can lead to a monopolistic or oligopolistic market, rather than the perfectly competitive market envisioned in earlier models (Krugman et al. 2012). These models enrich our understanding of the complex dynamics of international trade.

2.3.3 Globalization and trends in international trade

Globalization has evolved through several stages, each significantly impacting international trade and economic policies. Early globalization can be traced back to the Hellenistic Age and later through the Silk Road, which facilitated the exchange of goods, cultures, and technologies across vast regions from the Far East to Europe. This early form of globalization laid the groundwork for more structured trade practices (Sachs 2020). The modern era of globalization began post-World War II, marked by substantial reductions in trade barriers and the establishment of international economic institutions like the World Trade Organization (WTO). This period saw an exponential growth in trade volumes, driven by advances in technology and reductions in transportation and communication costs. The liberalization of trade has been fundamental in integrating global markets, making goods and services more accessible across different regions, thereby boosting economic growth (Sachs 2020). Economic integration has been a significant aspect of globalization, where free trade zones, customs/economic unions, and common markets were established. Each stage represents a deeper level of integration, aiming to reduce economic restrictions between member countries. For example, the European Union represents one of the most integrated economic regions, where member states enjoy free movement of goods, services, capital, and labor. Such integrations facilitate increased economic interdependence, which enhances resource allocation efficiency and market expansion.

Despite its benefits, globalization has also faced significant backlash, primarily due to its uneven benefits and impacts across different socio-economic groups. Critics argue that while globalization has enriched wealthier nations and multinational corporations, it has often done so at the expense of smaller economies and less competitive industries. This has led to job losses and economic disruptions in sectors exposed to international competition. The backlash has manifested in rising protectionism and anti-globalization sentiments, challenging the sustainability of open trade policies and questioning the fairness of the global economic order.

We might better understand the complexities of globalization by examining a key historical example: the General Agreement on Tariffs and Trade (GATT). As a major multilateral trade accord, GATT was widely recognized as a catalyst for the so-called Second Wave of Globalization. Notwithstanding, it should be noted that declining transportation costs, reduced protectionist measures, and enhanced specialization in manufacturing also played significant roles. Formed in 1948, GATT aimed to lower trade barriers and enhance trade conditions among its initial 23 member countries (Oatley 2022). By the time it was integrated into a new framework in 1994, GATT had expanded to 128 member nations. Reaching agreement among such a diverse group was challenging, and over time, the influence of developing countries waned relative to industrial powers like the United States, the United Kingdom, and Japan. Consequently, the agreement increasingly catered to the priorities of these developed nations, transforming what began as a multilateral effort into a consortium dominated by wealthier countries. This shift underscored the need for an international body capable of governing trade through equitable, non-discriminatory measures. The World Trade Organization (WTO) was established in 1995 to address these issues. However, questions remain about whether the WTO has merely perpetuated the shortcomings of GATT or successfully addressed them.

To critically assess the WTO's effectiveness, it's essential to revisit its foundational goals. The WTO aims to enhance global trade capacity, boost employment, and elevate living standards for its members by serving as a platform for negotiating trade agreements. It is vital for the WTO to maintain equitable trade practices among all member states to overcome the limitations faced by GATT (Oatley 2022). Principles like Most-Favored Nation (MFN) and National Treatment are designed to foster equality and prevent discriminatory practices such as non-tariff barriers that favor domestic industries. Yet rather than collectively minimizing trade barriers as initially intended, member countries often use negotiation rounds to advance national interests. This outcome, predictable through economic and game theory perspectives (O'Neill 1994; Peinhardt and Sandler 2015), reflects inherent challenges in multilateral negotiations.

Moreover, while the formation of WTO was not recent, the organization has struggled with some of the same issues that troubled GATT. An expanded membership has further complicated consensus-building between developing and industrialized nations. The failure of the Doha round and subsequent negotiations highlighted the WTO’s difficulties in establishing an effective dispute resolution mechanism. As a result, countries are increasingly turning to bilateral or regional trade agreements (RTAs), which, while promoting trade liberalization, may also entrench discriminatory practices, running counter to the WTO’s core principles (Oatley 2022).

To sum up, globalization has undeniably transformed international trade, contributing significantly to economic growth and development worldwide. However, the evolving challenges it presents require careful management to ensure that the benefits of globalization are more equitably distributed, mitigating the adverse effects on vulnerable populations. The renegotiation of trade agreements and shifts toward more nationalist economic policies in various countries are direct consequences of the backlash towards globalization. These changes aim to protect domestic industries and preserve jobs but can lead to a fragmented global trade landscape, potentially slowing global economic growth and reducing international cooperation on broader economic and environmental issues. As globalization continues to evolve, so too will its impact on international trade dynamics, necessitating adaptive policies and cooperation to harness its full potential while addressing its drawbacks.

2.3.4 Trade barriers, regulations, safe-haven assets, and capital flight

The complex nature of international trade requires a governing body to practice certain regulatory decisions such as providing support for critical industries like health and military and preventing complete dependance on foreign sources. These regulations are often intended to protect consumers and ensure the safety. It is possible for certain industries to benefit from restrictions such as tariffs if the decisions of the regulating body are accurate and timely. From the point of view of domestic producers in smaller nations, tariffs, for example, can increase the producer surplus of the domestic producers operating in the beneficiary industry and poses an opportunity for them to create competitive advantage in the long run (Krugman et al. 2012). Large nations can also enjoy the benefits of the tariffs. Exporters in the international arena often do not want to lose their customer base and reduce their prices when faced with high tariffs instead of reflecting them to the customers. This phenomenon is also supported by the Theory of Overlapping Demands by Stephen Linder which explains that the nations with high per capita income will demand and trade more. Therefore, this creates a more significant market for the exporting companies. Therefore, large nations can leverage their bargaining power and benefit from this situation as in the example of United States' tariff on import automobiles.

Use of barriers and restrictions are however not without costs, there are major drawbacks that must be considered before applying or altering them. While providing benefit from certain aspects, regulations and barriers inevitably cause some parties to suffer losses and such instruments create a burden on other industries. As explained by Adam Smith, David Ricardo and other following theories prove from various perspectives that international trade can be beneficial for both developing and developed countries and trading between nations makes it possible to reach production and consumption levels that is not possible under autarky. However, all kinds of trade barriers and restrictions, including the ones applied to cryptocurrencies, has a limiting effect on the trade volume, which creates a contrary situation to the positive effects of international trade explained by such theories (Parkin 2019).

2.4 Hypotheses

This study aims to uncover underlying patterns and correlations that may exist between international trade and cryptocurrency flows. The hypotheses developed in this section are informed by the existing body of literature on trade economics, cryptocurrency adoption, and network analysis that we have discussed so far. The hypotheses also seek to offer insights into how geopolitical events, regulatory changes, and market dynamics influence the interconnectedness of these domains.

2.4.1 H1: There is a correlation between a country's trade volume and the volume of cryptocurrency transactions

Countries with high volumes of international trade may require more flexible and efficient means of payment and financial transactions. cryptocurrencies, notably Bitcoin, with its global reach and ease of transfer, might be used increasingly in such countries to complement traditional trade financing methods.

2.4.2 H2: Economic and political instabilities lead to an increase in cryptocurrency transactions

During times of geopolitical uncertainty, Bitcoin might be considered a digital gold to hedge against risks associated with traditional financial systems. As one example, Selmi assesses the role of Bitcoin as a hedge, a safe haven and/or a diversifier against extreme oil price movements. And finds that Bitcoin and gold would serves that purpose, conditional to Bitcoin's and gold's different (bear, normal or bull) market conditions (Selmi et al. 2018). Similarly, Su et al. explores the sensitivity of Bitcoin to geopolitical events. And found that there are positive and negative influences that stem from geopolitical risks towards Bitcoin prices (Su et al. 2020).

2.4.3 H3: Countries with significant trade deficit are in more central positions in the cryptocurrency transaction network

There are three components to this hypothesis: We compare the centrality in the cryptocurrency network with trade deficit, capital account deficit, and financial account deficit. We analyze each subbranch individually. However, the underlying reasoning is based on the same assumption that residents in countries with trade deficits would rely on cryptocurrencies as an alternative means to balance the lack of foreign currency reserves or to facilitate cheaper and faster cross-border transactions.

2.4.4 H4: Stringent trade regulations are positively correlated with the volume of cryptocurrency transactions

Studies suggest that cryptocurrencies might be used as a tool to circumvent restrictive trade practices, such as capital control restrictions allowing businesses and individuals to engage in international trade with fewer limitations (Alnasaa et al. 2022; Hu, Lee, and Putninš 2018; Hu, Lee, and Putniņš 2020).

2.4.5 H5: There is a positive correlation between the Average Weighted Degree of the trade and cryptocurrency networks

Average Weighted Degree represents the average strength of connectivity across all nodes in the network, taking into account the sum of weights of the edges (Barabási 2013). Therefore, a higher average weighted degree would suggest more intensive economic interaction among the nodes involved. In the case of Bitcoin, this would imply not just frequent transactions, but transactions of significant value. This may correlate with heightened activity in traditional trade, as businesses and individuals that engage heavily in cryptocurrency might also participate actively in the conventional economy.

2.4.6 H6: Central countries in the cryptocurrency network also hold significant influence in international trade

Countries that are central in the Bitcoin transaction network likely exhibit strong economic integration and influence. Therefore, it is expected for these countries to rank higher in terms of Direction of Trade centrality. PageRank centrality measures the influence of a node based on the number and quality of links it receives from other nodes.

2.4.7 H7: A higher diameter positively correlates with a higher transaction volume for cryptocurrency and trade networks

Studies posit that a larger diameter of a trade network could indicate a larger reach of a country's transactions. This is mainly because as the number of trade connections increase, the more steps required and more countries are involved between transactions (Newman 2003).

2.4.8 H8: Cryptocurrency network becomes more and more complex over time

Cryptocurrency transaction patterns are constantly evolving in response to economic shifts, technological advancements, and changes in regulations. The growing adoption of cryptocurrencies by individual and institutional investors, their expansion into new markets, and the incorporation of advanced blockchain technologies like smart contracts are all contributing to the increasing complexity of these networks. Additionally, regulatory responses differ significantly across jurisdictions, affecting transaction patterns and network structures.

2.4.9 H9: Trade openness is positively correlated with cryptocurrency centrality

Countries with high trade openness may see increased use of cryptocurrencies, driving their central roles in the cryptocurrency network due to the need for efficient, low-cost, cross-border transactions mechanisms. To understand the interplay, we calculate trade openness indices from trade volume and GDP data, and correlate these with centrality measures in the cryptocurrency transaction networks.

2.4.10 H10: Higher governance scores are negatively correlated with cryptocurrency centrality

We expect countries with higher governance indicators, suggesting stability and effective regulation (Kaufmann and Kraay 2023), expected have less central roles in the cryptocurrency network, due to robust financial systems and less reliance on alternative currencies.

CHAPTER 3

DATA AND SAMPLE

The approach of the research is based on quantitative data to uncover the interplay between international trade and cryptocurrency movements. The Geography of Bitcoin Transaction Dynamics (‘Bitcoin Data’) by Crystal Blockchain is chosen as the primary dataset for this study since it offers an in-depth perspective on the geographical dynamics of Bitcoin transactions. In addition, value of merchandise exports, GDP as well as information on countries’ tax rates, financial secrecy rates, voice and governance indicators are used for the comparative analysis. Under this section, we discuss the data and sample of the research.

3.1 Bitcoin transactions

First and foremost, it is crucial to acknowledge the limitations inherent in datasets used in cryptocurrency research. Due to the anonymous nature of cryptocurrencies, there are only a limited number of ways to track the geographical transfers of cryptocurrencies. The most common data collection method for cryptocurrencies is presented by Foley et al., and it involves obtaining ‘user-level’ data by extracting a full record of bitcoin transactions from the public blockchain. This approach includes unique transaction hash, the transaction amount, the fee, the sender and recipient addresses, the timestamp, and the block number (Foley et al. 2019). However, this method does not capture the geographical direction of transactions for countries and was not suitable for a geographical comparison with other data sources. Therefore, we did not use this approach in our study.

Other popular methods used to uncover trends for cryptocurrency transactions proposed by Du et Al, which involves creating an index based on Google trends to capture the Bitcoin adoption speed (Du et al. 2021). There are also other research papers and datasets based on surveys including the Global Cryptocurrency Adoption Data by Triple-A and Cryptocurrency Adoption Among Consumers report by Statista. These researches focus on understanding cryptocurrency adoption trends however, neither of the approaches provide the directed movement information required for a direct comparison between trade statistics (Statista 2021; Triple-A 2023).

Considering the foregoing, the primary dataset for this study is taken from Geography of Bitcoin Transactions Report by Crystal Blockchain, which offers an in-depth perspective on the geographical dynamics of Bitcoin transactions. This dataset spans the critical years in Bitcoin's emergence starting from 2014 to 2021, providing a comprehensive view of the evolving trends in capital flows through cryptocurrency assets. The dataset brings together data from 694 international exchanges and encompasses various metrics required for this research including the names of exchanges, their geographical locations, and transaction volumes, enabling a nuanced understanding of capital transfers between 22 countries for which the data is presented explicitly. The transactions included in this dataset are calculated by aggregating bitcoin addresses that belong to the same entity, and the valuation of transactions are in USD according to the Bitcoin exchange rate on the day and hour of the transaction. More information regarding the methodology of data collection can be found in the report (Crystal Blockchain 2021).

Whilst being rich in detail regarding directed Bitcoin transactions between countries, it is equally important to highlight the limitations of Geography of Bitcoin

Transactions dataset by Crystal Blockchain. First, the dataset only includes transaction information for Bitcoin. Although Bitcoin is the most common cryptocurrency with 49.54% market dominance at the time of this writing (CoinMarketCap 2024), this means our dataset does not paint the full picture for the cryptocurrency market, excluding transaction information for other cryptocurrencies. Second, as the year 2014 lacks sufficient transaction data for analysis, it was removed from our sample. Third, although the Geography of Bitcoin Transactions data includes transaction information for 78 countries, the dataset provides explicit information for only 22 countries. The remaining 57 countries are presented in aggregated format, 'EU' for the 23 EU countries and 'Others' for the remaining 34 countries, limiting the generalizability of our findings (Crystal Blockchain 2021). A list of the countries as part of each cluster are detailed in Appendix B: List of Countries Included in the 'EU' Cluster and Appendix C: List of Countries Included in the 'Others' Cluster.

The aforementioned limitations related to cryptocurrency transaction data also constitutes the fundamental basis for our sample. In addition, Russia is removed from the sample due to lack of reliable transfer data until the year of 2020. The reason for the lack of information is not explicitly expressed in Crystal Blockchain's research. However, this might be attributed to the low Voice and Accountability score for the country between these years (Kaufmann and Kraay 2023). The full list of 21 countries and 2 clusters included in our research is available in Table 4.

3.2 Direction of Trade & Balance of Payment Statistics

In addition to the Bitcoin Transactions data from Crystal Blockchain, International Monetary Fund (IMF) serves as a crucial source of numerical data, contributing to the comparative aspect of this research. To understand the correlation between bitcoin transaction and trade flows between major areas of the world, we use the exports data from the Direction of Trade Statistics (DOTS) of IMF, which are readily available in directed and weighted format on a free on board (FOB) basis (International Monetary Fund 2023b). The import metrics was obtained using the same dataset by inverting the country directions for Exports.

Table 4. List of Countries Included

ISO Code	Bitcoin Data	DOTS Data	BOP Data
ARG	Argentina	Y	Y
AUS	Australia	Y	Y
BRA	Brazil	Y	Y
VGB	British Virgin Islands	N	N
CAN	Canada	Y	Y
CYM[1]	Cayman Islands	N	Y
CHN	China	Y	Y
HKG	Hong Kong	Y	Y
IND	India	Y	Y
IDN	Indonesia	Y	Y
JPN	Japan	Y	Y
LIE[1]	Liechtenstein	N	N
MEX	Mexico	Y	Y
PAN	Panama	Y	Y
RUS	Russian Federation	Y	Y
SYC	Seychelles	Y	Y
SGP	Singapore	Y	Y
ZAF	South Africa	Y	Y
KOR	South Korea	Y	Y
TUR	Turkey	Y	Y
GBR	United Kingdom	Y	Y
USA	United States	Y	Y
EUN	European Union	Y	Y
OTH	Others	Y	Y

Another important dataset we gathered from IMF is the Balance of Payments and International Investment Position, which provides insights into a country's economic transactions with the rest of the world, highlighting the financial inflows and outflows. The dataset includes the goods and services account, the primary income account, the secondary income account, the capital account, and the financial account, based on the data regularly provided by each country (International Monetary Fund 2023a). It is also important to highlight the limitations inherited from this data source. First, Direction of Trade Statistics (DOT) data from IMF does not contain any information regarding British Virgin Islands, Cayman Islands, and Liechtenstein (International Monetary Fund 2023b), which are originally included in our sample of Bitcoin transactions. Therefore, these countries are also excluded from our comparisons of Bitcoin transactions with Direction of Trade Statistics. Similarly, Balance of Payments (BOP) dataset does not report on British Virgin Islands and Liechtenstein (International Monetary Fund 2023a). Therefore, these 2 countries were removed from our sample where we present a direct comparison with the BOP data.

3.3 Others

We employ the Constant Prices GDP in USD, serving as a fundamental measure of a country's economic output while accounting for inflation (World Bank 2024). This metric is pivotal in assessing the economic impact of capital flight through cryptocurrency assets in comparison to the overall economic performance of regions. Corporate Tax Haven Index sourced from (Tax Justice Network 2022), adds a unique dimension to the analysis by identifying jurisdictions with favorable corporate tax environments. This index aids in understanding the correlation between capital flight through cryptocurrency assets and corporate tax policies. Financial Secrecy Index sourced from (Tax Justice Network 2023), sheds light on the level of financial secrecy in different jurisdictions. This index is essential for comprehending the role of financial secrecy in influencing capital flight through cryptocurrency assets. Worldwide Governance Indicators sourced from World Bank (Kaufmann and Kraay 2023), includes various metrics to regarding governance across countries and over time and is helpful in exploring the potential interaction between regulatory changes/stability and capital flight thorough cryptocurrencies. Last but not least, Klein provides a simplified framework that classifies countries as Open, Gates, or Walls based on capital control restrictions (Klein 2012). We use the data provided by IMF to include the capital control restrictions into our comparison model (Fernández et al. 2016).

CHAPTER 4

METHODOLOGY

This section is designed to provide a comprehensive understanding of the approach employed to analyze the interplay between cryptocurrency transactions and international trade from a network perspective. To provide a comprehensive analysis of the node and network metrics related to Bitcoin transactions and international trade data from 2014 to 2021, and their evolution in response to global political-economic trends, we begin by cleaning the data. We then explore the correlations between major geopolitical events, economic sanctions, trade agreements, and regulatory changes in cryptocurrency and international trade. Each metric will be explained in the context of its definition and implications within the broader economic and political environment. Due to the directed, weighted nature of our cross-country transaction data for Bitcoin and the Direction of Trade Statistics data from IMF, we employ various methods to clean the data, visualize it, analyze the patterns, and uncover potential relationships in the directional flow of capital across borders, either via cryptocurrencies or conventional financial instruments. To ensure the accuracy and reliability of our analysis, we first employed backbone extraction to refine the Crystal Blockchain Geography of Bitcoin Transaction Dynamics dataset, as well as the Direction of Trade Statistics obtained from the International Monetary Fund (IMF). In the following parts of this chapter, we explore in detail the utilized methods and how each step of data analysis was conducted.

4.1 Backbone extraction

“Backbone extraction offers several advantages, including reduced data volume and storage, faster graph algorithms and queries, support for interactive analysis, and noise elimination.” (Yassin et al. 2023) Cryptocurrency transactions and international trade data are inherently complex, often containing noise and irrelevant details. Therefore, backbone extraction process was crucial for our data set to enhance the signal-to-noise ratio by isolating the most significant and relevant connections within the datasets and helped us remove the ‘outlier’ countries that were not connected to others. This process is often referred to as ‘Pruning’ in literature (Coscia and Neffke 2017).

As part of this study, we have evaluated various backbone extraction methods, each categorized by their approach—statistical, structural, and hybrid—emphasizing their relevance and application to network types, filtering mechanisms, and parameterization. Statistical methods are predominantly applied to weighted networks, focusing on local edge properties. Methods such as the Disparity Filter (DF) and Noise Corrected (NC) are paramount for analyzing trade and cryptocurrency networks where edge weight significance varies greatly. Both DF and NC employ a significance level parameter, crucial for distinguishing statistically significant weights from noise. Disparity Filter (DF) operates under the premise that the weight distribution of network connections for a node deviates from randomness. By setting a significance level, it filters out edges that do not meet the critical threshold, thus focusing on more meaningful, statistically significant connections. Noise Corrected (NC) method extends this concept by adjusting for network-wide noise and variability in connection weights. This correction aids in mitigating false positives, enhancing the reliability of network insights derived from the data.

Structural methods apply a global or local approach to determine the backbone by considering structural properties. For instance, methods like Global Threshold and Modularity Backbone focus on overarching network structures to identify key nodes and connections that are central to network integrity and functionality. Hybrid methods incorporate both local and global perspectives, hybrid methods like Globally and Locally Adaptive Backbone utilize parameters that adjust based on the involvement level across different parts of the network, offering a balanced view that captures both micro and macro network characteristics. A comprehensive list of backbone extraction methods evaluated as part of this research is also detailed in Appendix A: List of Backbone Extraction Methods.

Choosing the correct Backboning method requires comprehensive understanding of the capabilities of each approach. This precision is critical in analyzing complex networks, where edge importance can directly influence the interpretation of the data. Yassin tackles this important challenge by introducing a Python package comprising of an extensive collection of methods, including six statistical, thirteen structural, and one hybrid backbone extraction methods. According to Yassin, this package is capable of applying multiple backbone extraction methods to the same network and is specifically designed for comparing the performance and effectiveness of backbone extraction methods (Yassin et al. 2023).

When it comes to data related to trade or cryptocurrencies, networks are usually complex, weighted, and directed. Based on these properties, a number of methods are automatically eliminated since they cannot be applied to Weighted and/or Directed graphs. In addition, we want to preserve the strongly connected edges. This means, we need to work with a Backboning method that is both compatible with these network properties and that allows for manual selection of a Thresholding value. After applying this criteria, Backboning methods perform well with noisy trade networks and Disparity Filter (DF) and Noise-Correction (NC) come to the fore as the most robust approaches. These methods are also highlighted due to their effectiveness in local filtering based on statistical significance and are predominantly applied to weighted networks, focusing on local edge properties. (Coscia and Neffke 2017; Serrano, Boguná, and Vespignani 2009).

During our tests with both methods, we saw that for both Disparity Filter and Noise Correction, significance of an edge is determined by a p-value attributed to each edge based on their relative significance in a network and both were successful in assigning a ‘score’ to each edge based on their relative weights in the network. However, the difference between noise-corrected and disparity filter in backbone extraction lies in their approach to handling larger datasets. Being the newer approach, Noise-corrected outperforms other methods in terms of scalability and effectiveness especially when dealing with networks with millions of edges (Coscia and Neffke 2017). Although the Noise Correction method comes to the fore as a more novel approach and claims to use a more realistic null model for the edge weight creation process than prior work, we noticed that Noise Corrected networks were not pruned based on the assigned thresholding value. This was a critical challenge in terms of determining the significant edges. Therefore, we decided to proceed with Disparity Filter for the backbone extraction for both networks in all years.

Our approach with backbone extraction was to prune the disconnected edges, in other words, finding the optimal thresholding value that maintains a “Strongly Connected” network (Hagberg, Swart, and S Chult 2008) while eliminating disconnected edges. At the time of the writing, there was not a readily available solution to determine the optimal thresholding value. Instead of manually testing each thresholding value, we created an automation. The automation is a simple adjustment to the Disparity Filter examples kindly provided by Coscia (Michele Coscia 2017). The Python code converts a DataFrame to a NetworkX graph to check a range of thresholding values. It then breaks the loop when the network is no longer Strongly Connected and exports the results in Csv format. This approach allowed us to remove only the disconnected edges and find the Backboned networks with the highest number of significant edges. The Python code example for replicating the results is provided in Appendix F: Python Code Used For Backboning Using Disparity Filter. We have applied the same approach to all of our distinct networks. In more particular, to both import and export values from the Direction of Trade dataset as well as to the Bitcoin Transactions data for each year. The full list of highest threshold values where each network is fully connected is included in Appendix D: Thresholding Values Used For Backbone Extraction.

4.2 Analysis

After extracting the backbone of our network, our next crucial step was to apply relevant network analysis methods to the resulting networks. Overall, these metrics provide a broad view of the network's structure, focusing on connectivity and path characteristics. They help understand how information or capital flows through the network, identifying central nodes, and overall network efficiency. Due to the nature of our dataset, our approach involves a dual perspective, focusing on both Network Metrics and Country Metrics. This dual approach helps us get a nuanced understanding of the results, allowing us to analyze the network at both at a network level for all three datasets and from the perspective of individual nodes (countries) for each year. As a reminder, the three datasets we use are Direction of Trade (Exports), Direction of Trade (Imports) and cross-country Bitcoin transactions calculated based on the Bitcoin exchange rate on the day and hour of the transaction. In this section, we explain all metrics utilized as part of this research for both approaches, along with their descriptions and sources. Additionally, it is important to highlight that we used Gephi as the main tool to generate the network metrics, and to conduct the centrality and community detection analyses as well as for visualizing the networks. A list of settings and parameters used to obtain the results is added to the Appendix section of this thesis (Appendix E Gephi Parameters for network and node metrics). Lastly, we used Stata for regression analysis and for visualizing the tables.

4.2.1 Network-level analysis approach

From a network analysis perspective, we delve into several critical components to gain insights into network behavior. These components include relative strength metrics, such as Average Weighted Degree, Radius, Density, and Path Length calculations. Table 5 provides detailed descriptions of the network analysis metrics used in this research including their types, variable names, and sources, which are essential for understanding the structural properties and community dynamics within the network. By examining these metrics, we can understand how each dataset evolves year over year and cross-examine any changes. Additionally, the full list of settings and parameters used to obtain our results is available in the Appendix section of this thesis (Appendix E Gephi Parameters for network and node metrics)

Table 5. Descriptions for the Network Analysis Metrics

Network Analysis Metrics			
Type	Variable Name	Description	Source
Network Overview	Avg_Wdeg	Average Weighted Degree - This metric calculates the average strength of connections for each node in the network. It is useful for understanding the importance of nodes based on their connectivity strength. For example, in a financial network, nodes with a high average weighted degree might represent institutions that have significant influence due to their strong connections with other nodes.	(Newman 2010)
	Diameter	The diameter of a network is the maximum shortest path length between any pair of nodes. It provides a measure of how far apart the most distant nodes are in the network. In the context of capital flight analysis, a large network diameter might indicate that capital can flow through many intermediaries before reaching its destination.	(Brandes 2001)
	Radius	The radius of a network is the minimum eccentricity (the maximum distance from that node to all other nodes in the network. Essentially, it measures how far a node is from the farthest other nodes in terms of shortest paths) of any node in the network. It provides a measure of the network's "center," indicating how quickly information or capital can spread from a central node to other nodes in the network.	
	Avg_Path_Len	Average Path Length - This metric calculates the average shortest path length between all pairs of nodes in the network. It provides a measure of how efficiently information or capital can flow through the network.	
	Density	Graph density is the ratio of the number of edges in the network to the total number of possible edges. It provides a measure of how interconnected or 'dense' the nodes are in the network.	(Estrada 2011)
Community Detection	Resolution	Refers to the resolution value set when running the modularity module.	(Blondel et al. 2008; Lambiotte et al. 2014)
	Modularity	Modularity is a measure of the quality of a network's division into communities. It compares the number of edges within communities to the number of edges expected if the edges were distributed randomly.	
	Modul_Res	This is a variant of modularity that incorporates the resolution parameter. It allows for the detection of communities at different scales within the network.	
	Modul_Commun	The Number of Communities value represents the number of clusters detected within the network. It provides a measure of the network's community structure.	
	Desc_Len	Description length is a measure of the complexity of a network. It quantifies the amount of information needed to describe the network's structure, often in the context of model selection.	(Peixoto 2019; Zhang and Peixoto 2020).
	Inf_Commun	Statistical Inference approach assigns a group to each country based on statistical inference of assortative community structures, which is a methodology for identifying and analyzing communities within complex network. In essence, in a network, nodes tend to connect with others who are similar to them. Assortative communities are groups of nodes that exhibit this tendency. The resulting value represents the number of communities detected by Statistical Inference for the three main datasets (DOTe, DOTi, BTC) per year.	

On the other hand, we also approach network analysis from a clustering standpoint. However, it's essential to acknowledge that questions persist in network science literature regarding the effectiveness of community detection methods. Specifically, based on research where community detection methods are applied to discover communities, Coscia posits that the success of community detection significantly relies on the algorithm specifications used (Coscia 2019). With that in mind, the community detection methods we applied are Modularity and Statistical Inference.

4.2.2 Node-level analysis approach

Under this section, we discuss the method by which we analyzed the country (node) level metrics. This approach includes comparing financial transfers provided by direction of trade and balance of payment statistics with Bitcoin transfers and the metrics produced with these datasets. The comparison is made both between the metrics of different countries but also across different years for a given country. We also support this analysis by comparing the results with political-economic indicators such as GDP, World Governance Indicators, and based on whether or not cryptocurrencies are legal in a given country or region. Furthermore, we used the centrality metrics to generate an "importance ranking" of each country for each year, which allows us to analyze the centrality trends and pinpoint countries that act either in parallel with or in contrast to the trade dynamics. Most notably, the PageRank algorithm (Page et al. 1999) has been instrumental in generating these analyzes. Finally, we also compare our findings with the results generated using a number of clustering methods including Modularity, Statistical Inference, and Leiden algorithms.

Under Appendix G, we provide detailed descriptions of the variables, their names, explanations, and sources for all data and metrics we utilized for the node. The table also serves as a glossary for the analyzes we conducted in terms of providing the abbreviations that are also used in the charts. The list of settings and parameters used to obtain these results is available in Appendix E Gephi Parameters for network and node metrics.

CHAPTER 5

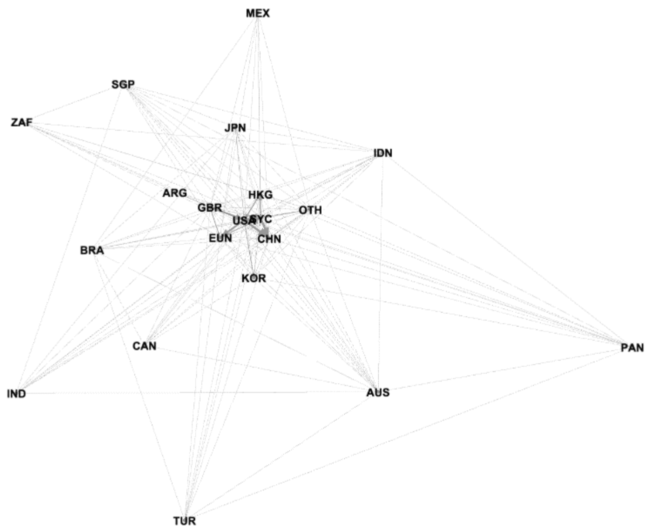
ANALYSES & RESULTS

This chapter presents the empirical analyses and results derived from the network analysis conducted on international trade data and cryptocurrency transaction patterns. The core objective of this analysis is to unravel the intricate relationships between global trade dynamics and cryptocurrency movements, leveraging quantitative data sources, including IMF Direction of Trade Statistics (Exports and Imports) and cross-country Bitcoin transaction data. The analyses address several hypotheses designed to reveal the underlying patterns and correlations within and between these networks, focusing on the influences of economic indicators, governance metrics, and trade policies. To analyze the interplay between international trade and Bitcoin transactions, the examination is conducted results are presented in network visualizations, two-way graphs, bar charts, and multivariable tables for regression analyses.

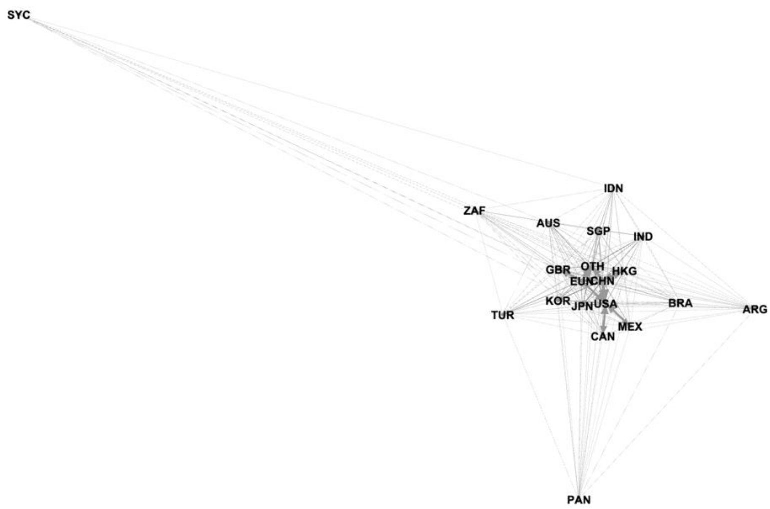
5.1 Network-level analysis

For the network-level analysis of the results, the visualizations for the network analysis metrics broken down by years and data sources have been created. The network graphs provided in Figure 1 through Figure 7 help us visually and clearly observe the trends and patterns illustrating the network dynamics over the years. Furthermore, we analyze the Average Weighted Degree, Diameter, Radius, Average Path Length, and Density metrics across all datasets to understand the changes which can later be attributed to varying economic and political contexts in Figure 8. Initial Results From a high-level overview, we can draw several conclusions and insights regarding the trends of nodes in different network datasets (BTC, DOTe, and DOTi) from 2015 to 2021. Notably, as can be seen in Figure 8, the Bitcoin networks has exhibited significant fluctuations over the period potentially mirroring the volatile nature of cryptocurrency markets and the attendant economic conditions. Meanwhile, the Average Path Length and Density metrics have also displayed minor variations, hinting at the relatively stable efficiency and interconnectedness of the network over time. On the other hand, the Direction of Trade Networks have remained relatively stable, suggesting a consistent breadth and centrality in the connections amongst nodes.

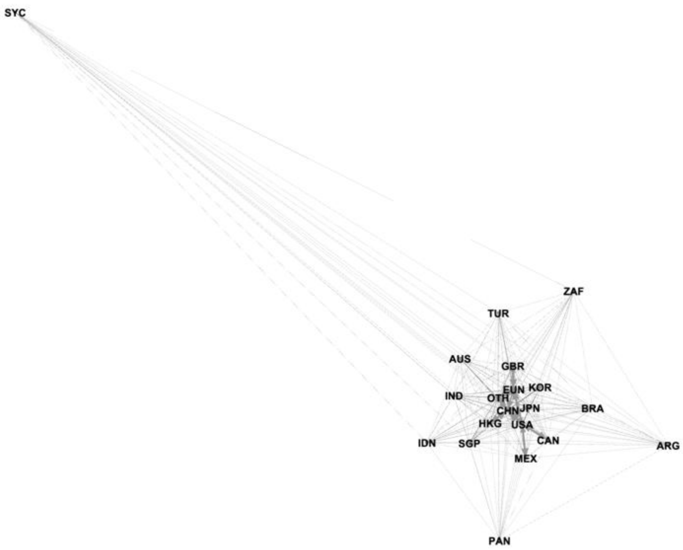
First, from the initial analysis, it is evident that Direction of Trade networks are more stable and established compared to the Bitcoin network. All network metrics including Density, Average Path Length, Average Weighted Degree, and Diameter are supporting this finding. Second, the upward trend in Average Weighted Degree across all datasets from 2015 to 2021 can be partially attributed to the increasing complexity and interconnectedness of global financial and trade networks. This observation aligns with the broader narrative of globalization and the expansion of digital financial transactions, including cryptocurrencies like Bitcoin. In the realm of cryptocurrencies, specifically Bitcoin, there was a substantial increase in Average Weighted Degree between 2015 and 2021. This surge could reflect the growing acceptance and integration of cryptocurrencies within the global financial system, despite the inherent volatility and regulatory challenges. It's also indicative of the increasing size and frequency of Bitcoin transactions, which have gained significant momentum as digital currencies have become more mainstream.



Bitcoin Network

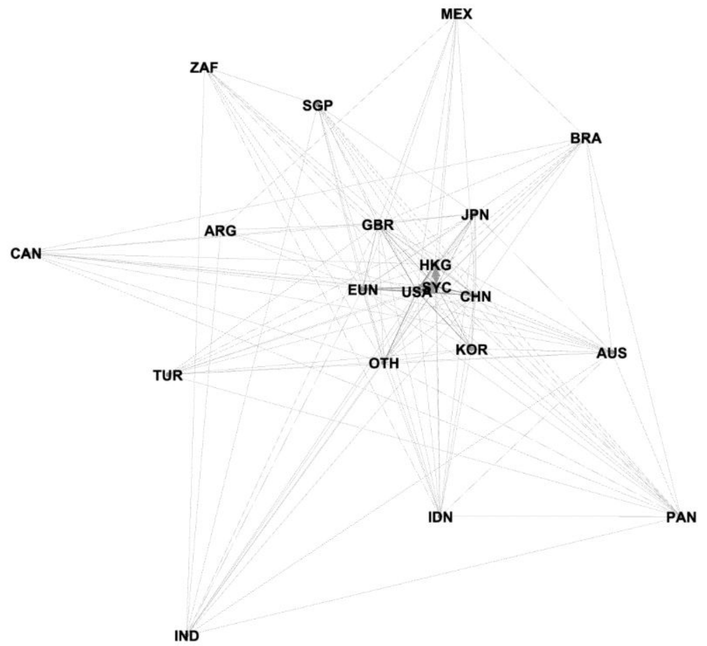


Direction of Trade (Exports) Network

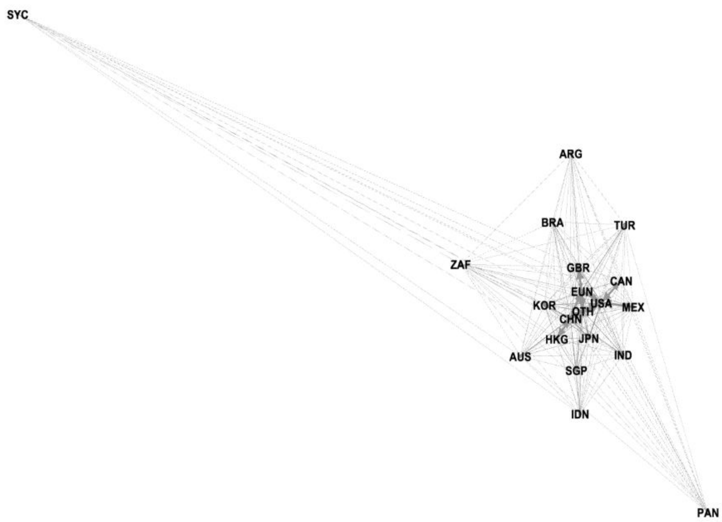


Direction of Trade (Imports) Network

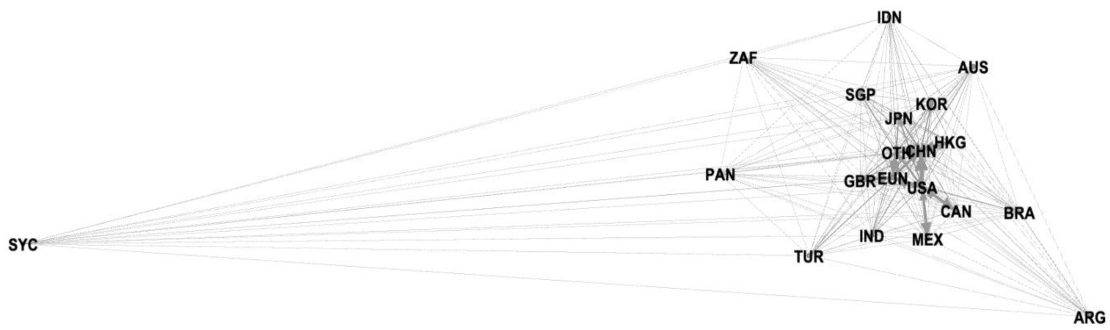
Figure 1. Network graphs of Bitcoin and DOTS networks for 2015



Bitcoin Network

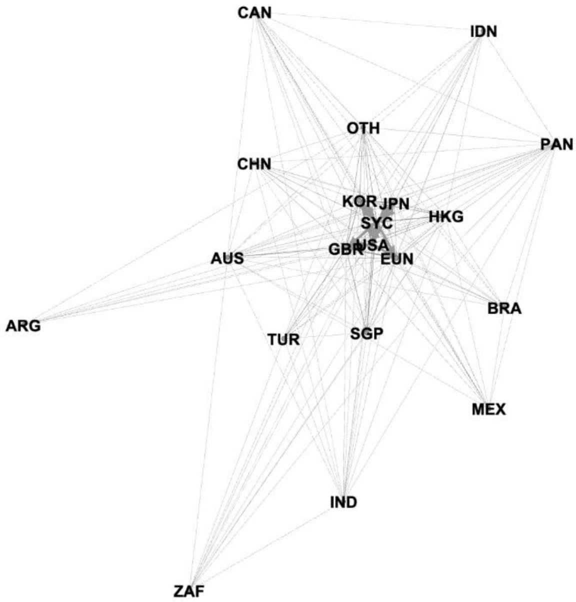


Direction of Trade (Exports) Network

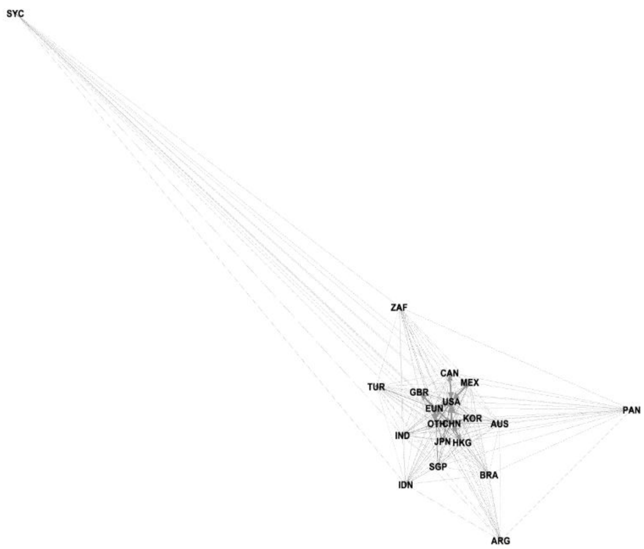


Direction of Trade (Imports) Network

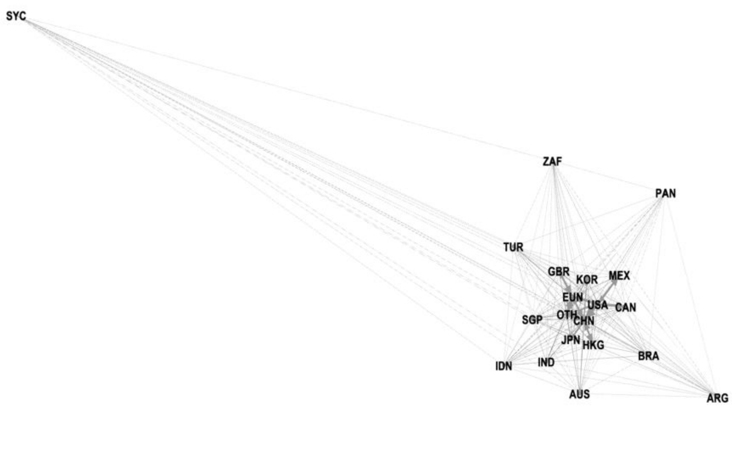
Figure 2. Network graphs of Bitcoin and DOTS networks for 2016



Bitcoin Network

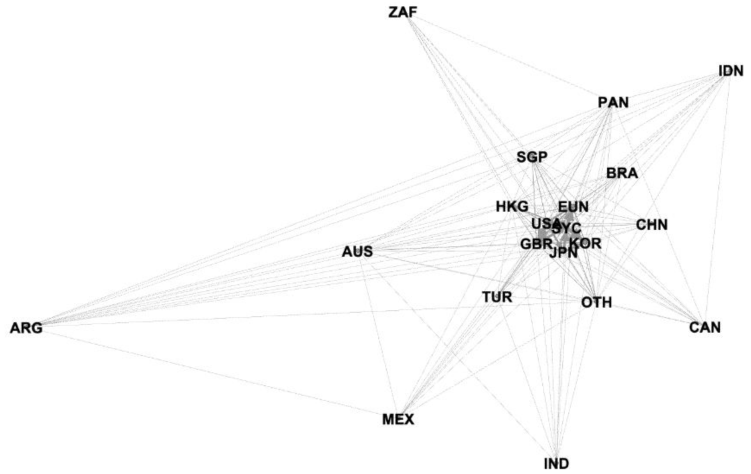


Direction of Trade (Exports) Network

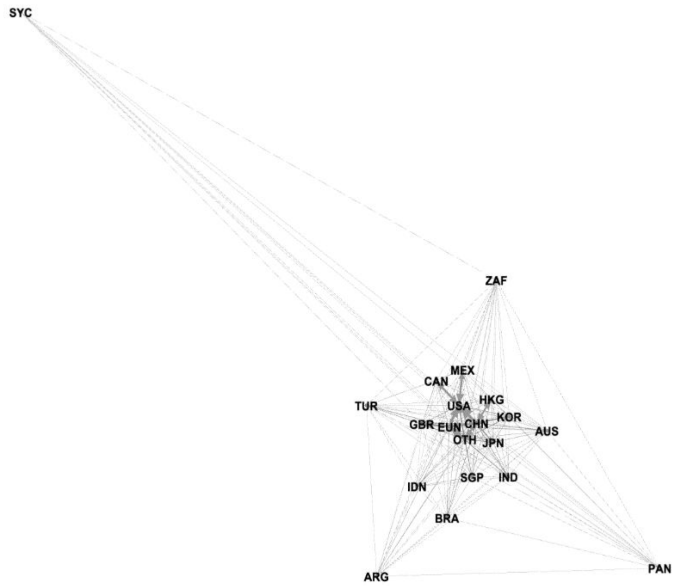


Direction of Trade (Imports) Network

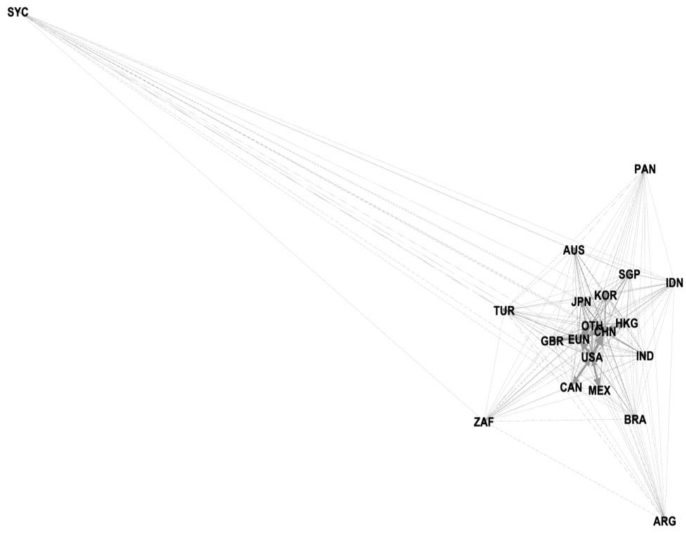
Figure 3. Network graphs of Bitcoin and DOTS networks for 2017



Bitcoin Network

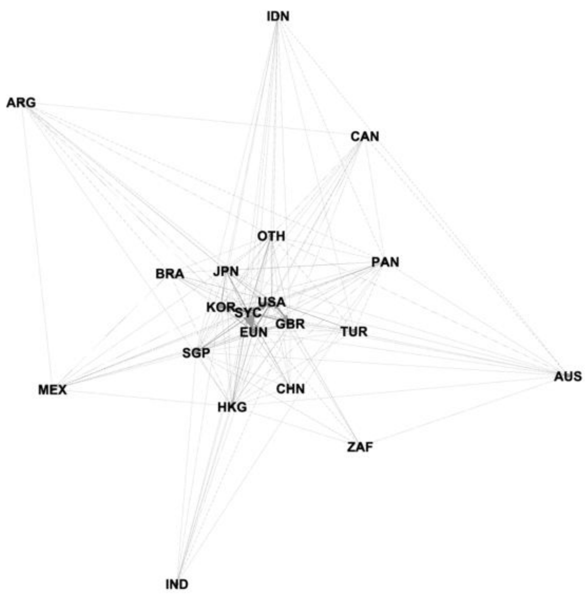


Direction of Trade (Exports) Network

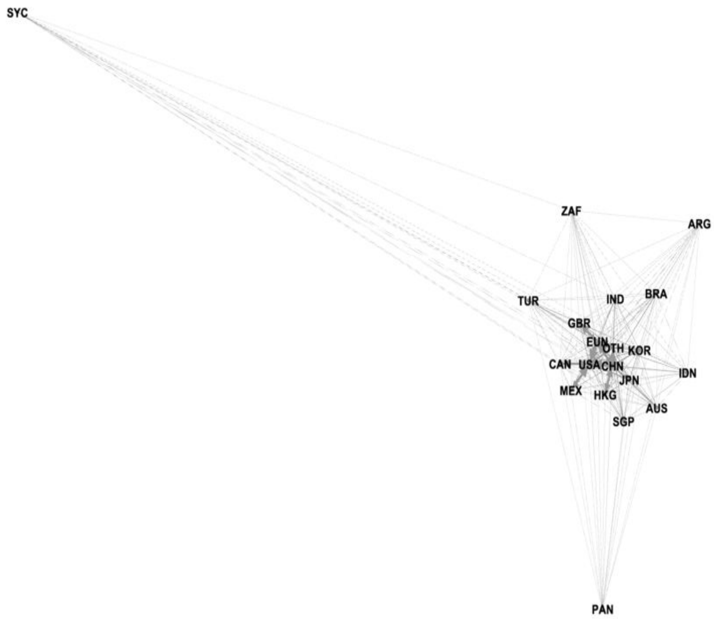


Direction of Trade (Imports) Network

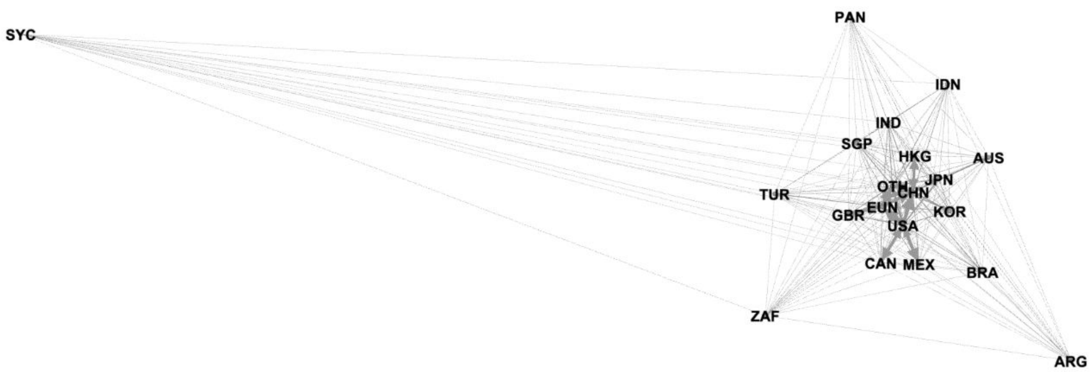
Figure 4. Network graphs of Bitcoin and DOTS networks for 2018



Bitcoin Network

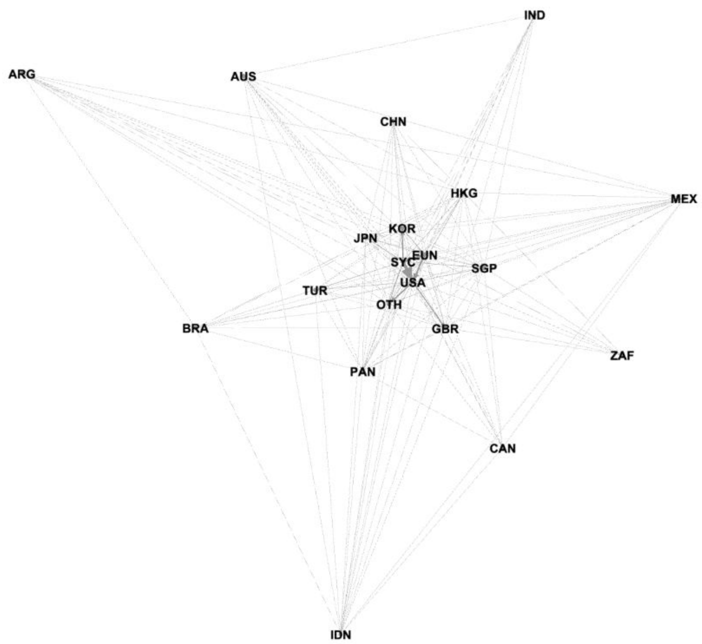


Direction of Trade (Exports) Network

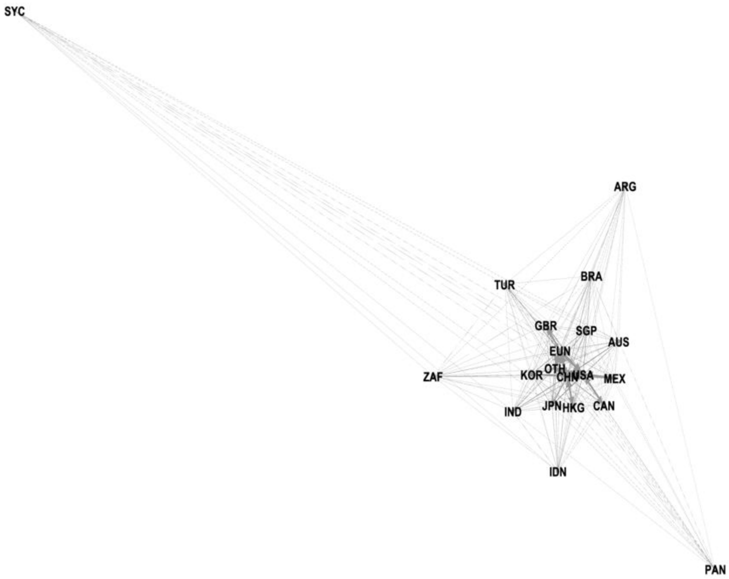


Direction of Trade (Imports) Network

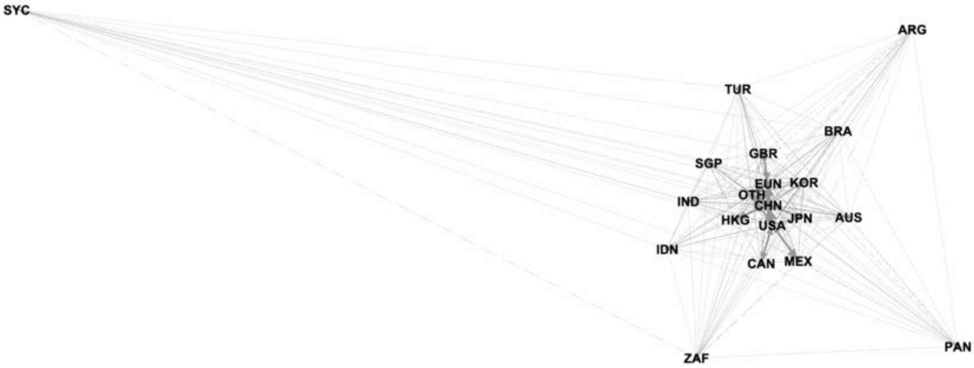
Figure 5. Network graphs of Bitcoin and DOTS networks for 2019



Bitcoin Network

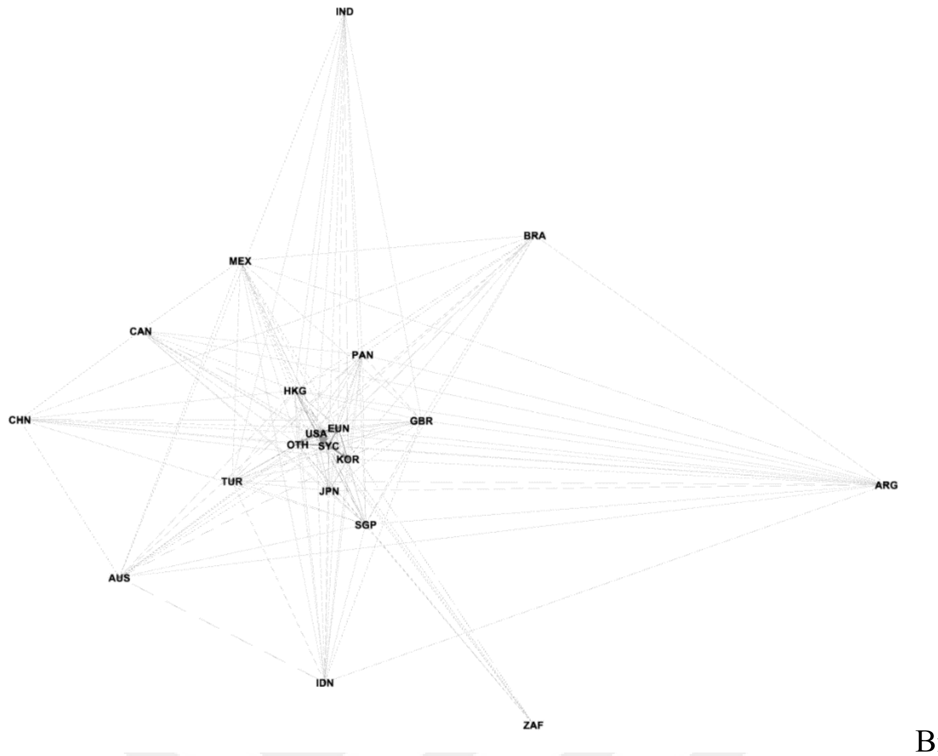


Direction of Trade (Exports) Network

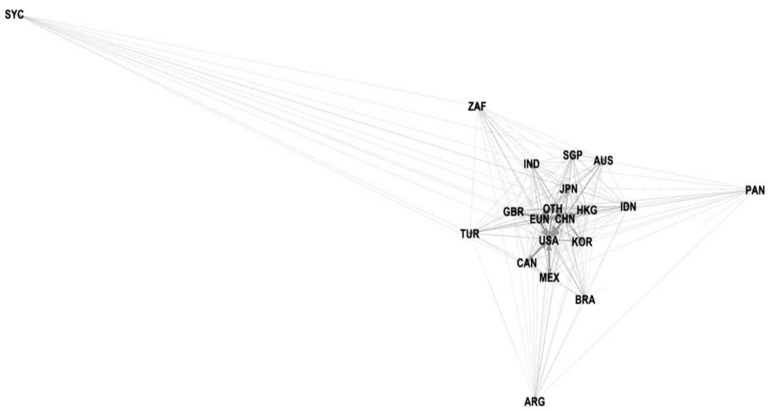


Direction of Trade (Imports) Network

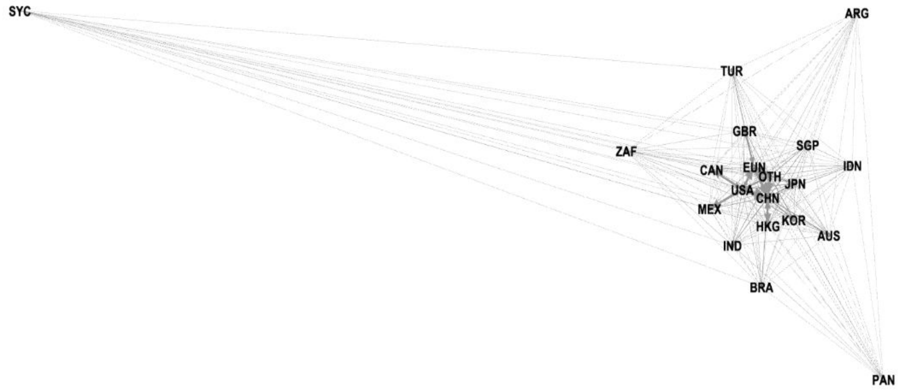
Figure 6. Network graphs of Bitcoin and DOTS networks for 2020



Bitcoin Network



Direction of Trade (Exports) Network



Direction of Trade (Imports) Network

Figure 7. Network graphs of Bitcoin and DOTS networks for 2021

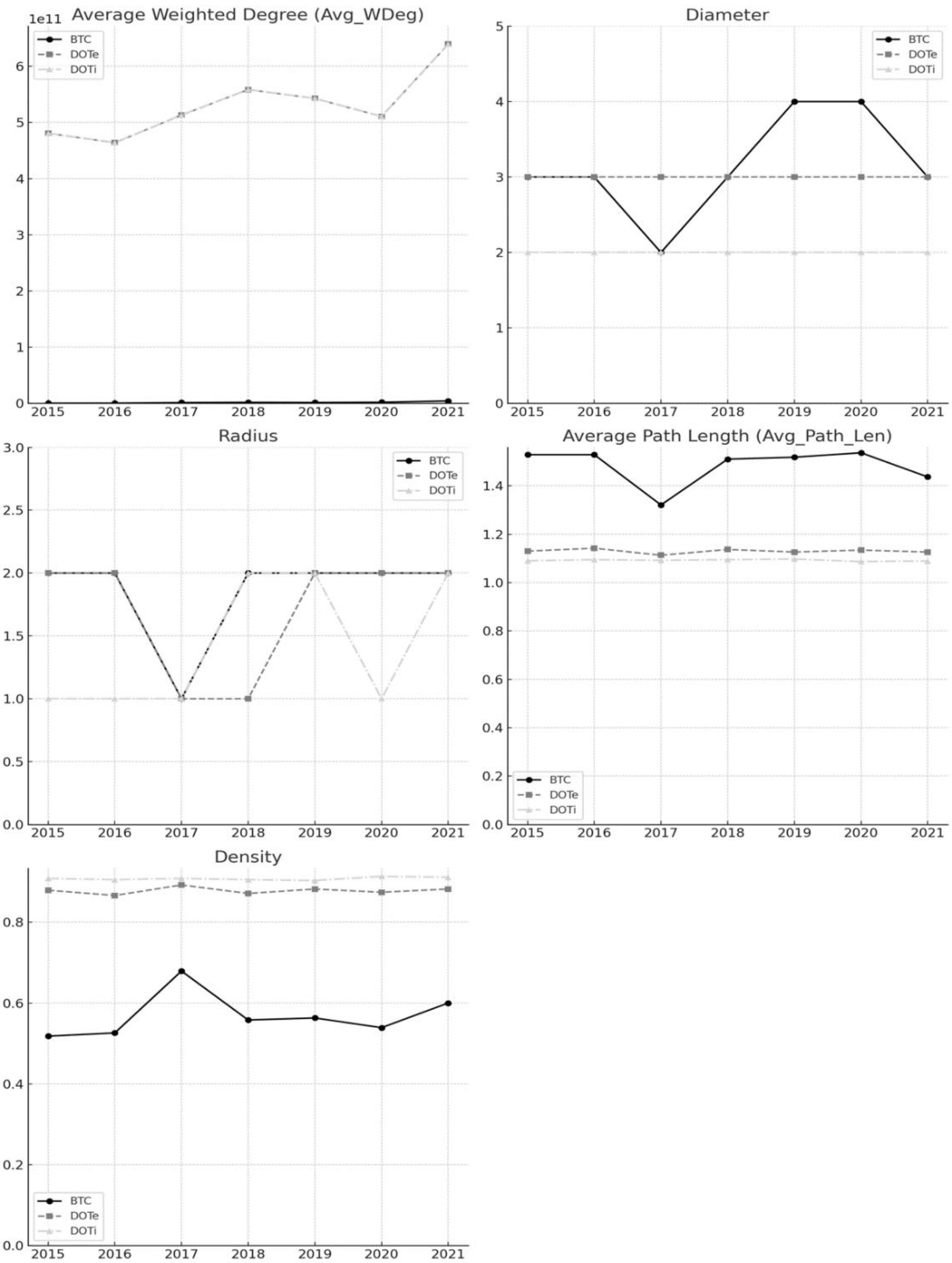


Figure 8. Line charts comparing the evolution of network metrics over the years

The observed shifts in the network analysis metrics can potentially be correlated with certain geopolitical events and trends. Each metric reflects a different dimension of the complex interplay between international trade and cryptocurrency movements within the geopolitical landscape of 2014-2021. However, further analysis on a node-level is needed to understand any causation relationship is present between trade and Bitcoin transaction networks.

5.2 Hypothesis testing

We analyze the community and clustering aspect of the same networks. To visualize the trends and changes, inspect the network using Modularity, Modul with Resolution, Number of Communities detected by Modularity, Description Length, and Inferred Number of Communities over the years, as demonstrated in Figure 9. We utilize the relevant metrics to test each hypothesis individually and provide the results for each hypothesis individually.

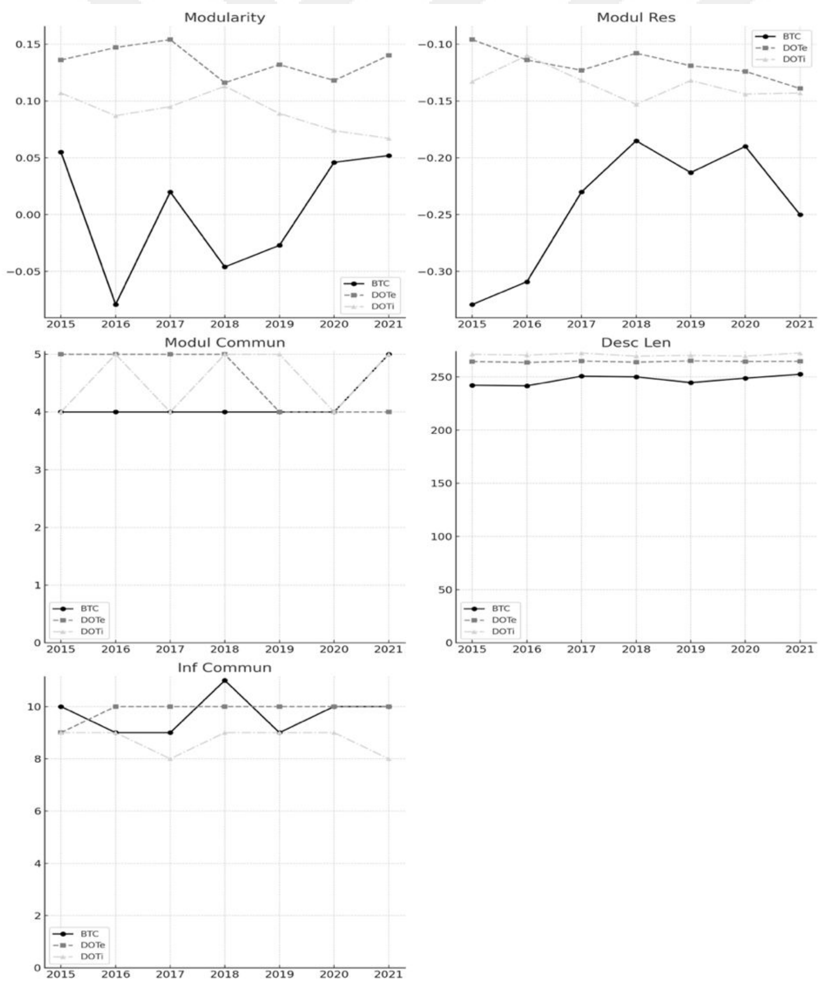


Figure 9. Line charts comparing the clustering trends

5.2.1 H1a: There is a correlation between a country's trade volume and the volume of cryptocurrency transactions

Countries with high volumes of international trade may require more flexible and efficient means of payment and financial transactions. Cryptocurrencies, notably Bitcoin, with its global reach and ease of transfer, might be used increasingly in such countries to complement traditional trade financing methods. To explore the relationship, we first use two-way graphs with Fit Fractional polynomial as provided in Figure 10 and Figure 11. The confidence interval is set at the default value of 95% for the plot.

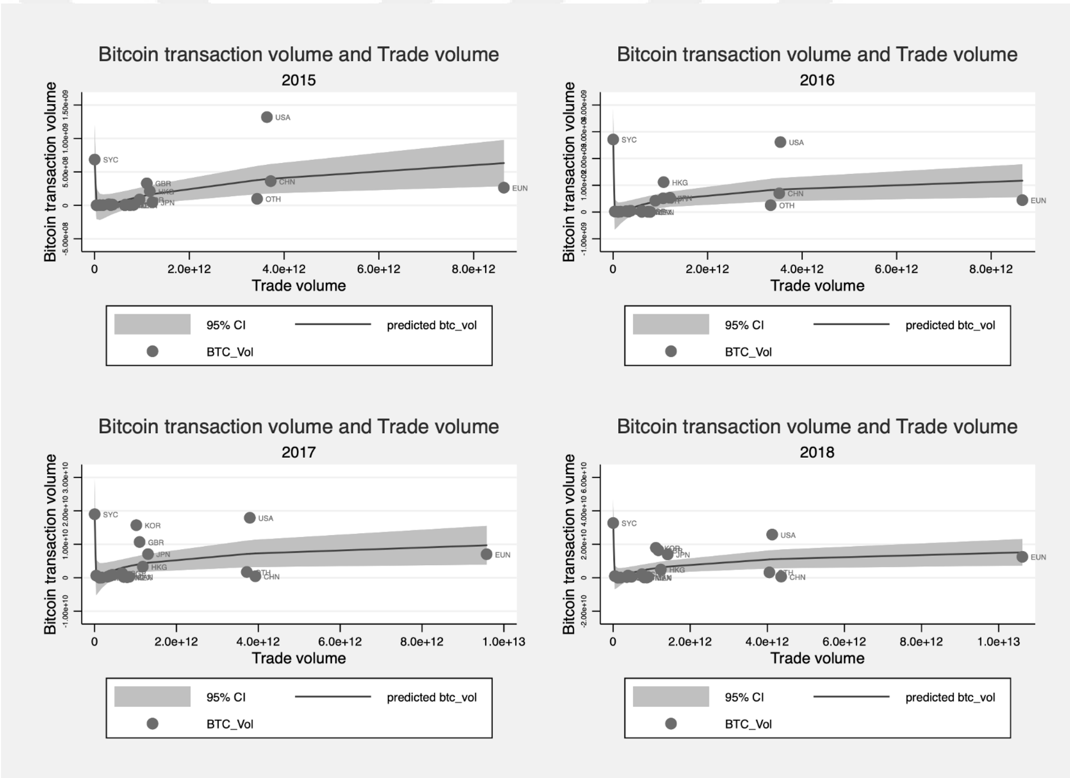


Figure 10. Two-way graph comparing Bitcoin transaction volume and trade volume from the year 2015 through 2018 with fit fractional polynomial

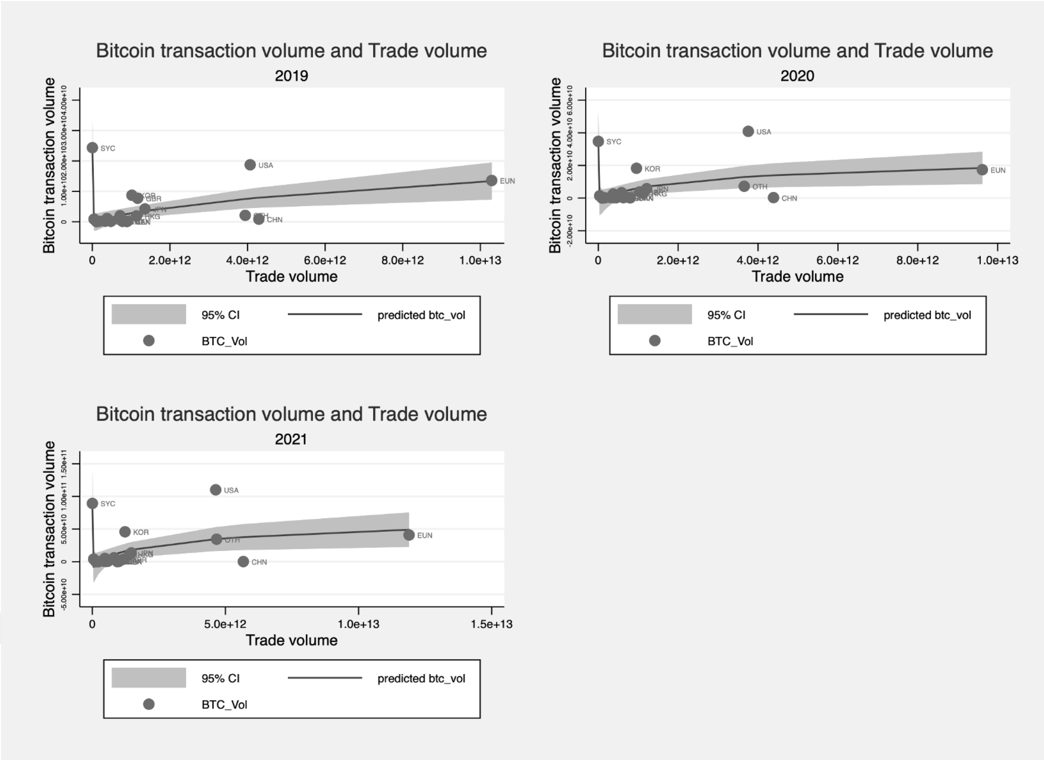


Figure 11. Two-way graph comparing Bitcoin transaction volume and trade volume from the year 2019 through 2021 with fit fractional polynomial

As can be seen from the Figure 10 and Figure 11, there is initially a high Bitcoin transaction volume observed at the low trade volumes however this doesn't have a significant impact after a certain threshold. The confidence interval is also observed to be very narrow at the low trade volumes however increases with time. It is not possible to reach a conclusive result solely by inspecting the two-way graphs. Therefore, we further analyzed the same data by applying natural algorithm to both variables. As can be observed from the Figure 12 and Figure 13, we can see a clear U-curve formed after transforming both variables with natural logarithm. During the early years, the relationship between trade volume and Bitcoin transactions appears to be moderately positive. As trade volume increases, there is a corresponding increase in Bitcoin transaction volume, suggesting that higher economic activity might be fostering greater utilization of Bitcoin for various transactional purposes.

There is a noticeable shift in the pattern by 2018 and 2019. The confidence interval widens significantly, and the scatter of the data points becomes more pronounced. This change could indicate external factors influencing Bitcoin transactions that are not solely dependent on traditional trade volume, such as regulatory changes, increased market volatility, or macroeconomic variables. In the most recent years, the correlation stabilizes somewhat with a clearer upward trend. This could reflect a maturation of the cryptocurrency market and its increasing integration with traditional economic activities. The narrower confidence interval in these years suggests a stronger predictive power of trade volume over Bitcoin transaction volume.

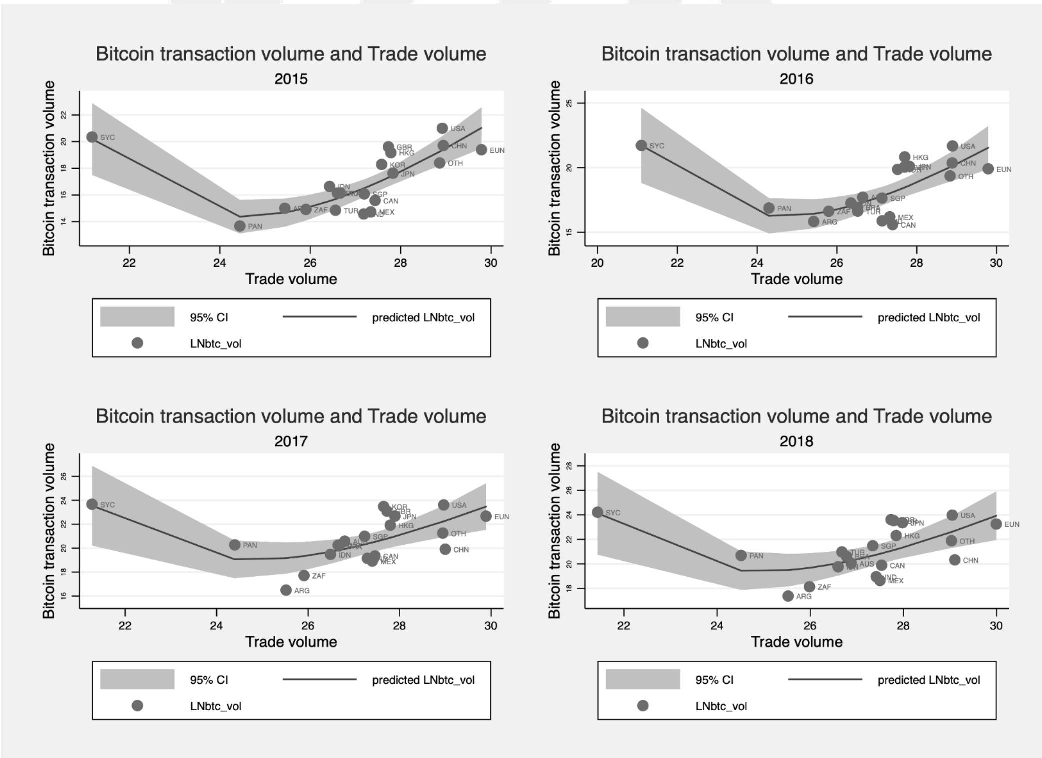


Figure 12. Two-way graph comparing Bitcoin transaction volume and trade volume from the year 2015 through 2018 with fit fractional polynomial

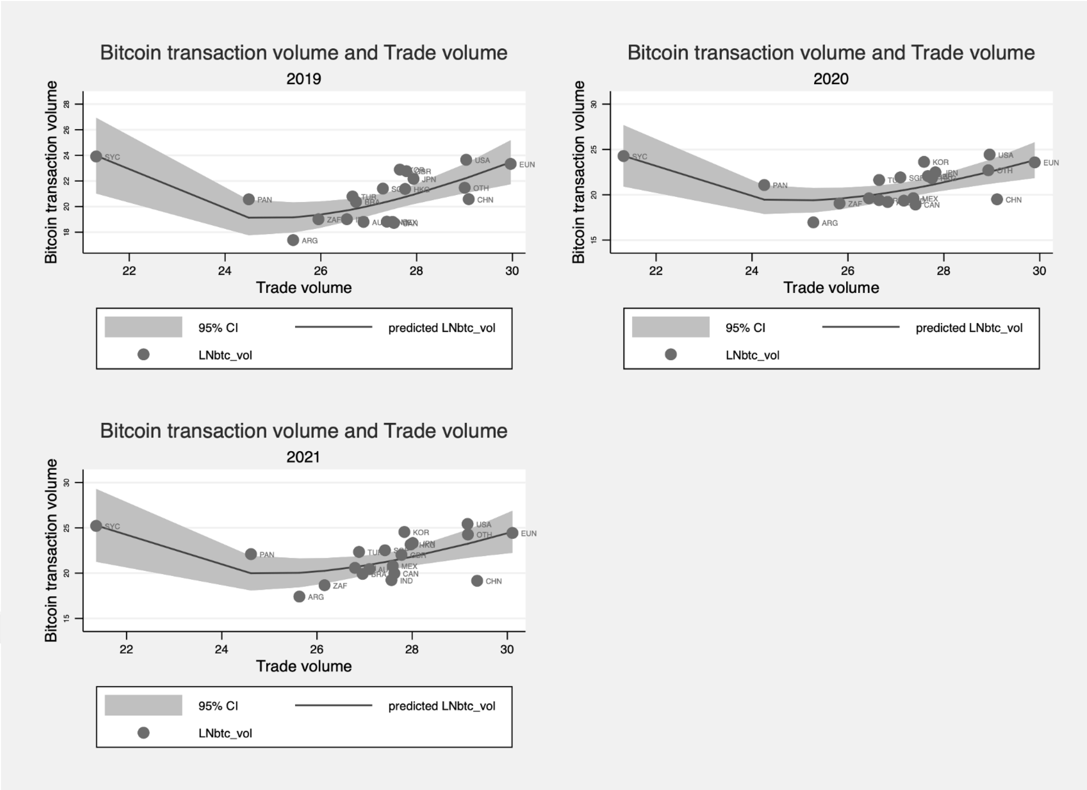


Figure 13. Two-way graph comparing Bitcoin transaction volume and trade volume from the year 2019 through 2021 with fit fractional polynomial

Statistically, the graphs depict a varying but generally positive correlation between trade volume and Bitcoin transaction volume over the observed period. The polynomial regression lines plotted through the data points help in understanding that while trade volume can be a predictor of Bitcoin transaction volume, the strength and nature of this relationship are susceptible to external economic and political events, which indicates a correlation between Bitcoin transaction volumes and trade volumes between the years 2015 and 2021. To further analyze the interplay, the regression results provided in Table 6 provide an enriched understanding of the relationship between trade volume and Bitcoin transaction volume by offering statistical evidence. Coefficients across models 1-7 for trade volumes are generally positive, with model 2 showing a statistically significant coefficient (0.0070, $p < 0.05$).

Table 6. Regression Analysis for Bitcoin Exports and Trade Values

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol
tradevol	0.0081	0.0070**	0.0072**	0.0068*	0.0068**	0.0065*	0.0065*
	(0.0061)	(0.0030)	(0.0030)	(0.0033)	(0.0032)	(0.0034)	(0.0034)
realgdp		0.0012	0.0021	0.0016	0.0015	0.0017	0.0014
		(0.0080)	(0.0081)	(0.0079)	(0.0076)	(0.0075)	(0.0075)
btc_legal			7.6260e+09	8.3742e+09	8.7112e+09	9.7172e+09	9.4468e+09
			(7.2903e+09)	(7.3863e+09)	(7.7073e+09)	(7.9758e+09)	(7.7173e+09)
btc_regul				-5.7497e+09	-5.9017e+09	-5.9037e+09	-5.7286e+09
				(4.9063e+09)	(5.1322e+09)	(5.1434e+09)	(5.1201e+09)
stability					-5.3576e+09	-7.3935e+09	-7.8559e+09
					(9.6941e+09)	(1.0446e+10)	(1.0576e+10)
polinstab						-3.6174e+09	-3.4598e+09
						(2.9024e+09)	(2.9661e+09)
regulations							5.4204e+09
							(6.8074e+09)
2016.year	6.1231e+08**	4.6189e+08	3.8937e+08	4.1977e+08	3.4350e+08	8.6271e+08	6.3671e+08
	(2.4514e+08)	(7.4450e+08)	(7.5052e+08)	(7.4511e+08)	(8.8893e+08)	(7.3906e+08)	(8.2480e+08)
2017.year	3.5954e+09**	3.4391e+09*	3.6404e+09*	3.8292e+09*	3.8616e+09*	4.4986e+09**	4.1492e+09**
	(1.5527e+09)	(1.7973e+09)	(1.7645e+09)	(1.8270e+09)	(1.9205e+09)	(1.9537e+09)	(1.8798e+09)
2018.year	4.8996e+09*	4.7463e+09	4.8221e+09	6.3407e+09*	6.3180e+09*	7.3353e+09*	7.1377e+09*
	(2.6536e+09)	(2.9709e+09)	(2.8906e+09)	(3.5353e+09)	(3.5964e+09)	(3.7792e+09)	(3.7086e+09)
2019.year	2.8288e+09	2.5134e+09	2.5148e+09	4.0627e+09	3.6963e+09	4.3670e+09	4.3940e+09
	(1.8873e+09)	(3.0355e+09)	(2.9327e+09)	(3.4036e+09)	(3.7892e+09)	(3.7192e+09)	(3.7677e+09)
2020.year	6.1220e+09**	5.8371e+09**	5.5512e+09**	8.1702e+09*	7.9536e+09*	8.9839e+09**	9.0819e+09*
	(2.7018e+09)	(2.5093e+09)	(2.4157e+09)	(4.0370e+09)	(4.0398e+09)	(4.2350e+09)	(4.3347e+09)
2021.year	1.3741e+10*	1.3563e+10*	1.3413e+10*	1.6349e+10*	1.6144e+10*	1.6750e+10*	1.7087e+10*
	(7.2013e+09)	(7.0021e+09)	(6.9781e+09)	(8.8498e+09)	(8.7863e+09)	(8.9583e+09)	(9.2073e+09)
Constant	-1.0451e+10	-1.3060e+10	-2.3782e+10	-2.2266e+10	-2.1554e+10	-2.1910e+10	-2.4648e+10
	(8.5666e+09)	(2.5727e+10)	(2.9244e+10)	(2.8697e+10)	(2.6787e+10)	(2.6560e+10)	(2.7347e+10)
Observations	133	133	133	133	133	133	133
R-squared	0.2667	0.2677	0.2773	0.2931	0.2991	0.3069	0.3096
Number of countries	19	19	19	19	19	19	19

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This indicates that, as expected, an increase in trade volume is generally associated with an increase in Bitcoin transaction volume. The significance in model 2 supports the hypothesis that greater economic activity (measured through trade volume) promotes higher utilization of Bitcoin.

5.2.2 H1b: There is a correlation between a country's imports and the volume of cryptocurrency exports

Cryptocurrencies can be used as a defacto currency to purchase goods and services. Therefore, we anticipate an increase in the imports of a country as the export of cryptocurrencies increase. The examination of the graphs from 2015 through 2021 reveals evolving dynamics between the volume of Bitcoin exports and trade imports across countries. Across the seven-year span, the relationship between trade imports and Bitcoin exports generally exhibits a U-shaped or flattened U-shaped pattern. This suggests that countries at the extremes of trade import volumes—either very high or very low—are associated with higher Bitcoin export activities. The middle range of trade imports often corresponds to a lower volume of Bitcoin exports. This pattern might indicate different strategic uses of Bitcoin, either as a necessity in economies with fewer trade opportunities or as an optimization strategy in more robust economies.

In 2015, the graph shows a distinct U-shaped relationship between Bitcoin exports and trade imports. As can be observed in Figure 14 and Figure 15, Bitcoin exports tend to be higher at lower and higher levels of trade imports, while Bitcoin exports show a tendency to decrease at mid-range import levels. The fit line, representing the Bitcoin exports, suggests a significant correlation, where countries with either low or high import volumes exhibit increased Bitcoin export activity.

This implies that countries with smaller or larger economies engage more actively in Bitcoin trading, possibly due to different economic strategies or levels of market maturity. Over time, the graphs from 2015 to 2018 show a U-shaped pattern gradually becoming more pronounced and then starting to stabilize from 2019 onwards. This stabilization and the gradual flattening of the curve in 2020 and 2021 could indicate an increasing normalization of Bitcoin's role in international trade, reflecting both growing market maturity and broader economic integration. Throughout these years, the predictive models (depicted as the fit fractional polynomial lines) generally maintain a good fit with the observed data, especially noted in the later years. The narrowing of the 95% confidence intervals in the later years suggests increasing accuracy and reliability of the model's predictions about Bitcoin exports based on trade import volumes.

The correlation is also supported by the regression analysis as can be seen in Table 7. In the first model, imports are associated with an increase of 0.0097 in Bitcoin exports, significant at the 10% level ($p < 0.1$). In the second model, this effect is larger and more significant, with a coefficient of 0.0395 ($p < 0.01$), indicating a robust positive relationship between trade imports and Bitcoin exports when controlling for exports.

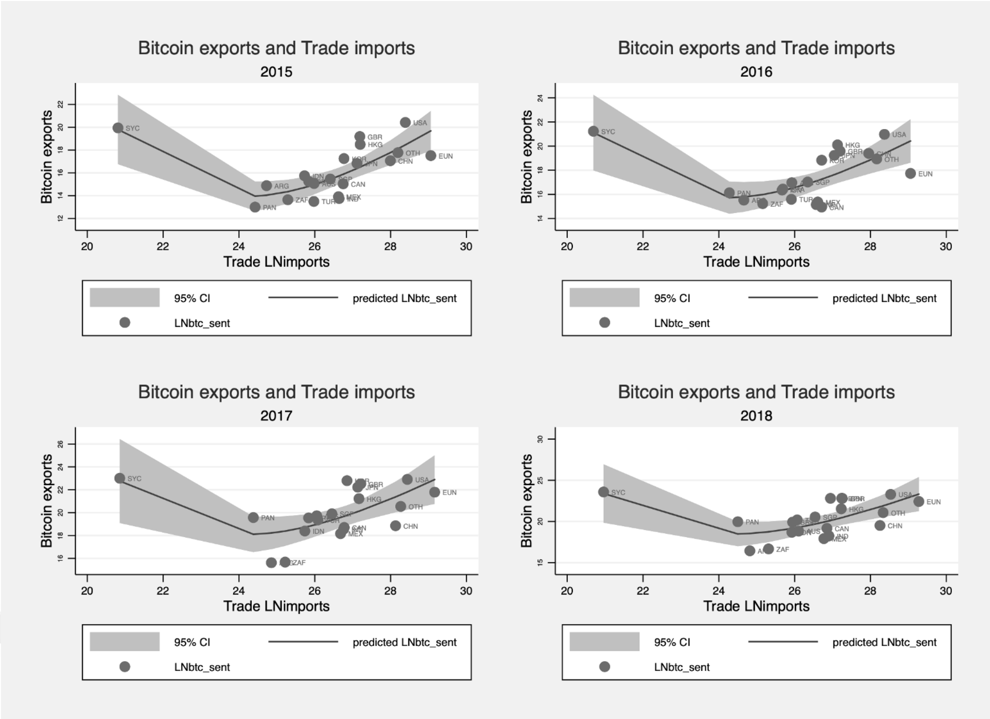


Figure 14. Two-way graph comparing Bitcoin exports and trade volume from the year 2019 through 2021 with fit fractional polynomial

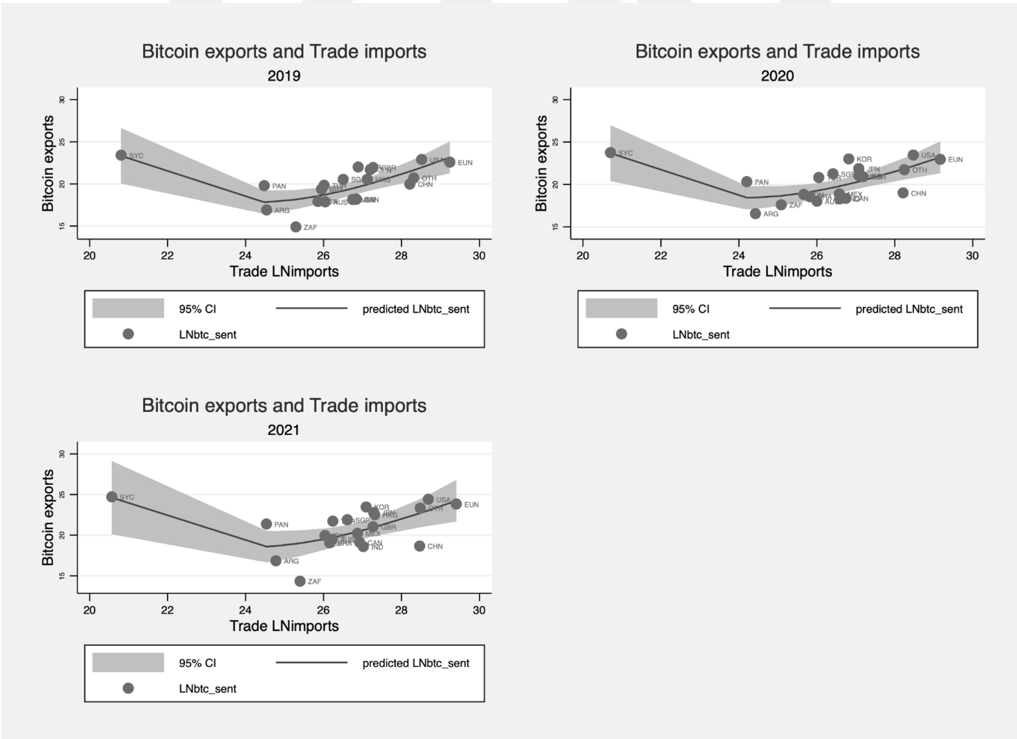


Figure 15. Two-way graph comparing bitcoin transaction volume and trade volume from the year 2019 through 2021 with fit fractional polynomial

Table 7. Regression Analysis for Bitcoin Transaction Volume and Trade Volume

	(1)	(2)
VARIABLES	btc_sent	btc_sent
imports	0.0097*	0.0395***
	(0.0056)	(0.0116)
exports		-0.0339***
		(0.0114)
2016.year	3.5108e+08***	2.9304e+08
	(1.2205e+08)	(2.3441e+08)
2017.year	1.6320e+09*	1.7481e+09*
	(8.0323e+08)	(9.5934e+08)
2018.year	2.0057e+09	2.2090e+09
	(1.4245e+09)	(1.5044e+09)
2019.year	1.1186e+09	1.4181e+09
	(1.1011e+09)	(1.1653e+09)
2020.year	2.8704e+09**	3.0534e+09**
	(1.3110e+09)	(1.3174e+09)
2021.year	6.0656e+09	6.8608e+09*
	(3.6501e+09)	(3.6696e+09)
Constant	-6.7980e+09	-3.6232e+09
	(3.9746e+09)	(2.1034e+09)
Observations	140	140
R-squared	0.3144	0.4219
Number of countries	20	20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.3 H2: Economic and political instabilities lead to an increase in cryptocurrency transactions

During times of geopolitical uncertainty, Bitcoin might be considered a digital gold to hedge against risks associated with traditional financial systems. As one example, Selmi assesses the role of Bitcoin as a hedge, a safe haven and/or a diversifier against extreme oil price movements. And finds that Bitcoin and gold would serves that purpose, conditional to Bitcoin's and gold's different (bear, normal or bull) market conditions (Selmi et al. 2018). Similarly, Su et al. explores the sensitivity of Bitcoin to geopolitical events. And found that there are positive and negative influences that stem from geopolitical risks towards Bitcoin prices (Su et al. 2020).

For this hypothesis, we have two approaches. For the first one, we have gathered a list of all significant economic and political events for the period of 2015 and 2021 and we compare the transaction data with this yearly political stability metric for each country. Furthermore, we focus on the Political Stability and Absence of Violence/Terrorism index (Kaufmann and Kraay 2023). This dataset helps assess the probability that a government will be destabilized or overthrown through unconstitutional or violent methods, such as political violence or terrorism.

As shown in the Figure 16, the bar chart doesn't demonstrate a significant correlation between the Bitcoin transaction volumes and political instability. On the other hand, the two-way plots provided as Figure 17 and Figure 18, form an inverted U curve shape. They show a noticeable clustering of data points at lower stability indices with higher Bitcoin volumes, particularly in countries like Venezuela (VEN), Turkey (TUR), and Syria (SYC).

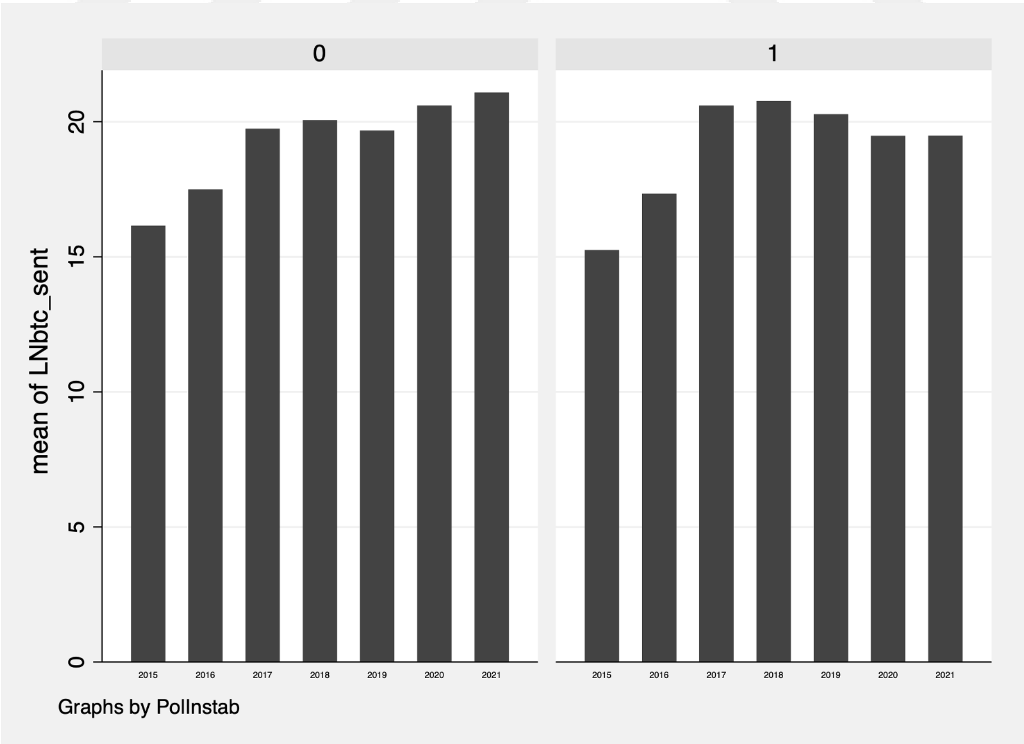


Figure 16. Bar chart comparing the average Bitcoin sent and political instability

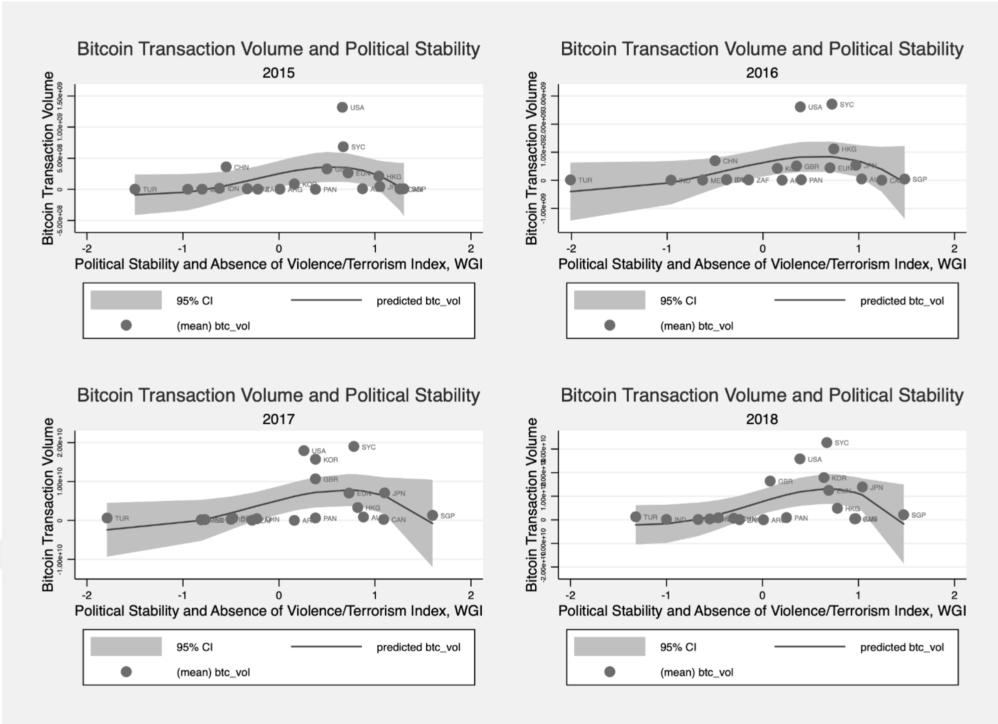


Figure 17. Two-way graph comparing Bitcoin transaction volume and WGI Political Stability Index from the year 2015 through 2018 with fit fractional polynomial

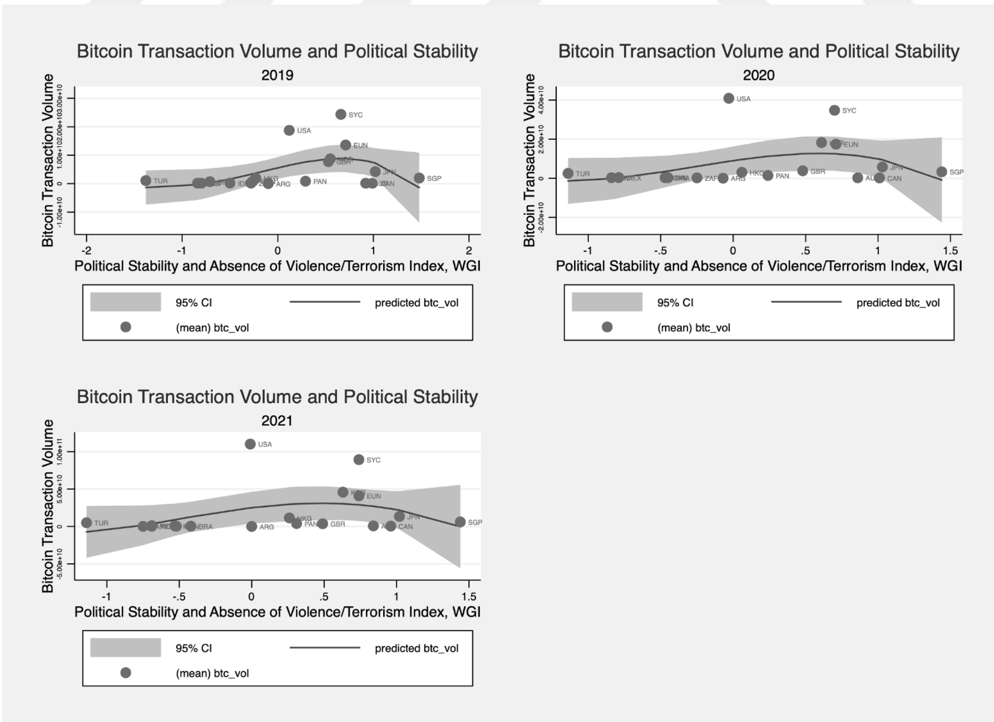


Figure 18. Two-way graph comparing Bitcoin transaction volume and WGI Political Stability Index from the year 2019 through 2021 with fit fractional polynomial

In addition, we also inspect the two-way graphs comparing Log of Bitcoin transaction volume and WGI Political Stability Index under Figure 19 and Figure 20. However, they also do not indicate a clear relationship or correlation between the two data points. Therefore, the lack of statistical significance for the political stability coefficient suggests that the initial hypothesis—that political instability drives increased Bitcoin transaction volumes—may not be supported by the findings. The results provided under Table 8, in the regression analysis for Bitcoin transaction volume and trade volume, further indicates that within the scope of this analysis, political stability, as measured, does not have a discernible impact on Bitcoin transaction volumes.

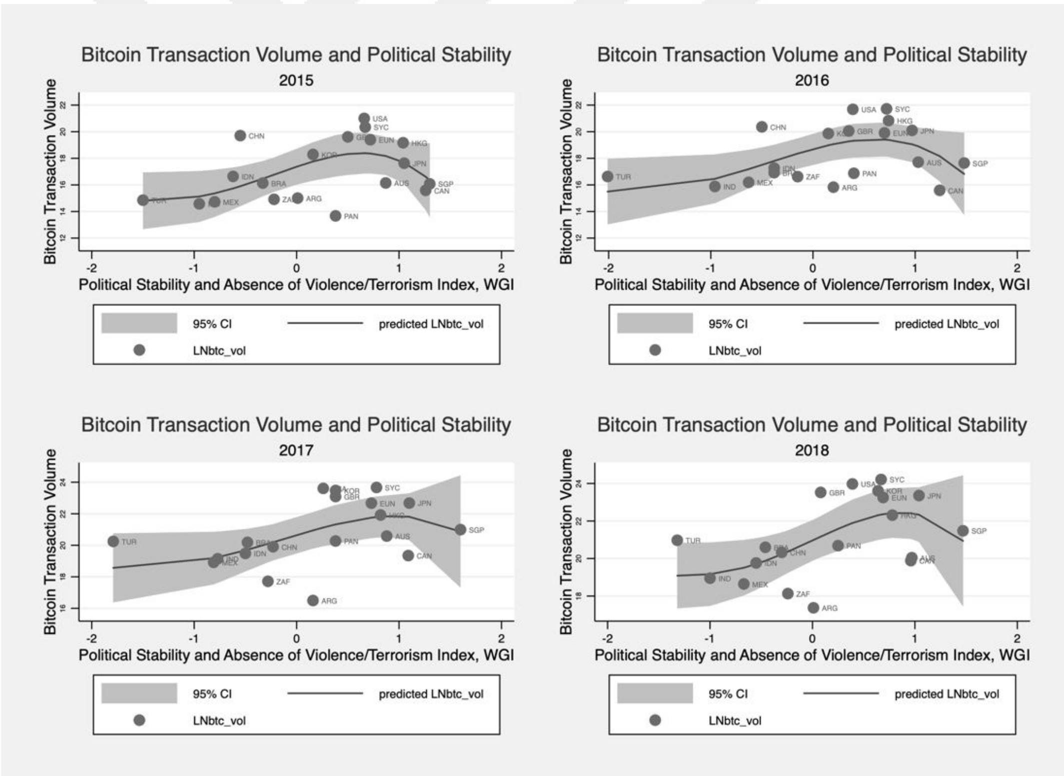


Figure 19. Two-way graph comparing log of Bitcoin transaction volume and WGI Political Stability Index from the year 2015 through 2018 with fit fractional polynomial

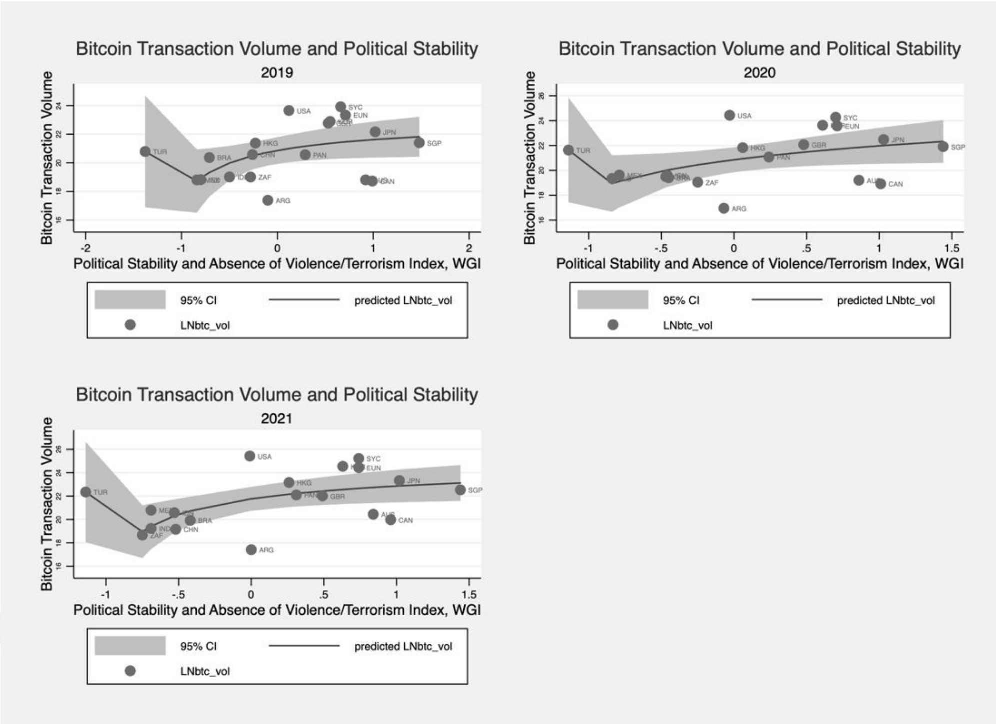


Figure 20. Two-way graph comparing the log of Bitcoin transaction volume and WGI Political Stability Index from the year 2019 through 2021 with fit fractional polynomial

Table 8. Regression Analysis for Bitcoin Transaction Volume and Trade Volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol
tradevol	0.0081	0.0070**	0.0072**	0.0068*	0.0068**	0.0065*	0.0065*
	(0.0061)	(0.0030)	(0.0030)	(0.0033)	(0.0032)	(0.0034)	(0.0034)
realgdp		0.0012	0.0021	0.0016	0.0015	0.0017	0.0014
		(0.0080)	(0.0081)	(0.0079)	(0.0076)	(0.0075)	(0.0075)
btc_legal			7.6260e+09	8.3742e+09	8.7112e+09	9.7172e+09	9.4468e+09
			(7.2903e+09)	(7.3863e+09)	(7.7073e+09)	(7.9758e+09)	(7.7173e+09)
btc_regul				-5.7497e+09	-5.9017e+09	-5.9037e+09	-5.7286e+09
				(4.9063e+09)	(5.1322e+09)	(5.1434e+09)	(5.1201e+09)
stability					-5.3576e+09	-7.3935e+09	-7.8559e+09
					(9.6941e+09)	(1.0446e+10)	(1.0576e+10)
polinstab						-3.6174e+09	-3.4598e+09
						(2.9024e+09)	(2.9661e+09)
regulations							5.4204e+09
							(6.8074e+09)
2016.year	6.1231e+08**	4.6189e+08	3.8937e+08	4.1977e+08	3.4350e+08	8.6271e+08	6.3671e+08
	(2.4514e+08)	(7.4450e+08)	(7.5052e+08)	(7.4511e+08)	(8.8893e+08)	(7.3906e+08)	(8.2480e+08)
2017.year	3.5954e+09**	3.4391e+09*	3.6404e+09*	3.8292e+09*	3.8616e+09*	4.4986e+09**	4.1492e+09**
	(1.5527e+09)	(1.7973e+09)	(1.7645e+09)	(1.8270e+09)	(1.9205e+09)	(1.9537e+09)	(1.8798e+09)
2018.year	4.8996e+09*	4.7463e+09	4.8221e+09	6.3407e+09*	6.3180e+09*	7.3353e+09*	7.1377e+09*
	(2.6536e+09)	(2.9709e+09)	(2.8906e+09)	(3.5353e+09)	(3.5964e+09)	(3.7792e+09)	(3.7086e+09)
2019.year	2.8288e+09	2.5134e+09	2.5148e+09	4.0627e+09	3.6963e+09	4.3670e+09	4.3940e+09
	(1.8873e+09)	(3.0355e+09)	(2.9327e+09)	(3.4036e+09)	(3.7892e+09)	(3.7192e+09)	(3.7677e+09)
2020.year	6.1220e+09**	5.8371e+09**	5.5512e+09**	8.1702e+09*	7.9536e+09*	8.9839e+09**	9.0819e+09*
	(2.7018e+09)	(2.5093e+09)	(2.4157e+09)	(4.0370e+09)	(4.0398e+09)	(4.2350e+09)	(4.3347e+09)
2021.year	1.3741e+10*	1.3563e+10*	1.3413e+10*	1.6349e+10*	1.6144e+10*	1.6750e+10*	1.7087e+10*
	(7.2013e+09)	(7.0021e+09)	(6.9781e+09)	(8.8498e+09)	(8.7863e+09)	(8.9583e+09)	(9.2073e+09)
Constant	-1.0451e+10	-1.3060e+10	-2.3782e+10	-2.2266e+10	-2.1554e+10	-2.1910e+10	-2.4648e+10
	(8.5666e+09)	(2.5727e+10)	(2.9244e+10)	(2.8697e+10)	(2.6787e+10)	(2.6560e+10)	(2.7347e+10)
Observations	133	133	133	133	133	133	133
R-squared	0.2667	0.2677	0.2773	0.2931	0.2991	0.3069	0.3096
Number of countries	19	19	19	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.4 H3a: Countries with significant trade deficit are in more central positions in the cryptocurrency transaction network

There are three components to this hypothesis, and we analyze each subbranch individually; however, the underlying reasoning is based on the same logic. Countries running trade deficits may utilize cryptocurrencies more actively, potentially placing them centrally in the cryptocurrency network. At the same time, the residents in countries with trade deficits might use cryptocurrencies as an alternative means to balance the lack of foreign currency reserves or to facilitate cheaper and faster cross-border transactions (Selmi et al. 2018). We use regression analysis to explore the relationship between trade deficit (trade balance, capital account, and financial account) and the PageRank centrality for Bitcoin transactions as provided under Table 9.

For the first sub-hypothesis, we first compare the centrality in the cryptocurrency network with trade deficit. As demonstrated in Figure 23 and Figure 24, countries like the United States, which consistently show a trade deficit (as indicated by their positioning on the negative side of the Net Trade Balance axis), generally maintain a relatively stable or increasing PageRank Score over the years. This suggests that despite economic outflows on the trade front, these countries might be leveraging cryptocurrencies either as a balancing asset or as an alternative transaction medium. In addition, we also provide the same analysis with PageRank rankings under Figure 21 and Figure 22, which reinforce our findings. The trend lines across the years suggest that the PageRank for such countries either stabilizes or slightly improves, indicating a sustained or growing importance in the cryptocurrency network.

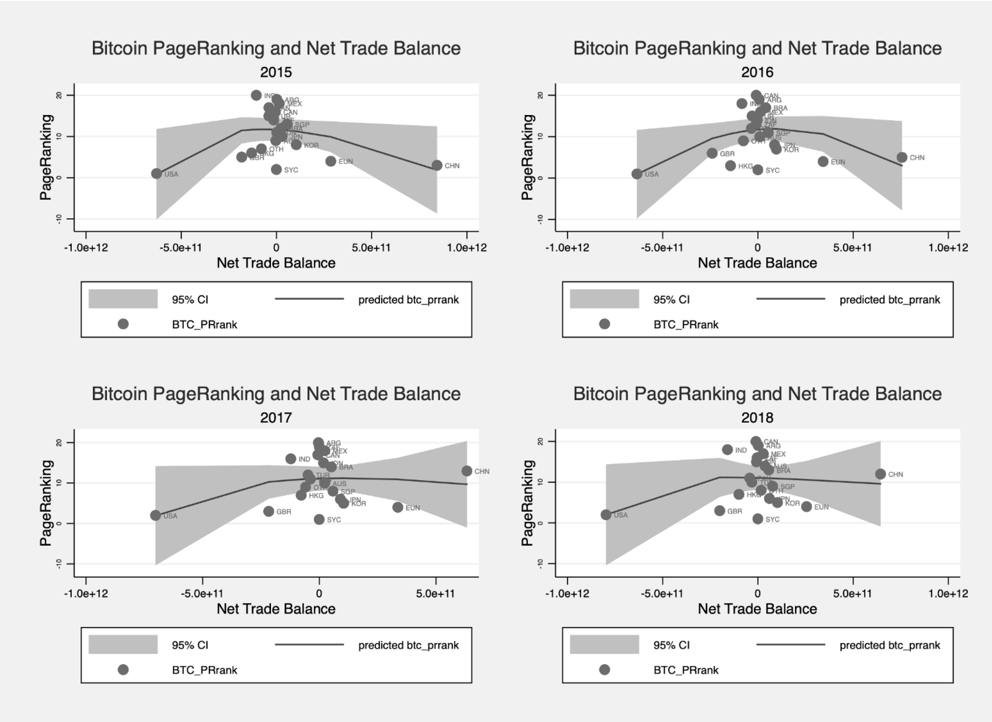


Figure 21. Two-way graph comparing Bitcoin PageRank ranking and net trade balance from the year 2015 through 2018 with fit fractional polynomial

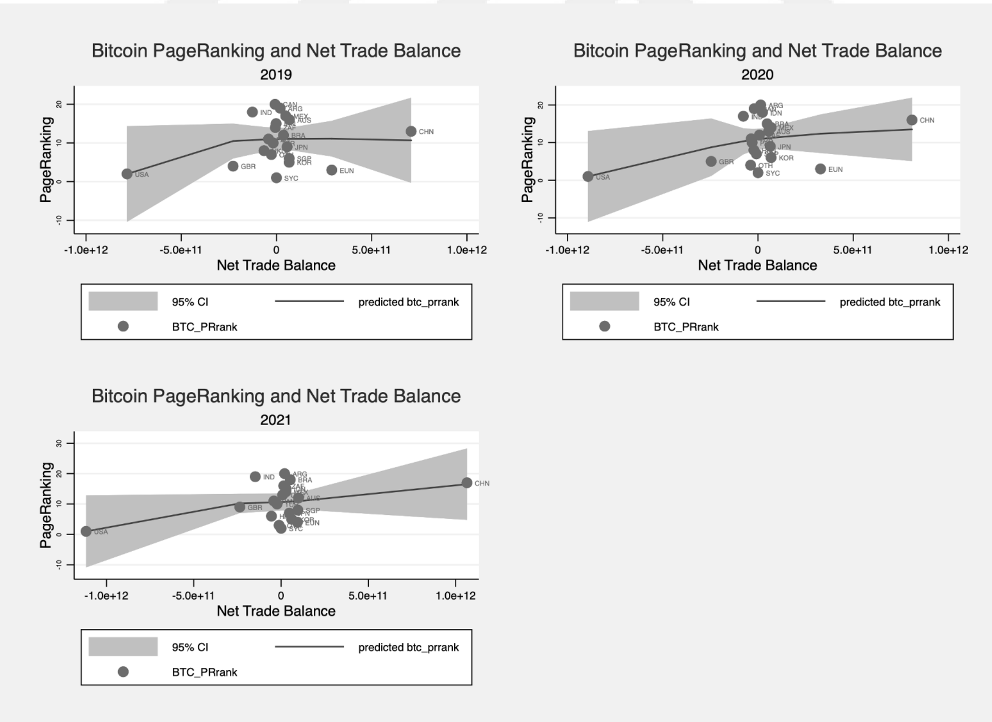


Figure 22. Two-way graph comparing Bitcoin PageRank ranking and net trade balance from the year 2019 through 2021 with fit fractional polynomial

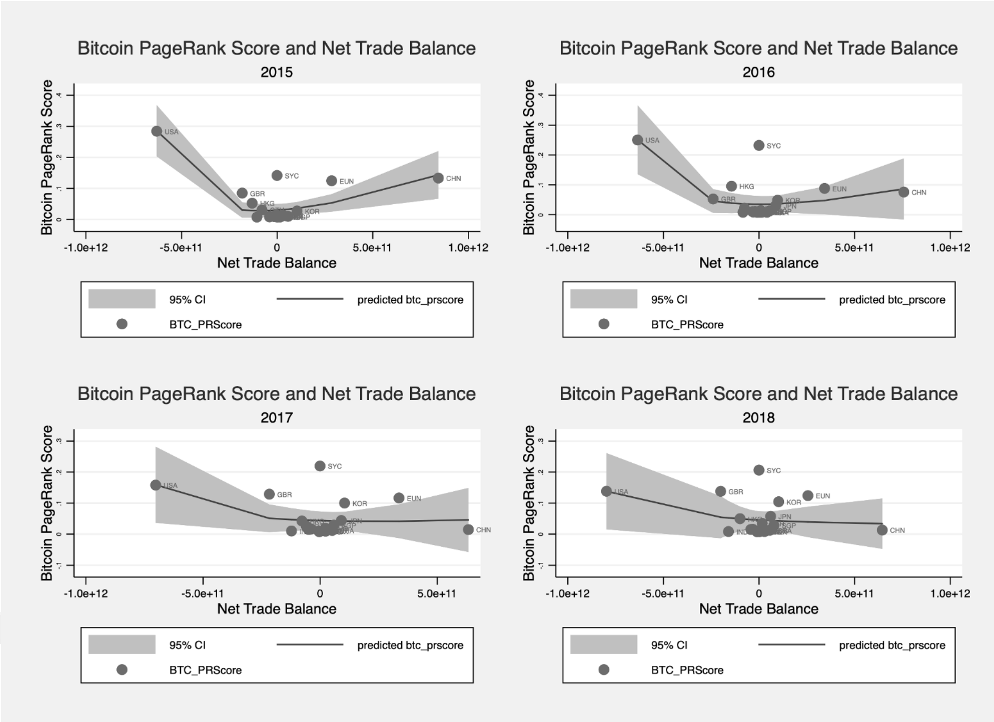


Figure 23. Two-way graph comparing Bitcoin PageRank score and net trade balance from the year 2015 through 2018 with fit fractional polynomial

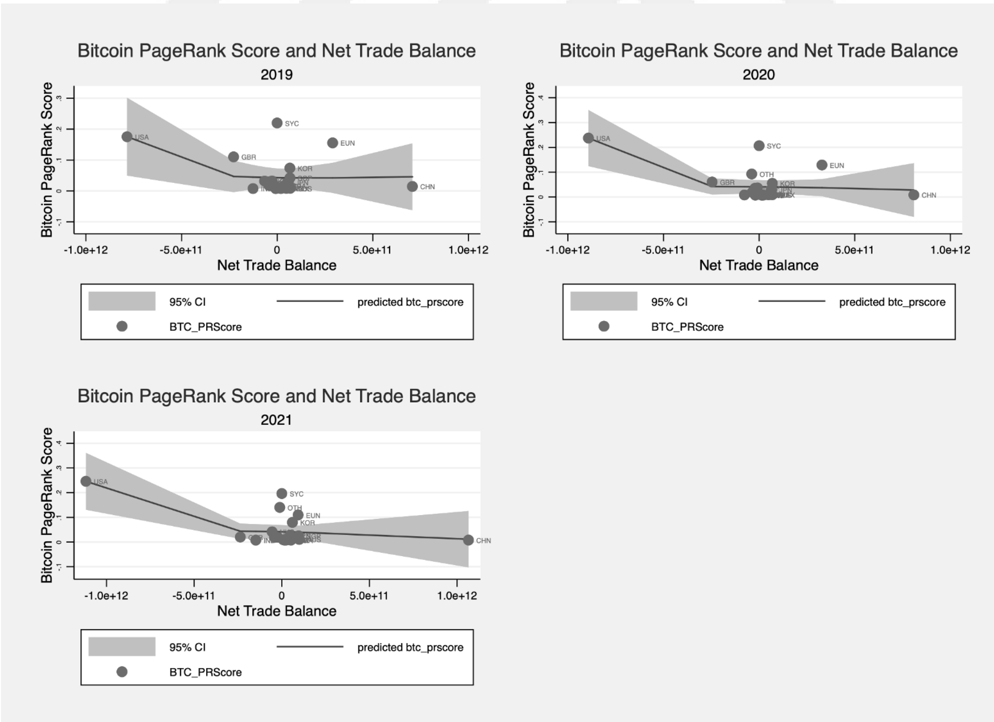


Figure 24. Two-way graph comparing Bitcoin PageRank score and net trade balance from the year 2019 through 2021 with fit fractional polynomial

On the other hand, nations such as China, which often exhibit a trade surplus, do not necessarily correlate with lower PageRank scores. In some years, such as 2018 and 2019, China and other similar countries show relatively central roles in the cryptocurrency network, potentially due to their significant economic scale and engagement with digital currencies. The analysis indicates that the position of countries in the cryptocurrency network does not conclusively depend on their trade balance status alone. The variability in PageRank and PageRank Score for surplus countries suggests a more complex interplay of factors beyond mere trade balance figures. While one might hypothesize that countries with trade deficits could use cryptocurrencies to alleviate some financial pressures, the data shows a more nuanced picture where both deficit and surplus countries actively participate in the cryptocurrency markets.

5.2.5 H3b: Countries with capital account deficit are in more central positions in the cryptocurrency transaction network

For the second section of our third hypothesis, we focus on comparing the centrality in the cryptocurrency network with capital account deficit. The scatter plots across the years consistently show a cluster of points where countries with a capital account deficit (negative balance) frequently appear in positions of greater centrality within the Bitcoin transaction network. This observation is supported by the trend lines that generally ascend from left (deficit) to right (surplus), suggesting that countries with lower capital account balances tend to have higher Bitcoin PageRank values. 2015-2017

In the early years, 2015 through 2017, countries like USA, CHN (China), and RUS (Russia) that might have experienced fluctuations in their capital account balances are observed to retain relatively high centrality in Bitcoin transactions. As demonstrated in Figure 25 and Figure 27, this could indicate an early adoption or higher engagement with cryptocurrencies possibly as a diversification or hedging mechanism against capital account imbalances. A noticeable shift occurs in later years (2018 onwards), where the prediction intervals widen, and more countries, regardless of their capital account status, tend to cluster towards higher centrality values. The fitted curves under Figure 26 and Figure 28, which focus on the years 2019 through 2021, suggest a complex, non-linear relationship between capital account balances and Bitcoin centrality. The polynomial fit, particularly in 2021, underscores a significant variance in centrality even among countries with similar capital account balances. In addition, the regression results provided in Table 9 support the observations from the scatter plots, where capital account balance is strongly significant with the centrality of countries in the Bitcoin network.

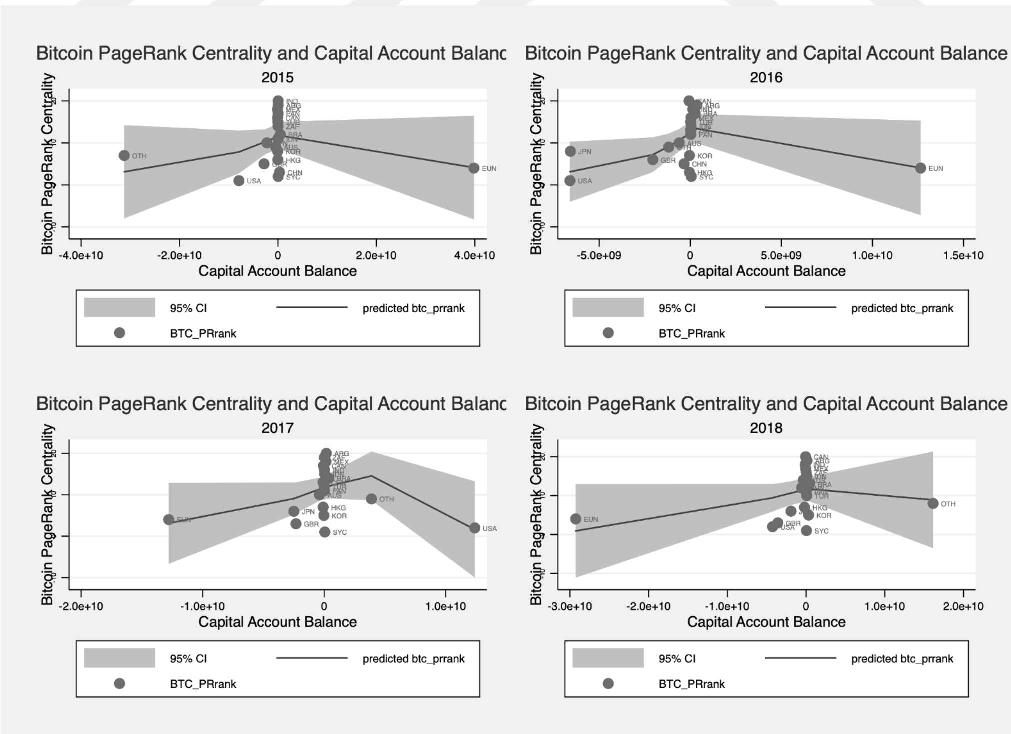


Figure 25. Two-way graph comparing Bitcoin PageRank centrality and capital account balance from the year 2015 through 2018 with fit fractional polynomial

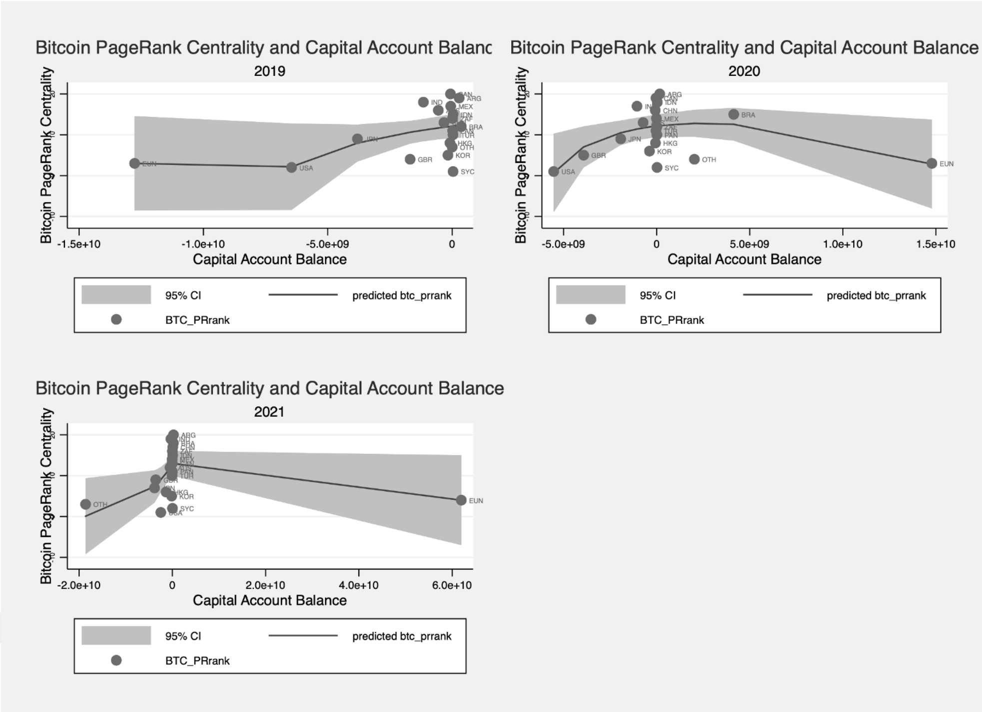


Figure 26. Two-way graph comparing Bitcoin PageRank centrality and capital account balance from the year 2019 through 2021 with fit fractional polynomial

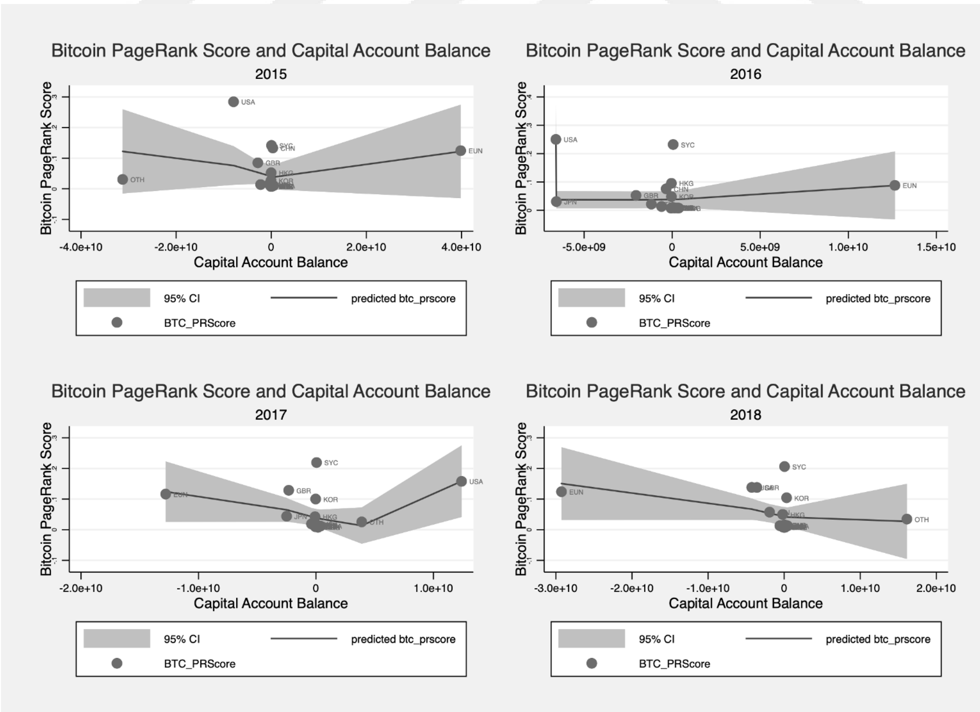


Figure 27. Two-way graph comparing Bitcoin PageRank score and capital account balance from the year 2015 through 2018 with fit fractional polynomial

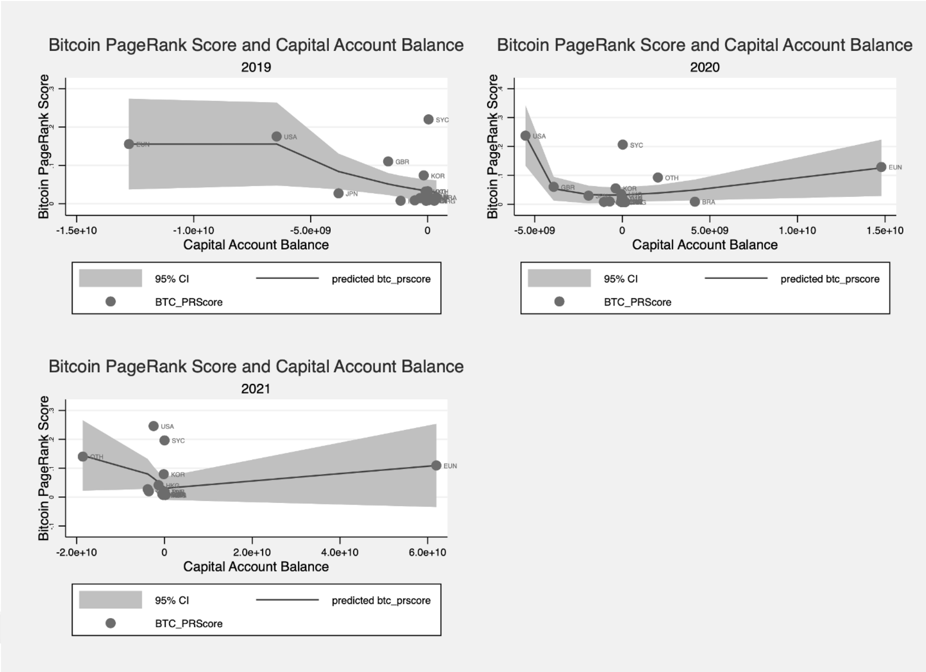


Figure 28. Two-way graph comparing Bitcoin PageRank score and capital account balance from the year 2019 through 2021 with fit fractional polynomial

5.2.6 H3c: Countries with financial account deficit are in more central positions in the cryptocurrency transaction network

We use a series of graphs provided illustrate the relationship between Bitcoin PageRank centrality and financial account balances from 2015 through 2021. From the initial analysis with PageRankings, the graphs presented in Figure 29 and Figure 30 focusing on comparing Bitcoin PageRank and Financial Account Balance exhibit an inverted U-curve, suggesting a non-linear relationship between the two metrics. Throughout the years, there appears to be a general trend where countries with a financial account deficit (negative balance) tend to exhibit higher Bitcoin PageRank centrality. As can be seen in Figure 31 and Figure 32, this is particularly noticeable in the graphs with PageRank Scores rather than rankings for years 2020 and 2021 where countries with lower or negative balances show increased centrality in the Bitcoin transaction network. Although it is important to highlight that the confidence intervals are generally wide, suggesting considerable volatility and potential external influences affecting the relationship.

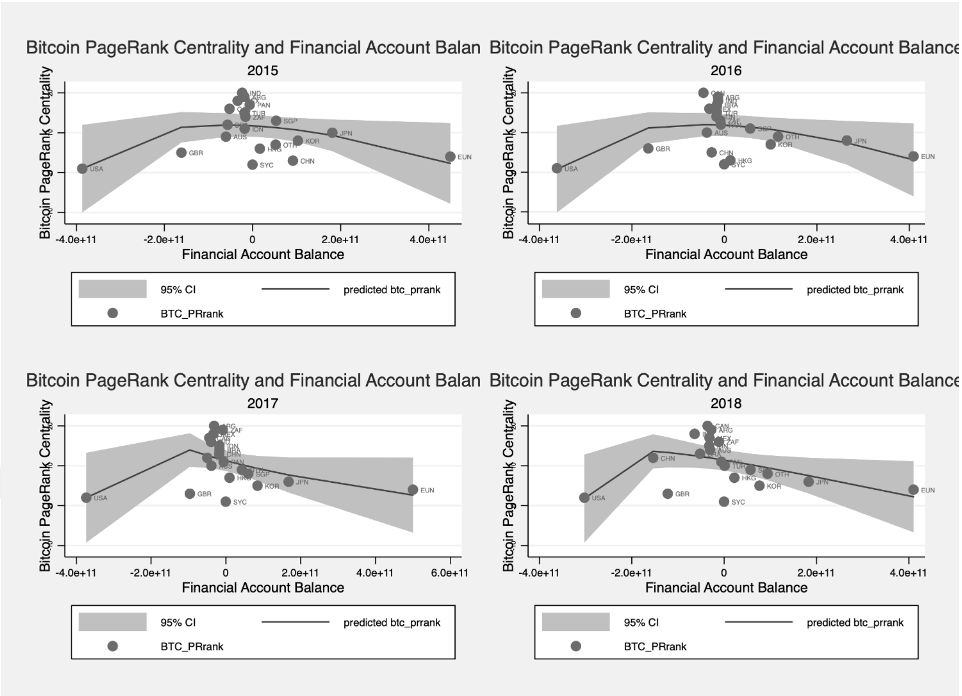


Figure 29. Two-way graph comparing Bitcoin PageRank ranking and financial account balance from the year 2015 through 2018 with fit fractional polynomial

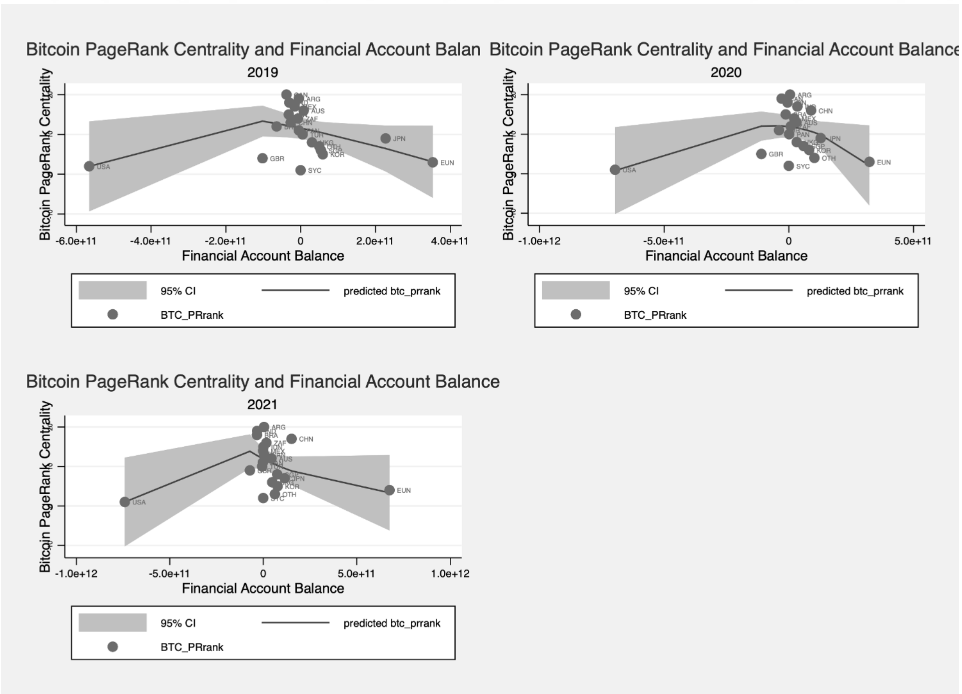


Figure 30. Two-way graph comparing Bitcoin PageRank ranking and financial account balance from the year 2019 through 2021 with fit fractional polynomial

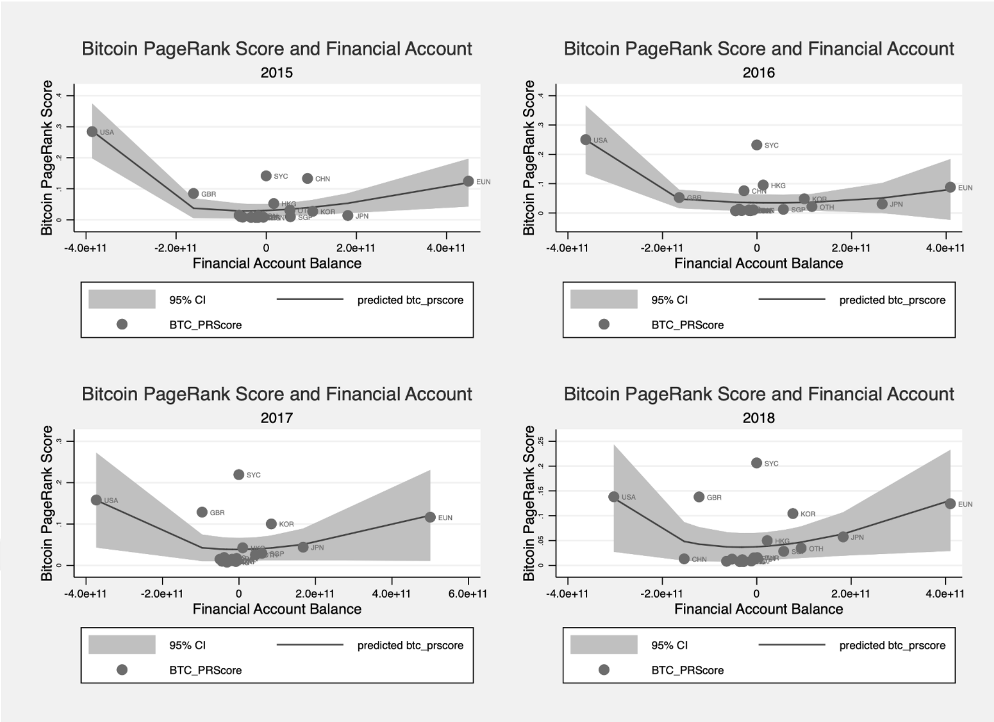


Figure 31. Two-way graph comparing Bitcoin PageRank score and financial account balance from the year 2015 through 2018 with fit fractional polynomial

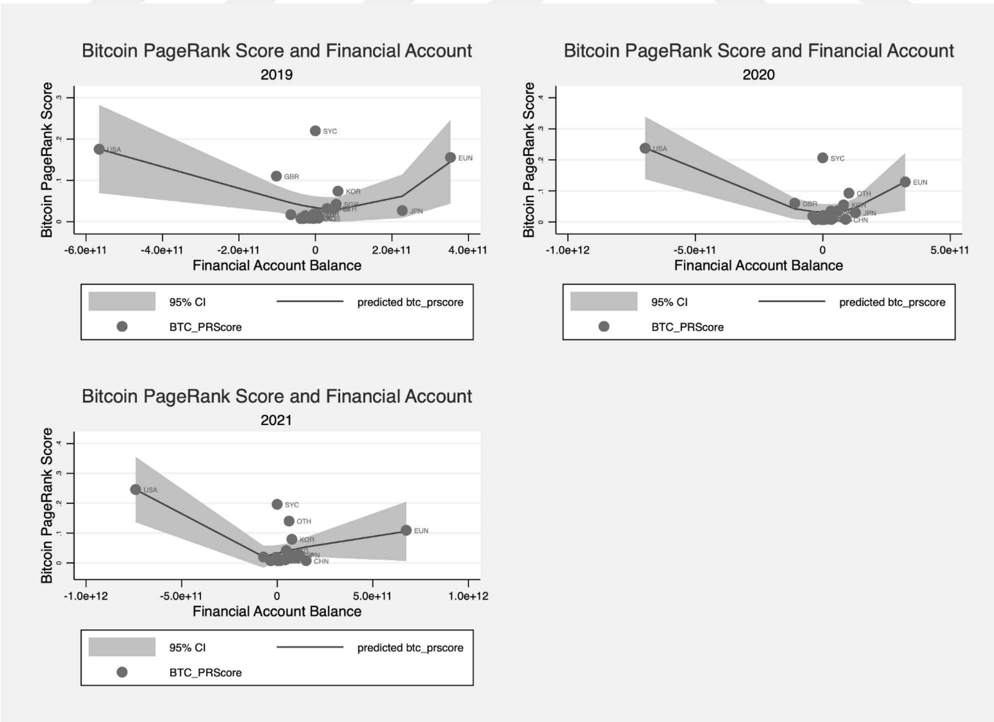


Figure 32. Two-way graph comparing Bitcoin PageRank score and financial account balance from the year 2019 through 2021 with fit fractional polynomial

Countries like China (CHN), Russia (RUS), and the USA frequently appear higher in Bitcoin PageRank centrality, indicating significant roles within the cryptocurrency network. Despite varying financial account balances, these countries maintain high centrality, suggesting robust crypto transaction networks. Smaller economies or those with more volatile financial conditions, such as Seychelles (SYC) and other smaller markets, also show relatively high centrality at various points.

Our findings are also supported with regression analysis for Bitcoin PageRank Scores and trade metrics where the Financial Account variable shows a consistently negative and significant relationship with Bitcoin centrality across all models, as can be seen in Table 9. This indicates that countries with a net outflow in their financial account (more liabilities than assets) are more central in the Bitcoin network

Table 9. Regression Analysis for Bitcoin PageRank Scores and Trade Metrics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_
realgdp	0.0062	0.0003	-0.0148***	-0.0085**	-0.0090**	-0.0152**	-0.0168**	-0.0204***
	(0.0167)	(0.0186)	(0.0032)	(0.0034)	(0.0038)	(0.0061)	(0.0067)	(0.0058)
tradevol		0.0139	0.0405***	0.0261**	0.0285***	0.0265**	0.0274**	0.0287***
		(0.0084)	(0.0073)	(0.0105)	(0.0080)	(0.0094)	(0.0099)	(0.0092)
netfinacc			-0.3299***	-0.2300***	-0.2903***	-0.2781***	-0.2859***	-0.2914***
			(0.1057)	(0.0730)	(0.0642)	(0.0614)	(0.0586)	(0.0624)
nettrade				-0.1540*	-0.0999	-0.1185	-0.1492	-0.1558
				(0.0764)	(0.0733)	(0.0882)	(0.1033)	(0.1096)
capacc					0.8196***	0.8238***	0.8557***	0.8447***
					(0.2087)	(0.2005)	(0.1915)	(0.1943)
dote_prscore						1.8632e+12	1.1994e+12	9.2314e+11
						(1.5907e+12)	(1.8860e+12)	(2.8589e+12)
doti_prscore							9.8798e+11	1.2042e+12
							(1.6564e+12)	(1.9438e+12)
wgi_avg								6.3839e+10
								(8.9503e+10)
c.wgi_avg#c.wgi_avg								-2.5722e+10
								(1.9566e+10)
2016.year	-5.9040e+08	4.9177e+08	3.5055e+09	2.3351e+09	3.8916e+09	4.1477e+09	4.5560e+09*	3.8210e+09
	(1.4791e+09)	(2.0412e+09)	(2.4615e+09)	(2.4168e+09)	(2.6789e+09)	(2.5121e+09)	(2.3818e+09)	(2.8955e+09)
2017.year	-1.3656e+09	-1.4233e+09	-7.1431e+08	-1.4096e+09	1.8222e+08	1.5354e+09	1.9089e+09	1.5471e+09
	(3.4654e+09)	(3.5254e+09)	(2.3394e+09)	(3.5358e+09)	(4.5758e+09)	(4.5168e+09)	(4.3604e+09)	(4.9592e+09)
2018.year	-2.1194e+09	-3.3987e+09	-7.6368e+09	-8.1316e+09	-5.1200e+09	-2.8558e+09	-2.7018e+09	-2.7236e+09
	(5.4268e+09)	(5.1851e+09)	(5.1906e+09)	(5.9544e+09)	(5.4944e+09)	(5.5960e+09)	(5.5676e+09)	(6.3480e+09)
2019.year	-2.7356e+09	-2.8023e+09	-4.9334e+09	-4.9998e+09	-3.0533e+09	-8.2993e+07	4.1139e+08	1.1806e+09
	(7.0032e+09)	(7.0526e+09)	(6.6774e+09)	(6.1547e+09)	(6.0035e+09)	(5.3394e+09)	(5.4150e+09)	(6.8233e+09)
2020.year	4.6365e+10***	4.6956e+10***	4.6911e+10***	4.7120e+10***	4.7562e+10***	4.9769e+10***	5.0018e+10***	5.0033e+10***
	(1.5509e+10)	(1.5353e+10)	(1.2949e+10)	(1.3225e+10)	(1.3125e+10)	(1.4233e+10)	(1.4362e+10)	(1.6324e+10)
2021.year	4.2861e+10**	3.9704e+10**	4.0526e+10**	4.0139e+10**	3.9860e+10**	4.3645e+10**	4.4065e+10**	4.5247e+10**
	(1.4895e+10)	(1.5681e+10)	(1.4305e+10)	(1.3962e+10)	(1.3906e+10)	(1.5828e+10)	(1.6009e+10)	(1.7815e+10)
Constant	-2.1355e+10	-1.9733e+10	-4.1531e+09	-4.7842e+09	-7.9922e+09	-7.3241e+10	-8.3238e+10	-8.0283e+10
	(5.9978e+10)	(5.8903e+10)	(1.5625e+10)	(1.2087e+10)	(9.7888e+09)	(5.4763e+10)	(6.1589e+10)	(6.1080e+10)
Observations	126	126	126	126	126	126	126	126
R-squared	0.3297	0.3360	0.5435	0.5746	0.5923	0.5967	0.5977	0.6061
Number of countries	18	18	18	18	18	18	18	18

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5.2.7 H4: Stringent trade regulations are positively correlated with the volume of cryptocurrency transactions

Studies suggest that cryptocurrencies might be used as a tool to circumvent restrictive trade practices, such as capital control restrictions allowing businesses and individuals to engage in international trade with fewer limitations (Alnasaa et al. 2022; Hu et al. 2018, 2020). We approached this hypothesis based on the classification provided by Klein for measuring capital controls. Countries classified as “Open” typically impose capital controls on fewer than 10 percent of their transaction subcategories throughout the sample period, and never experience years where controls affect more than 20 percent of these subcategories. On the contrast, countries classified as “Wall” tend to impose capital controls on more than 70 percent of their transaction subcategories throughout the sample period, and never experience years where controls affect less than 60 percent of these subcategories. Countries labeled as “Gate” do not fall into either the Walls or Open categories (Klein 2012).

The bar chart presented in Figure 33 provides details of the volume of Bitcoin transactions transformed with natural logarithm from 2015 through 2021, segmented under different capital control regimes labeled as "Gate," "Open," and "Wall." These labels represent varying degrees of regulatory stringency, with "Wall" indicating the most stringent controls. The years categorized under "Wall" consistently show lower transaction volumes compared to "Gate" and "Open" years. This observation suggests that there is no positive correlation between the stringency of trade regulations and the volume of Bitcoin transactions. Instead, it might indicate either a lack of correlation or a potential inverse correlation.

We further investigate the interplay with the two-way graph plot comparing the mean Bitcoin transaction volumes against the mean Regulatory Quality Index from 2015 to 2021 in Figure 34. The Regulatory Quality Index (RQI), as part of the World Governance Indicators (WGI), measures the ability of a government to formulate and implement sound policies and regulations that permit and promote private sector development. The graph includes a fitted fractional polynomial, showing the trend between these two variables, along with a 95% confidence interval. In addition, we also provide per year analysis for the same metrics under Figure 35 and Figure 36. In all three graphs, the fractional polynomial curve suggests a non-linear relationship between regulatory quality and Bitcoin transaction volumes. Initially, as regulatory quality improves (moving from left to right on the x-axis), Bitcoin transaction volumes tend to increase, peaking at a moderate level of regulatory quality, suggesting that extremely high regulatory environments might see lower transaction volumes. Contrary to typical expectations, Seychelles (SYC), characterized by lower regulatory quality, shows exceptionally high Bitcoin transaction volumes. This outlier suggests that low regulatory environments can sometimes lead to higher cryptocurrency transactions. Countries with high regulatory quality like USA, GBR, and CAN show significant Bitcoin transaction volumes but not the highest, indicating that very efficient and strict regulatory environments might not necessarily maximize cryptocurrency usage. It is not possible to reach a conclusive result solely by inspecting the bar chart and two-way graphs. In addition, the coefficient for the 'regulations' variable shows no statistically significant p-values (indicated by the absence of asterisks next to the coefficient values) in our regression analysis provided in Table 10. This suggests that changes in regulatory policies do not have a statistically significant impact on Bitcoin transaction volumes within the scope of this dataset.

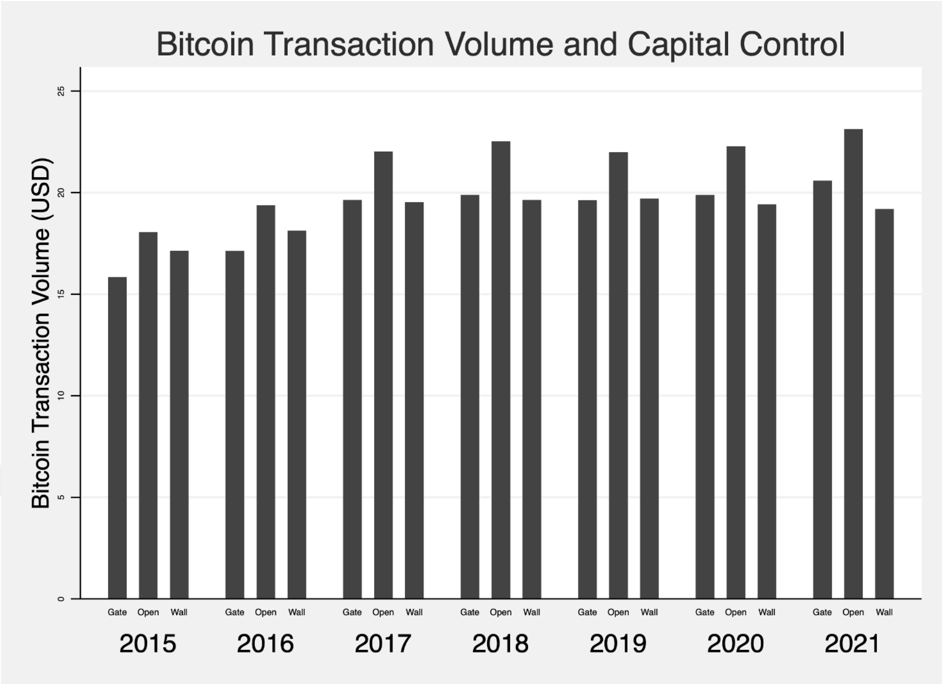


Figure 33. Bar chart comparing Bitcoin transaction volume and capital control restrictions from the year 2015 through 2021

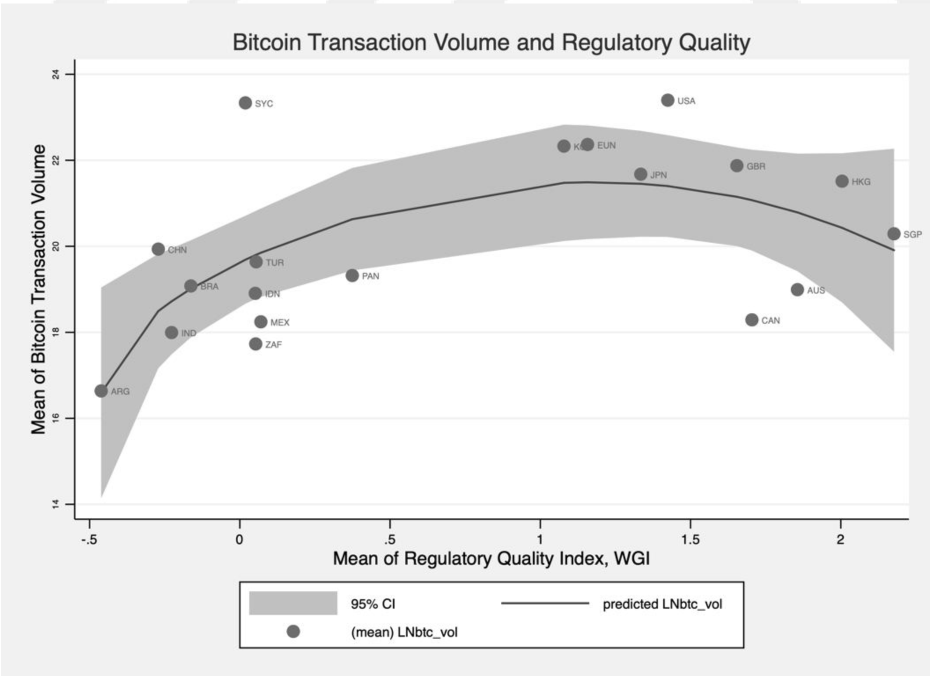


Figure 34. Two-way graph comparing the mean Bitcoin transaction volumes and mean regulatory quality index for years 2015 through 2021 with fit fractional polynomial

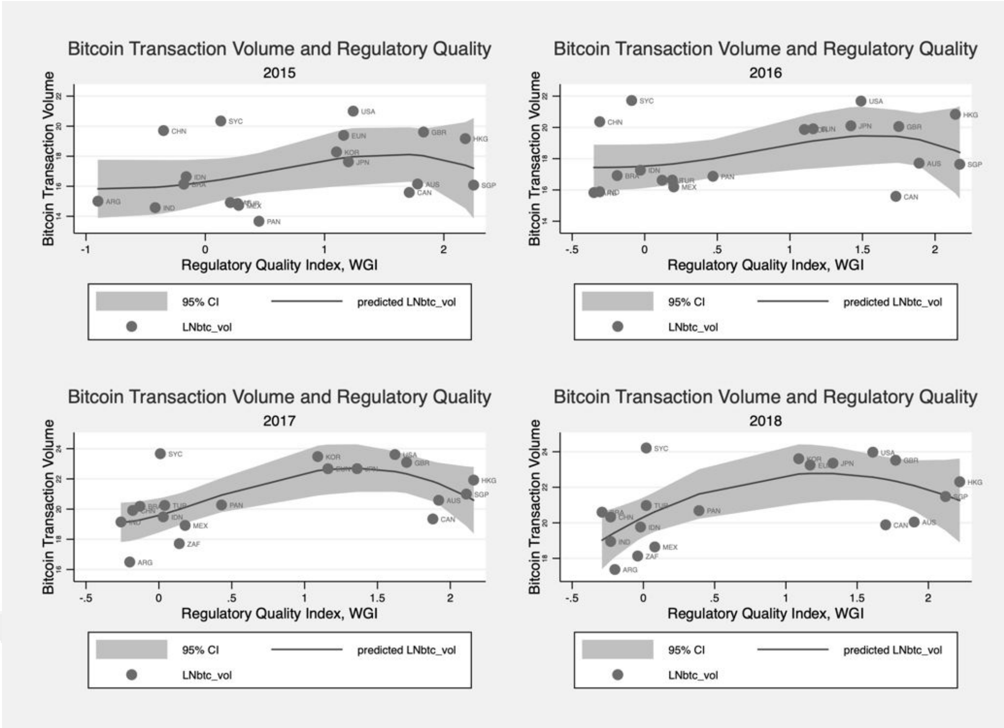


Figure 35. Two-way graph comparing the mean Bitcoin transaction volumes and mean Regulatory Quality Index for years 2015 through 2018 with fit fractional polynomial

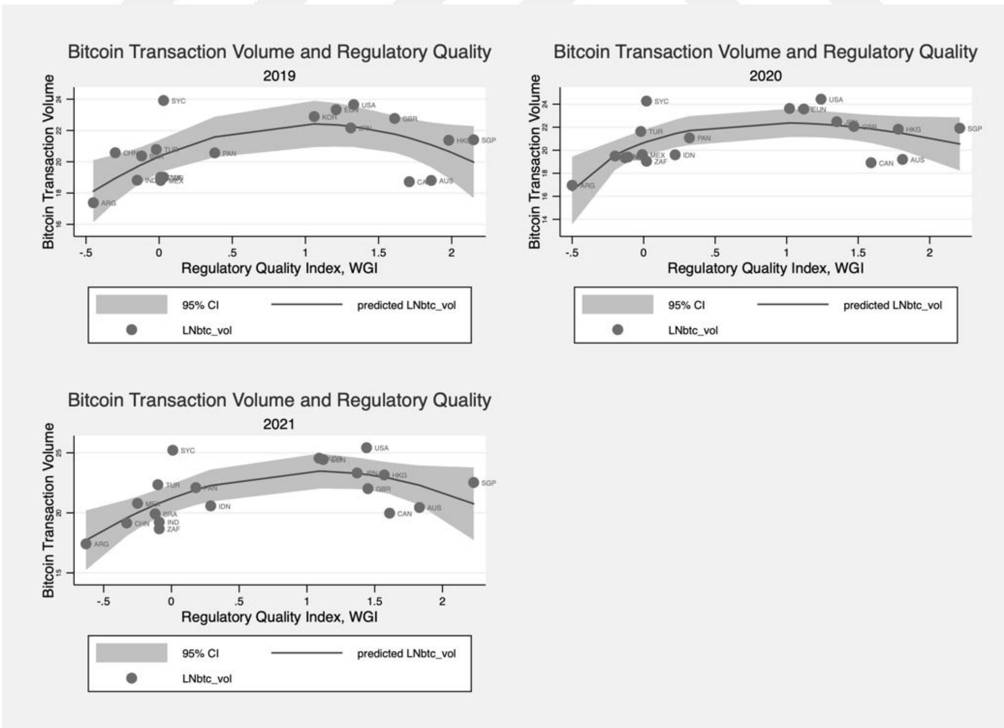


Figure 36. Two-way graph comparing the mean Bitcoin transaction volumes and mean Regulatory Quality Index for years 2019 through 2021 with fit fractional polynomial

Table 10. Regression Analysis for Bitcoin Transaction Volume and Trade Volume

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol	btc_vol
tradevol	0.0081	0.0070**	0.0072**	0.0068*	0.0068**	0.0065*	0.0065*
	(0.0061)	(0.0030)	(0.0030)	(0.0033)	(0.0032)	(0.0034)	(0.0034)
realgdp		0.0012	0.0021	0.0016	0.0015	0.0017	0.0014
		(0.0080)	(0.0081)	(0.0079)	(0.0076)	(0.0075)	(0.0075)
btc_legal			7.6260e+09	8.3742e+09	8.7112e+09	9.7172e+09	9.4468e+09
			(7.2903e+09)	(7.3863e+09)	(7.7073e+09)	(7.9758e+09)	(7.7173e+09)
btc_regul				-5.7497e+09	-5.9017e+09	-5.9037e+09	-5.7286e+09
				(4.9063e+09)	(5.1322e+09)	(5.1434e+09)	(5.1201e+09)
stability					-5.3576e+09	-7.3935e+09	-7.8559e+09
					(9.6941e+09)	(1.0446e+10)	(1.0576e+10)
polinstab						-3.6174e+09	-3.4598e+09
						(2.9024e+09)	(2.9661e+09)
regulations							5.4204e+09
							(6.8074e+09)
2016.year	6.1231e+08**	4.6189e+08	3.8937e+08	4.1977e+08	3.4350e+08	8.6271e+08	6.3671e+08
	(2.4514e+08)	(7.4450e+08)	(7.5052e+08)	(7.4511e+08)	(8.8893e+08)	(7.3906e+08)	(8.2480e+08)
2017.year	3.5954e+09**	3.4391e+09*	3.6404e+09*	3.8292e+09*	3.8616e+09*	4.4986e+09**	4.1492e+09**
	(1.5527e+09)	(1.7973e+09)	(1.7645e+09)	(1.8270e+09)	(1.9205e+09)	(1.9537e+09)	(1.8798e+09)
2018.year	4.8996e+09*	4.7463e+09	4.8221e+09	6.3407e+09*	6.3180e+09*	7.3353e+09*	7.1377e+09*
	(2.6536e+09)	(2.9709e+09)	(2.8906e+09)	(3.5353e+09)	(3.5964e+09)	(3.7792e+09)	(3.7086e+09)
2019.year	2.8288e+09	2.5134e+09	2.5148e+09	4.0627e+09	3.6963e+09	4.3670e+09	4.3940e+09
	(1.8873e+09)	(3.0355e+09)	(2.9327e+09)	(3.4036e+09)	(3.7892e+09)	(3.7192e+09)	(3.7677e+09)
2020.year	6.1220e+09**	5.8371e+09**	5.5512e+09**	8.1702e+09*	7.9536e+09*	8.9839e+09**	9.0819e+09*
	(2.7018e+09)	(2.5093e+09)	(2.4157e+09)	(4.0370e+09)	(4.0398e+09)	(4.2350e+09)	(4.3347e+09)
2021.year	1.3741e+10*	1.3563e+10*	1.3413e+10*	1.6349e+10*	1.6144e+10*	1.6750e+10*	1.7087e+10*
	(7.2013e+09)	(7.0021e+09)	(6.9781e+09)	(8.8498e+09)	(8.7863e+09)	(8.9583e+09)	(9.2073e+09)
Constant	-1.0451e+10	-1.3060e+10	-2.3782e+10	-2.2266e+10	-2.1554e+10	-2.1910e+10	-2.4648e+10
	(8.5666e+09)	(2.5727e+10)	(2.9244e+10)	(2.8697e+10)	(2.6787e+10)	(2.6560e+10)	(2.7347e+10)
Observations	133	133	133	133	133	133	133
R-squared	0.2667	0.2677	0.2773	0.2931	0.2991	0.3069	0.3096
Number of countries	19	19	19	19	19	19	19

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.8 H5: There is a positive correlation between the Average Weighted Degree of the trade and cryptocurrency networks

Average Weighted Degree represents the average strength of connectivity across all nodes in the network, taking into account the sum of weights of the edges (Barabási 2013). Therefore, a higher average weighted degree would suggest more intensive economic interaction among the nodes involved. In the case of Bitcoin, this would imply not just frequent transactions, but transactions of significant value. This may correlate with heightened activity in traditional trade, as businesses and individuals that engage heavily in cryptocurrency might also participate actively in the conventional economy.

The analysis of the relationship between the Average Weighted Degree of Bitcoin and export networks from 2015 to 2021 reveals insightful trends about the interaction between international trade volumes and cryptocurrency transactions. By examining the two-way graphs, we can infer a positive correlation between these two variables over the years. The data points displayed in the Figure 37 and Figure 38 represent the logarithmic values of average weighted degree of Bitcoin and export networks for each observed year. 2015-2017: In the initial years, the graphs show a pronounced upward trend, suggesting that as the value of exports increases, the weighted degree of Bitcoin transactions also tends to rise. This period may indicate an increasing integration of cryptocurrency transactions with traditional trade mechanisms. 2018-2021: The trend continues but with a slight fluctuation in the curve's steepness and confidence intervals. The confidence intervals widen slightly in some years, indicating variability in the data. The graphs clearly form a U-curve indicating a non-linear relationship between the two metrics; however, it is not possible to reach a conclusive result solely from the two-way graphs.

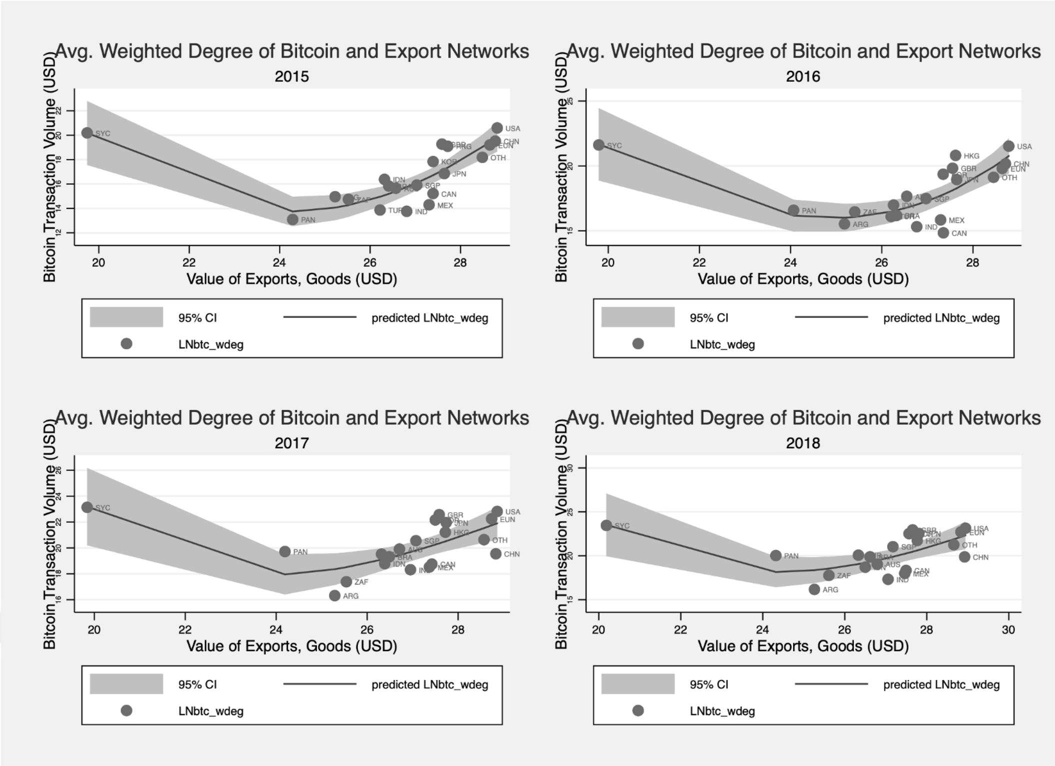


Figure 37. Two-way graph comparing the Average Weighted Degree of Bitcoin and export network for years 2015 through 2018 with fit fractional polynomial

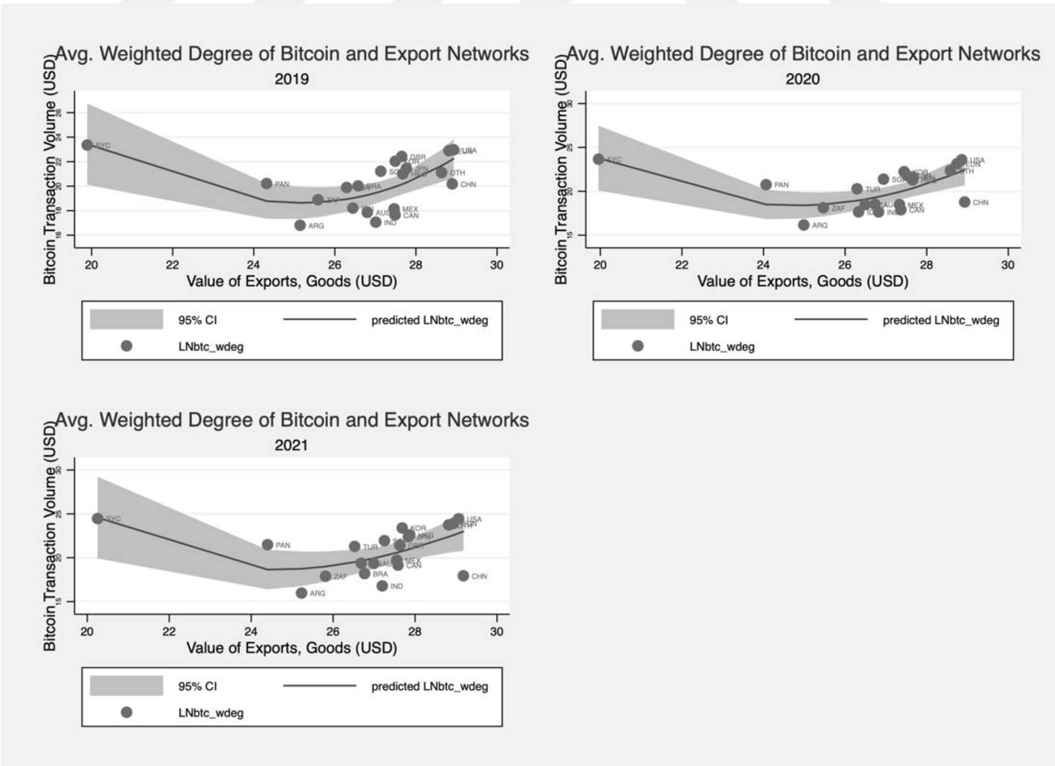


Figure 38. Two-way graph comparing the Average Weighted Degree of Bitcoin and export network for years 2019 through 2021 with fit fractional polynomial

To further explore our initial findings, we present a regression analysis of the Average Weighted Degree for Bitcoin and trade networks in Table 11, highlighting the statistical significance of various factors over the years. In Model 1, doti_wdeg has a coefficient of 0.0081, but it's not statistically significant (p>0.1), indicating weak or no evidence of a direct linear relationship between imports and the Bitcoin network's degree. In Model 2, where we control for the average weighted degree for exports, both imports and exports show slight significance at the 10% level ($p < 0.1$). This suggests that when controlling for exports, the relationship becomes positive and more pronounced. However, the correlation is not significant enough to support the hypothesis.

Table 11. Regression Analysis of Average Weighted Degree for the Bitcoin and Trade Networks

VARIABLES	(1) btc_wdeg	(2) btc_wdeg
doti_wdeg	0.0081	1.7680*
	(0.0088)	(0.9499)
dote_wdeg		-1.7604*
		(0.9494)
2016.year	5.3575e+08*	-1.3747e+08
	(2.8933e+08)	(5.5512e+08)
2017.year	1.5178e+09*	1.4197e+09
	(8.6644e+08)	(9.6494e+08)
2018.year	1.7826e+09	1.9734e+09
	(1.6218e+09)	(1.6039e+09)
2019.year	1.3917e+09	1.5089e+09
	(1.3265e+09)	(1.3079e+09)
2020.year	2.8261e+09**	2.9422e+09**
	(1.2229e+09)	(1.2863e+09)
2021.year	5.5392e+09	5.6460e+09
	(3.4407e+09)	(3.4343e+09)
Constant	-7.6797e+09	-7.5707e+09
	(8.7202e+09)	(7.8560e+09)
Observations	140	140
R-squared	0.3222	0.3552
Number of countries	20	20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2.9 H6: Central countries in the cryptocurrency network also hold significant influence in international trade

PageRank centrality measures the influence of a node based on the number and quality of links it receives from other nodes (Page et al. 1999). Using PageRank scores, this analysis measures each country's relative importance within both the cryptocurrency and export networks. A higher score indicates a greater level of centrality or influence within the network. These scores are plotted against each other for each year from 2015 through 2021, providing a comparative perspective. The Figure 39 and Figure 40 demonstrate an inverted U-curve hinting a non-linear relationship between the two metrics.

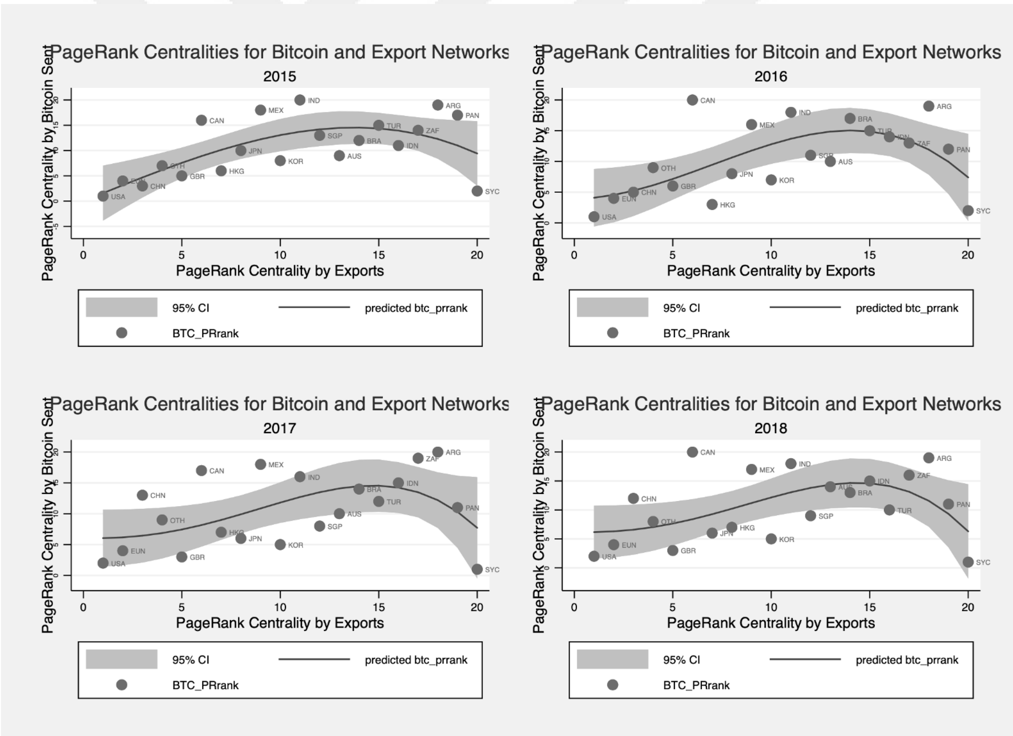


Figure 39. Two-way graph comparing the PageRank centralities of Bitcoin and export networks for years 2015 through 2018 with fit fractional polynomial

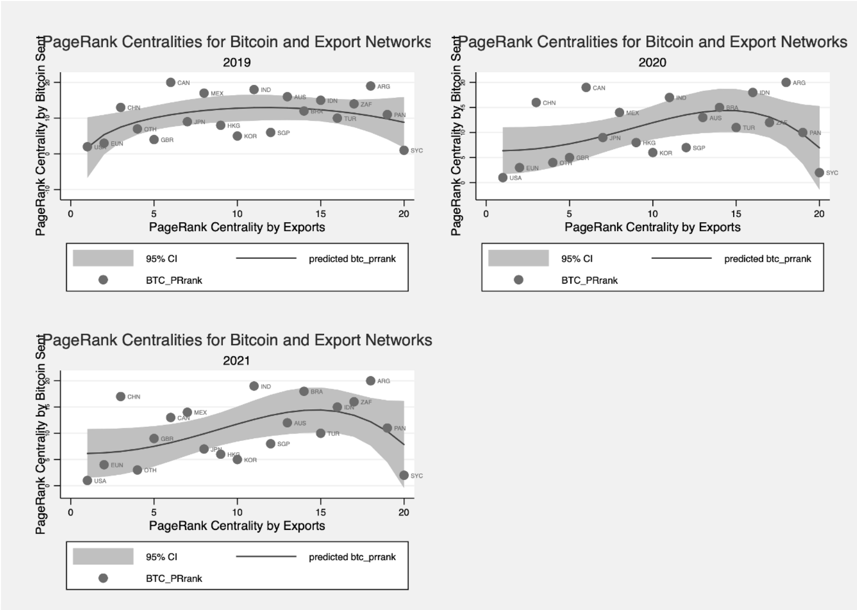


Figure 40. Two-way graph comparing the PageRank centralities of Bitcoin and export networks for years 2019 through 2021 with Fit Fractional polynomial

In contrast, we also analyze the interplay between PageRank Scores of Bitcoin and Export networks and as expected, the Figure 41 and Figure 42 demonstrate U-curve, reinforcing our findings. This suggests that the drivers of centrality in each network operate independently, reflecting different dimensions of national economic activities. For instance, while the United States consistently shows high centrality in both networks, this is more an exception than a rule. Other countries like South Korea, United Kingdom, and Seychelles exhibit significant disparities between their influence in cryptocurrency transactions and their global trade footprint. The regression analysis for Bitcoin PageRank Scores and trade metrics provided in Table 12 also supports the lack of correlation. On one hand, this aligns with the understanding that centrality in the cryptocurrency and trade markets are nascent and driven by dynamics not traditionally associated with the trade sector. On the other hand, the absence of a robust correlation opens up an area of vast exploration. As can be seen from the Figure 43, the centrality in the Bitcoin network is very volatile throughout the years whereas direction of trade networks is stable. The causation of this phenomenon was beyond the scope of this thesis, but we provide some anecdotal evidence drawing from political economic indicators in the discussion section.

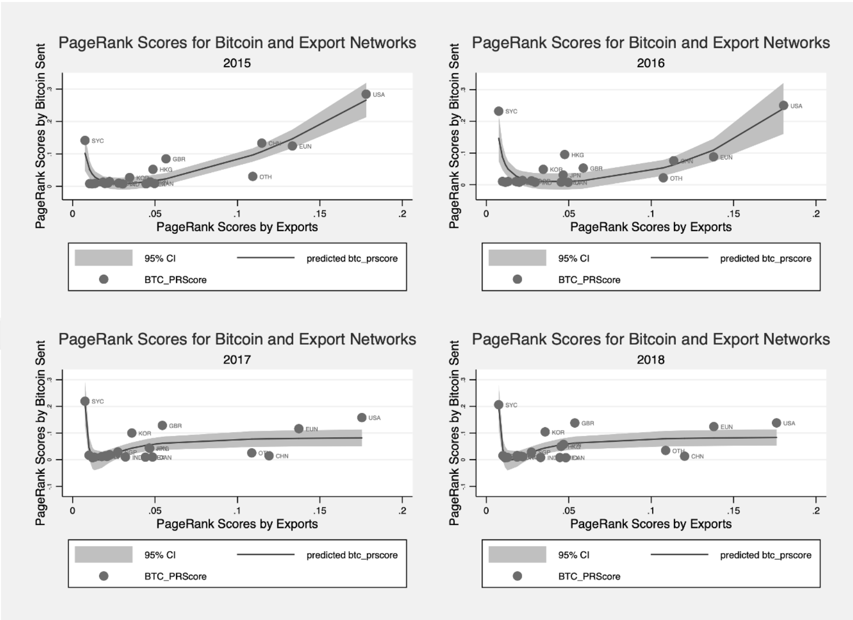


Figure 41. Two-way graph comparing the PageRank scores of Bitcoin and export networks for years 2015 through 2018 with fit fractional polynomial

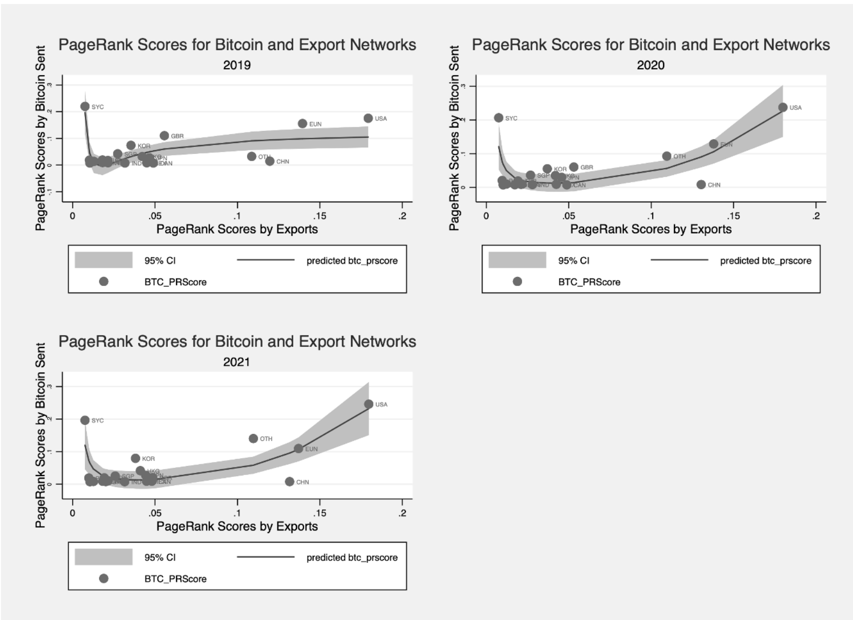


Figure 42. Two-way graph comparing the PageRank scores of Bitcoin and export networks for years 2019 through 2021 with fit fractional polynomial

Table 12. Regression Analysis for Bitcoin PageRank Scores and Trade Metrics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_
realgdp	0.0062	0.0003	-0.0148***	-0.0085**	-0.0090**	-0.0152**	-0.0168**	-0.0204***
	(0.0167)	(0.0186)	(0.0032)	(0.0034)	(0.0038)	(0.0061)	(0.0067)	(0.0058)
tradevol		0.0139	0.0405***	0.0261**	0.0285***	0.0265**	0.0274**	0.0287***
		(0.0084)	(0.0073)	(0.0105)	(0.0080)	(0.0094)	(0.0099)	(0.0092)
netfinacc			-0.3299***	-0.2300***	-0.2903***	-0.2781***	-0.2859***	-0.2914***
			(0.1057)	(0.0730)	(0.0642)	(0.0614)	(0.0586)	(0.0624)
nettrade				-0.1540*	-0.0999	-0.1185	-0.1492	-0.1558
				(0.0764)	(0.0733)	(0.0882)	(0.1033)	(0.1096)
capacc					0.8196***	0.8238***	0.8557***	0.8447***
					(0.2087)	(0.2005)	(0.1915)	(0.1943)
dote_prscore						1.8632e+12	1.1994e+12	9.2314e+11
						(1.5907e+12)	(1.8860e+12)	(2.8589e+12)
doti_prscore							9.8798e+11	1.2042e+12
							(1.6564e+12)	(1.9438e+12)
wgi_avg								6.3839e+10
								(8.9503e+10)
c.wgi_avg#c.wgi_avg								-2.5722e+10
								(1.9566e+10)
2016.year	-5.9040e+08	4.9177e+08	3.5055e+09	2.3351e+09	3.8916e+09	4.1477e+09	4.5560e+09*	3.8210e+09
	(1.4791e+09)	(2.0412e+09)	(2.4615e+09)	(2.4168e+09)	(2.6789e+09)	(2.5121e+09)	(2.3818e+09)	(2.8955e+09)
2017.year	-1.3656e+09	-1.4233e+09	-7.1431e+08	-1.4096e+09	1.8222e+08	1.5354e+09	1.9089e+09	1.5471e+09
	(3.4654e+09)	(3.5254e+09)	(2.3394e+09)	(3.5358e+09)	(4.5758e+09)	(4.5168e+09)	(4.3604e+09)	(4.9592e+09)
2018.year	-2.1194e+09	-3.3987e+09	-7.6368e+09	-8.1316e+09	-5.1200e+09	-2.8558e+09	-2.7018e+09	-2.7236e+09
	(5.4268e+09)	(5.1851e+09)	(5.1906e+09)	(5.9544e+09)	(5.4944e+09)	(5.5960e+09)	(5.5676e+09)	(6.3480e+09)
2019.year	-2.7356e+09	-2.8023e+09	-4.9334e+09	-4.9998e+09	-3.0533e+09	-8.2993e+07	4.1139e+08	1.1806e+09
	(7.0032e+09)	(7.0526e+09)	(6.6774e+09)	(6.1547e+09)	(6.0035e+09)	(5.3394e+09)	(5.4150e+09)	(6.8233e+09)
2020.year	4.6365e+10***	4.6956e+10***	4.6911e+10***	4.7120e+10***	4.7562e+10***	4.9769e+10***	5.0018e+10***	5.0033e+10***
	(1.5509e+10)	(1.5353e+10)	(1.2949e+10)	(1.3225e+10)	(1.3125e+10)	(1.4233e+10)	(1.4362e+10)	(1.6324e+10)
2021.year	4.2861e+10**	3.9704e+10**	4.0526e+10**	4.0139e+10**	3.9860e+10**	4.3645e+10**	4.4065e+10**	4.5247e+10**
	(1.4895e+10)	(1.5681e+10)	(1.4305e+10)	(1.3962e+10)	(1.3906e+10)	(1.5828e+10)	(1.6009e+10)	(1.7815e+10)
Constant	-2.1355e+10	-1.9733e+10	-4.1531e+09	-4.7842e+09	-7.9922e+09	-7.3241e+10	-8.3238e+10	-8.0283e+10
	(5.9978e+10)	(5.8903e+10)	(1.5625e+10)	(1.2087e+10)	(9.7888e+09)	(5.4763e+10)	(6.1589e+10)	(6.1080e+10)
Observations	126	126	126	126	126	126	126	126
R-squared	0.3297	0.3360	0.5435	0.5746	0.5923	0.5967	0.5977	0.6061
Number of countries	18	18	18	18	18	18	18	18

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 43. Line chart demonstrating the changes in the PageRank scores of Bitcoin and export networks for years 2015 through 2021

5.2.10 H7: A higher diameter positively correlates with a higher transaction volume for cryptocurrency and trade networks

Studies posit that a larger diameter of a trade network could indicate a larger reach of a country's transactions. This is mainly because as the number of trade connections increase, the more steps required and more countries are involved between transactions (Newman 2003). The data presented in the line chart in Figure 44 indicates that the diameter of the Bitcoin network exhibits notable fluctuations over the analyzed period. In contrast, the export network's diameter remains constant throughout the same timeframe. Without corresponding transaction volume data directly plotted against these diameter changes, a definitive correlation cannot be established solely based on the diameter.

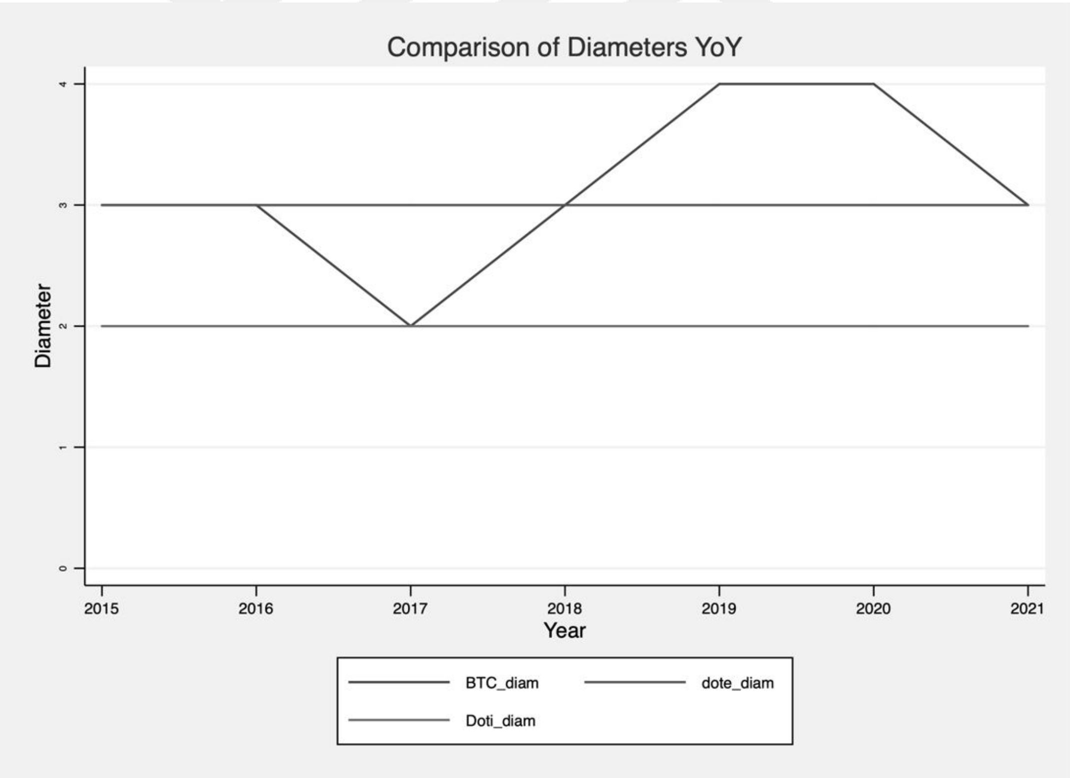


Figure 44. Line chart comparing the diameter of Bitcoin and export networks for years 2015 through 2021

5.2.11 H8: Cryptocurrency network becomes more and more complex over time

Cryptocurrency transaction patterns are constantly evolving in response to economic shifts, technological advancements, and changes in regulations. The growing adoption of cryptocurrencies by individual and institutional investors, their expansion into new markets, and the incorporation of advanced blockchain technologies like smart contracts are all contributing to the increasing complexity of these networks. Additionally, regulatory responses differ significantly across jurisdictions, affecting transaction patterns and network structures. The Bitcoin network's complexity can be analyzed through various network metrics illustrated in the provided charts, spanning from 2015 to 2021. These metrics include the volume of Bitcoin transactions, the number of significant edges in the Bitcoin network, and other network properties such as average weighted degree, diameter, average path length, radius, and density. The most commonly used static complexity measures are the number of elements (nodes or edges of the graph) or the topological parameters of the network (Goryashko, Samokhine, and Bocharov 2019).

The volume of Bitcoin transactions has seen an upward trend as seen in Figure 45, particularly sharp from 2020 to 2021, indicating increased usage and transfer of Bitcoin over the years. However, the number of significant edges within the Bitcoin network, which represent the connections between different nodes (e.g., users, wallets), shows a relatively stable trend with slight fluctuations. The discrepancy between the rapidly increasing transaction volume and relatively stable edge count suggests that while more transactions are occurring, they are concentrated among existing nodes rather than distributed across new connections. This could imply that the network is not necessarily becoming more complex in terms of new node connections but is processing more transactions among existing nodes.

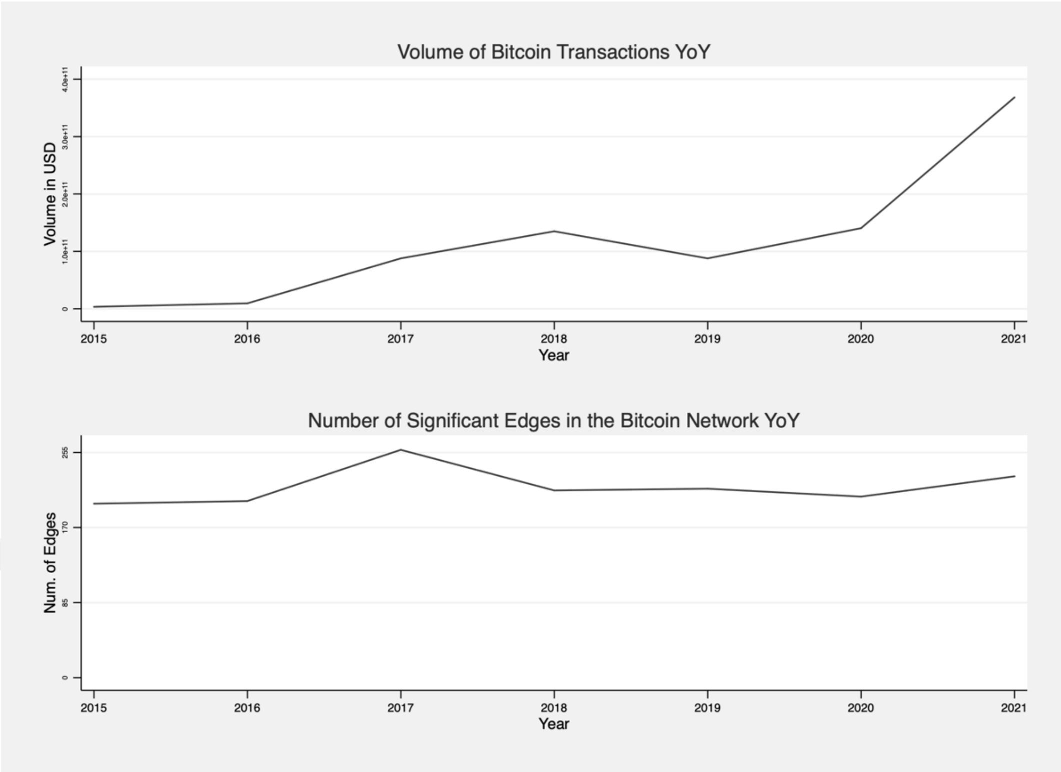


Figure 45. Line chart comparing the volume of Bitcoin transactions against the number of significant edges in the Bitcoin network for years 2015 through 2021

Further complexity analysis can be performed by comparing Bitcoin's network metrics as well as community detection metrics with those of international trade (both exports and imports). Figure 46 focuses on network metrics and provide a combination of charts comparing the evolution of Average Weighted Degree, Diameter, Radius, Density, and Average Path Length over the years. In addition, the evolution of the community detection metrics is observed under Figure 47.

First, Average Weighted Degree reflects the average strength of the connections per node, weighted by transaction volume. For Bitcoin, the average weighted degree shows significant variability and an upward trend, suggesting that nodes are engaging in higher volume transactions as time progresses. In contrast, the export and import networks show less variability, indicating a more stable transaction pattern among countries. Diameter and Average Path Length indicate the 'largeness' of the network, and the average number of steps required to connect any two nodes, respectively. The Bitcoin network experiences a notable peak in diameter around 2019, suggesting a temporary increase in network breadth, followed by a decline, which could indicate a consolidation of transactions among fewer, more central nodes. The average path length remains relatively constant, suggesting that despite the network's changes in diameter, the efficiency of connections remains stable. Radius reflects the minimum eccentricity of any node in the network. The radius of the Bitcoin network shows some fluctuations, suggesting changes in the network's central connectivity over time. Density measures the proportion of potential connections in the network that are actual connections. The density of the Bitcoin network is relatively stable, indicating a consistent level of network connectivity relative to its size over the years.

While the volume of transactions within the Bitcoin network has increased dramatically, indicating heightened activity, the number of significant edges and the density have not shown proportional growth. This suggests that the network's complexity, in terms of new node integration and connectivity diversity, has not increased at the same rate as the volume of transactions. The network metrics suggest that while more transactions are being processed, they are largely concentrated among existing or central nodes rather than dispersed through new or peripheral nodes. This pattern indicates a growth in transactional volume and node efficiency but not necessarily an increase in network complexity as would be characterized by a broader distribution of connections across a more diverse array of nodes.

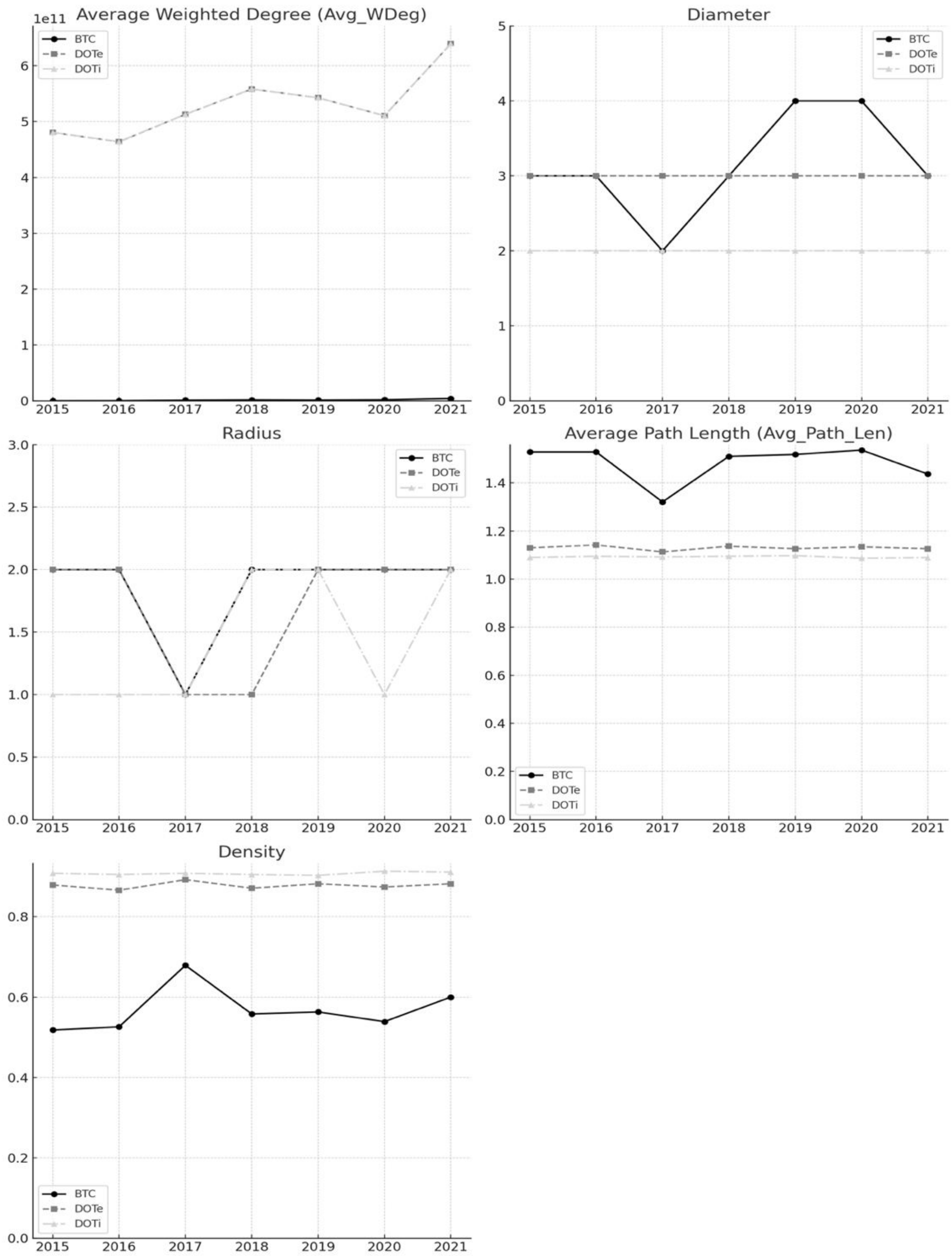


Figure 46. Line charts comparing the evolution of network metrics over the years

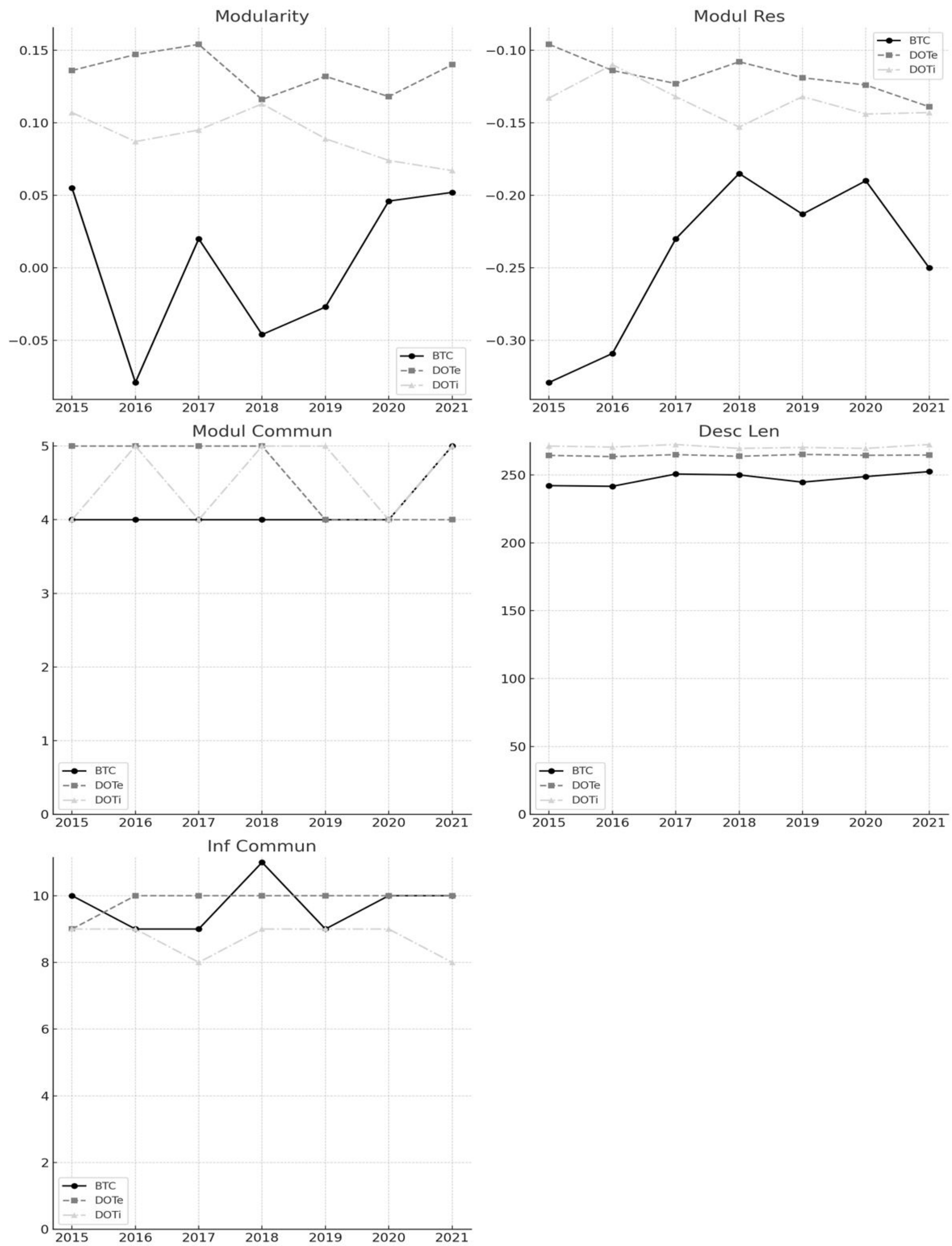


Figure 47. Line charts comparing the evolution of community detection metrics for Bitcoin, export, and import networks for years 2015 through 2021

5.2.12 H9: Trade openness is positively correlated with cryptocurrency centrality

Countries with high trade openness may see increased use of cryptocurrencies, driving their central roles in the cryptocurrency network due to the need for efficient,

low-cost, cross-border transactions mechanisms. To understand the interplay, we calculate trade openness indices from trade volume and GDP data, and correlate these with centrality measures in the cryptocurrency transaction networks.
The Figure 48 and Figure 49 depicting the relationship between Bitcoin's PageRank score and Real GDP form a U-curve. This shows a general positive correlation, suggesting that countries with higher GDP are likely to have greater centrality in Bitcoin transactions. This trend is particularly evident in years 2018 and 2020, where the data points cluster more tightly around the fitted regression line, indicating a stronger correlation in these years. Similarly, the correlation between Bitcoin's PageRank score and trade volume, as can be seen in Figure 50 and Figure 51, also appears to be positive across the years examined. The graphs consistently show that as trade volume increases, the centrality of Bitcoin within these trading networks also tends to increase. This relationship is particularly notable in the years 2019 and 2021, where the upward trends are more pronounced.

The hypothesis that trade openness is positively correlated with cryptocurrency centrality is also supported by the regression analysis, as can be seen in Table 13. For trade volumes, the first models show a P-value of 0.141, suggesting that while the relationship is positive, it is not statistically significant at conventional levels (e.g., $p < 0.05$). However, in model 2 through model 6, the P-values improve significantly (ranging from 0.040 to 0.074), indicating that as the model complexity increases and controls for more variables, the significance of trade volume in explaining Bitcoin PageRank scores also increases. The results are similar for Real GDP. While models 1 and 2 do not provide strong evidence of the hypothesis, the significance improves in more comprehensive models with additional control variables.

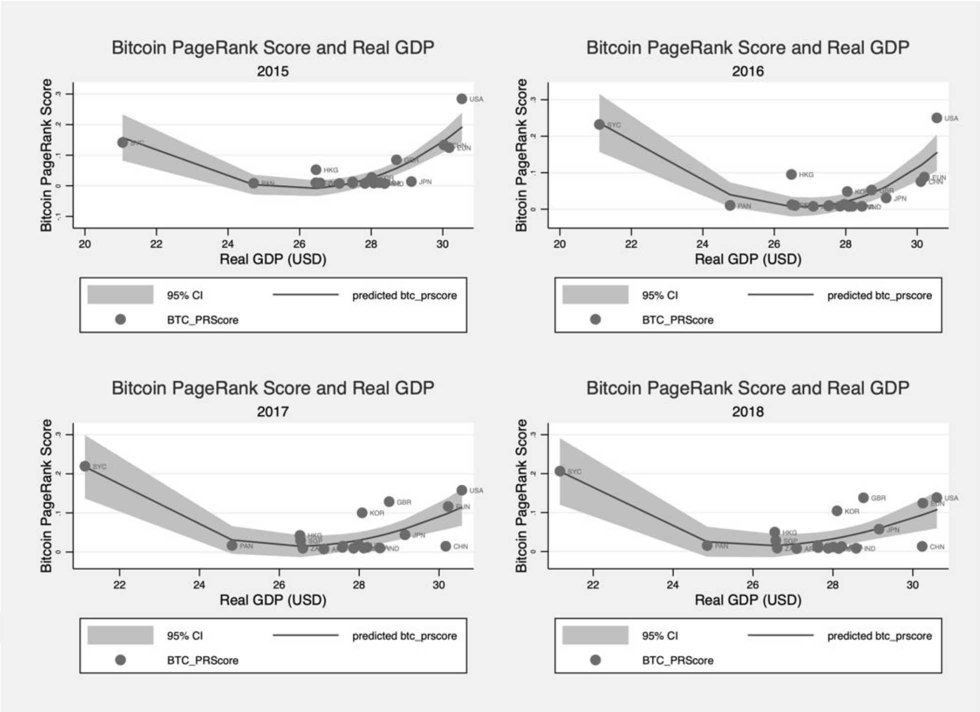


Figure 48. Two-way graph comparing the PageRank scores of Bitcoin and real GDP for years 2015 through 2018 with fit fractional polynomial

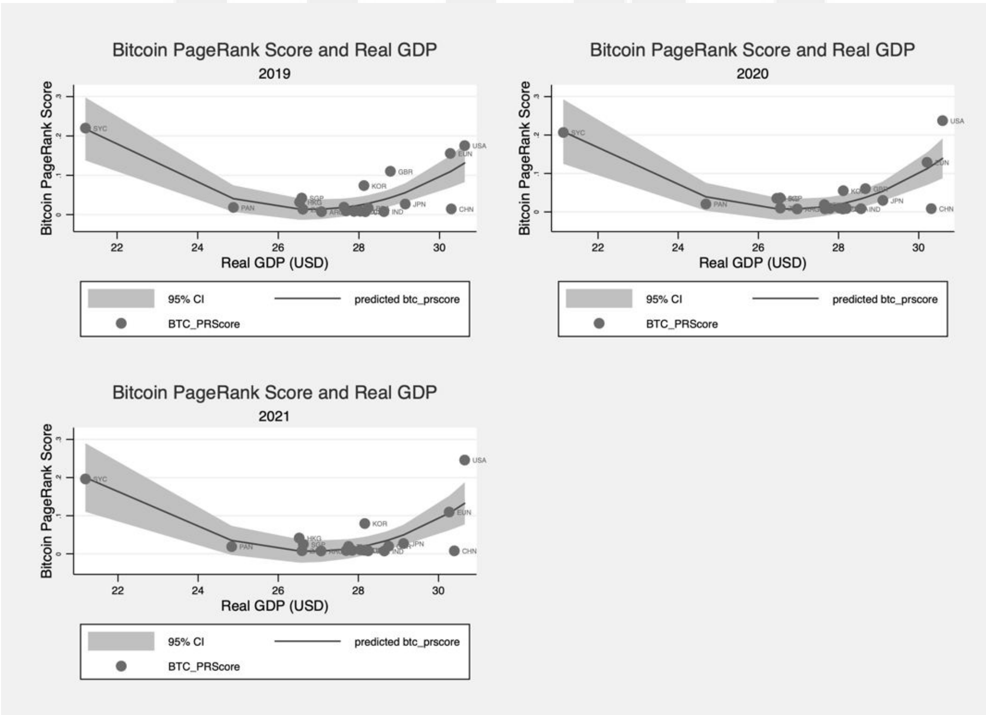


Figure 49. Two-way graph comparing the PageRank scores of Bitcoin and real GDP for years 2019 through 2021 with fit fractional polynomial

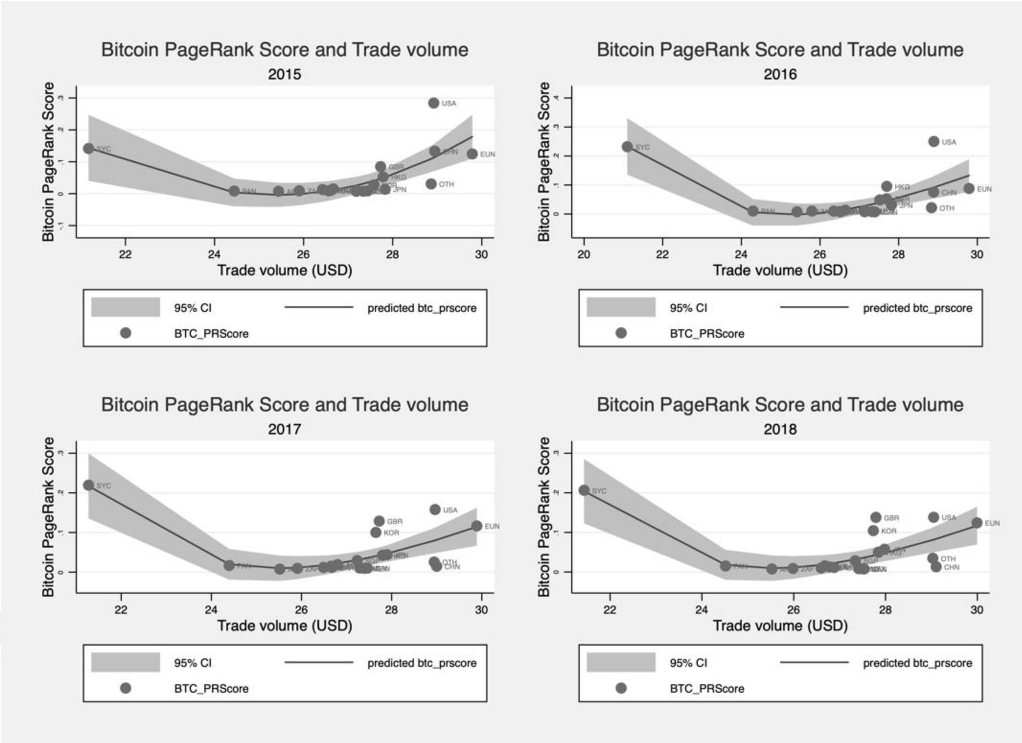


Figure 50. Two-way graph comparing the PageRank scores of Bitcoin and trade volumes for years 2015 through 2018 with fit fractional polynomial

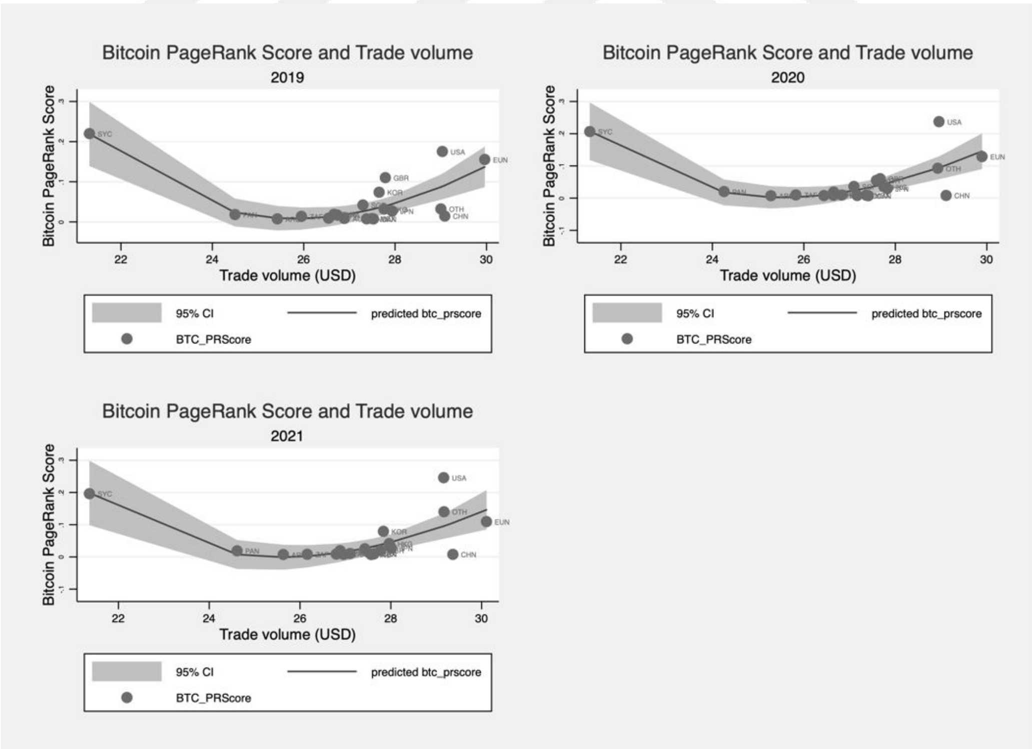


Figure 51. Two-way graph comparing the PageRank scores of Bitcoin and trade volumes for years 2019 through 2021 with fit fractional polynomial

Table 13. Regression Analysis for Bitcoin PageRank Scores and Trade Metrics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_
realgdp	0.0062	0.0003	-0.0148***	-0.0085**	-0.0090**	-0.0152**	-0.0168**	-0.0204***
	(0.0167)	(0.0186)	(0.0032)	(0.0034)	(0.0038)	(0.0061)	(0.0067)	(0.0058)
tradevol		0.0139	0.0405***	0.0261**	0.0285***	0.0265**	0.0274**	0.0287***
		(0.0084)	(0.0073)	(0.0105)	(0.0080)	(0.0094)	(0.0099)	(0.0092)
netfinacc			-0.3299***	-0.2300***	-0.2903***	-0.2781***	-0.2859***	-0.2914***
			(0.1057)	(0.0730)	(0.0642)	(0.0614)	(0.0586)	(0.0624)
nettrade				-0.1540*	-0.0999	-0.1185	-0.1492	-0.1558
				(0.0764)	(0.0733)	(0.0882)	(0.1033)	(0.1096)
capacc					0.8196***	0.8238***	0.8557***	0.8447***
					(0.2087)	(0.2005)	(0.1915)	(0.1943)
dote_prscore						1.8632e+12	1.1994e+12	9.2314e+11
						(1.5907e+12)	(1.8860e+12)	(2.8589e+12)
doti_prscore							9.8798e+11	1.2042e+12
							(1.6564e+12)	(1.9438e+12)
wgi_avg								6.3839e+10
								(8.9503e+10)
c.wgi_avg#c.wgi_avg								-2.5722e+10
								(1.9566e+10)
2016.year	-5.9040e+08	4.9177e+08	3.5055e+09	2.3351e+09	3.8916e+09	4.1477e+09	4.5560e+09*	3.8210e+09
	(1.4791e+09)	(2.0412e+09)	(2.4615e+09)	(2.4168e+09)	(2.6789e+09)	(2.5121e+09)	(2.3818e+09)	(2.8955e+09)
2017.year	-1.3656e+09	-1.4233e+09	-7.1431e+08	-1.4096e+09	1.8222e+08	1.5354e+09	1.9089e+09	1.5471e+09
	(3.4654e+09)	(3.5254e+09)	(2.3394e+09)	(3.5358e+09)	(4.5758e+09)	(4.5168e+09)	(4.3604e+09)	(4.9592e+09)
2018.year	-2.1194e+09	-3.3987e+09	-7.6368e+09	-8.1316e+09	-5.1200e+09	-2.8558e+09	-2.7018e+09	-2.7236e+09
	(5.4268e+09)	(5.1851e+09)	(5.1906e+09)	(5.9544e+09)	(5.4944e+09)	(5.5960e+09)	(5.5676e+09)	(6.3480e+09)
2019.year	-2.7356e+09	-2.8023e+09	-4.9334e+09	-4.9998e+09	-3.0533e+09	-8.2993e+07	4.1139e+08	1.1806e+09
	(7.0032e+09)	(7.0526e+09)	(6.6774e+09)	(6.1547e+09)	(6.0035e+09)	(5.3394e+09)	(5.4150e+09)	(6.8233e+09)
2020.year	4.6365e+10***	4.6956e+10***	4.6911e+10***	4.7120e+10***	4.7562e+10***	4.9769e+10***	5.0018e+10***	5.0033e+10***
	(1.5509e+10)	(1.5353e+10)	(1.2949e+10)	(1.3225e+10)	(1.3125e+10)	(1.4233e+10)	(1.4362e+10)	(1.6324e+10)
2021.year	4.2861e+10**	3.9704e+10**	4.0526e+10**	4.0139e+10**	3.9860e+10**	4.3645e+10**	4.4065e+10**	4.5247e+10**
	(1.4895e+10)	(1.5681e+10)	(1.4305e+10)	(1.3962e+10)	(1.3906e+10)	(1.5828e+10)	(1.6009e+10)	(1.7815e+10)
Constant	-2.1355e+10	-1.9733e+10	-4.1531e+09	-4.7842e+09	-7.9922e+09	-7.3241e+10	-8.3238e+10	-8.0283e+10
	(5.9978e+10)	(5.8903e+10)	(1.5625e+10)	(1.2087e+10)	(9.7888e+09)	(5.4763e+10)	(6.1589e+10)	(6.1080e+10)
Observations	126	126	126	126	126	126	126	126
R-squared	0.3297	0.3360	0.5435	0.5746	0.5923	0.5967	0.5977	0.6061
Number of countries	18	18	18	18	18	18	18	18

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Starting from model 3, the P-value for real GDP drops below 0.01 level and keeps consistent at the 0.05 level in the following models, indicating a robust relationship when additional variables are considered.

5.2.13 H10: Higher governance scores are negatively correlated with cryptocurrency centrality

We expect countries with higher governance indicators, suggesting stability and effective regulation (Kaufmann and Kraay 2023), expected have less central roles in the cryptocurrency network, due to robust financial systems and less reliance on alternative currencies. To analyze this hypothesis, we use World Governance Indicators and BTC data and we inspect the correlation of WGI scores with centrality metrics in the cryptocurrency network to explore inverse relationships. The graphical representation provided in the Figure 52 and Figure 53 uses a two-way graph to compare the Bitcoin PageRank Score and the mean WGI scores over the years.

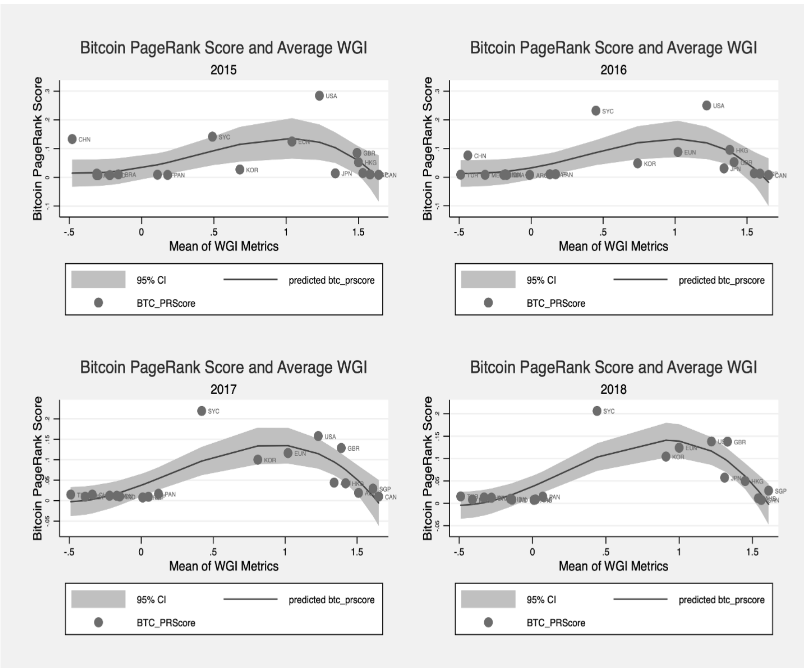


Figure 52. Two-way graph comparing the Bitcoin PageRank score and mean WGI scores for years 2015 through 2018 with fit fractional polynomial

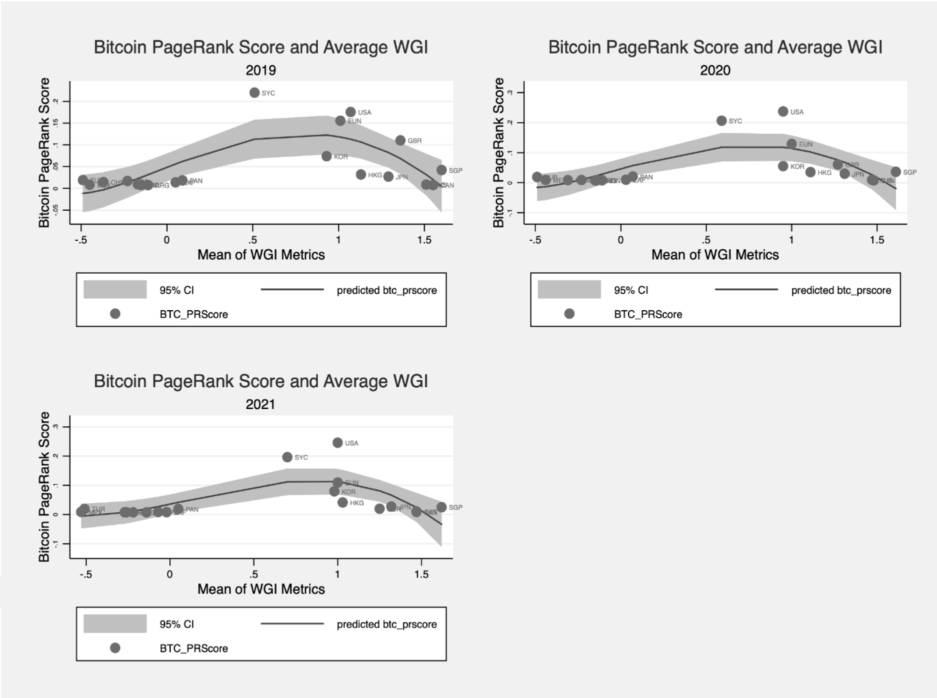


Figure 53. Two-way graph comparing the Bitcoin PageRank score and mean WGI scores for years 2019 through 2021 with Fit Fractional polynomial

The graphs depict an inverted U-curve increasing trend in both WGI scores and Bitcoin's PageRank scores. Initially, as the mean of WGI metrics increases, the Bitcoin PageRank score also tends to increase. However, after a certain threshold, the Bitcoin centrality starts to decline. The initial years between 2015-2017 show a steeper slope in the fitted line, suggesting a stronger association between higher governance scores and Bitcoin centrality. In the following years, although the positive trend continues, the slope of the line flattens slightly, which might indicate that while the correlation remains positive, other factors might also be influencing Bitcoin's centrality, possibly diluting the strength of the direct correlation with WGI. We provide the regression analysis results for Bitcoin PageRank Scores and WGI Metrics, highlighting the relationship between Bitcoin's PageRank scores and various World Governance Indicators (WGI) metrics under Table 14. The mean WGI (wgi_avg) variable does not achieve statistical significance in the regression analysis (p > 0.05), indicating that there is no statistically robust correlation between WGI scores and Bitcoin's centrality. This finding suggests that the hypothesis of a positive correlation cannot be supported by the regression analysis.

Table 14. Regression Analysis for Bitcoin PageRank Scores and WGI Metrics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_	btc_prscore_
wgi_avg	4.9269e+10	4.0526e+10	4.3090e+10	6.7950e+10	6.8439e+10	6.1295e+10	6.1295e+10
	(7.9539e+10)	(9.9447e+10)	(1.0113e+11)	(8.2204e+10)	(8.4589e+10)	(8.7426e+10)	(8.7426e+10)
c.wgi_avg#c.wgi_avg	-3.3091e+10	-2.9023e+10	-3.0598e+10	-2.1279e+10	-2.0544e+10	-2.5154e+10	-2.5154e+10
	(3.7238e+10)	(2.6180e+10)	(2.5664e+10)	(1.4059e+10)	(1.3856e+10)	(1.7906e+10)	(1.7906e+10)
realgdp		0.0041	-0.0025	-0.0184***	-0.0177***	-0.0144**	-0.0144**
		(0.0183)	(0.0200)	(0.0062)	(0.0039)	(0.0061)	(0.0061)
tradevol			0.0150*	0.0420***	0.0420***	0.0322***	0.0322***
			(0.0079)	(0.0066)	(0.0066)	(0.0090)	(0.0090)
netfinacc				-0.3372***	-0.3377***	-0.2680**	-0.2680**
				(0.1116)	(0.1125)	(0.1021)	(0.1021)
dote_prscore					-2.0331e+11	2.5657e+12	2.5657e+12
					(1.1934e+12)	(2.6077e+12)	(2.6077e+12)
doti_prscore						-2.4379e+12	-2.4379e+12
						(2.0849e+12)	(2.0849e+12)
o.wgi_avg							-
2016.year	-1.2015e+09	-1.4056e+09	-3.1359e+08	2.8551e+09	2.8271e+09	1.4378e+09	1.4378e+09
	(1.5988e+09)	(1.9919e+09)	(2.4845e+09)	(2.8269e+09)	(2.8685e+09)	(3.0623e+09)	(3.0623e+09)
2017.year	-1.0371e+09	-1.7498e+09	-1.8387e+09	-8.0922e+08	-9.4803e+08	-1.3717e+09	-1.3717e+09
	(1.6126e+09)	(3.7350e+09)	(3.7741e+09)	(3.1817e+09)	(2.8441e+09)	(3.2206e+09)	(3.2206e+09)
2018.year	-1.0162e+09	-2.2230e+09	-3.5880e+09	-7.1109e+09	-7.3358e+09	-6.4618e+09	-6.4618e+09
	(2.0635e+09)	(6.4080e+09)	(6.2227e+09)	(6.1277e+09)	(5.7585e+09)	(5.6077e+09)	(5.6077e+09)
2019.year	-1.5460e+09	-3.1474e+09	-3.2552e+09	-3.4362e+09	-3.6720e+09	-3.6837e+09	-3.6837e+09
	(4.9394e+09)	(1.1081e+10)	(1.1136e+10)	(8.5844e+09)	(8.2158e+09)	(7.8038e+09)	(7.8038e+09)
2020.year	4.5347e+10***	4.4277e+10**	4.4880e+10**	4.7470e+10***	4.7346e+10***	4.6399e+10***	4.6399e+10***
	(1.5540e+10)	(1.6133e+10)	(1.5990e+10)	(1.4840e+10)	(1.4415e+10)	(1.4546e+10)	(1.4546e+10)
2021.year	4.3491e+10**	4.1396e+10**	3.8082e+10**	4.1684e+10**	4.1375e+10**	4.1601e+10**	4.1601e+10**
	(1.5548e+10)	(1.7344e+10)	(1.7726e+10)	(1.6948e+10)	(1.5665e+10)	(1.5712e+10)	(1.5712e+10)
Constant	3.1954e+09	-8.9981e+09	-7.2065e+09	-1.2482e+10	-6.4222e+09	-1.2380e+10	-1.2380e+10
	(6.1668e+10)	(5.4189e+10)	(5.1227e+10)	(2.7795e+10)	(2.7976e+10)	(2.6794e+10)	(2.6794e+10)
Observations	133	133	133	133	133	133	133
R-squared	0.3377	0.3393	0.3465	0.5553	0.5554	0.5697	0.5697
Number of countries	19	19	19	19	19	19	19

CHAPTER 6

DISCUSSON & CONCLUSION

This study has uncovered various insights into the interaction between cryptocurrency transactions, particularly Bitcoin, and international trade, utilizing the Direction of Trade Statistics for both imports and exports, as well as the World Governance Indicators. The results reveal a complex relationship between political-economic events and cryptocurrency transactions worldwide. The analysis shows clear patterns in how geopolitical events impact international trade and finance through cryptocurrencies, contributing to the scholarly discussion on international trade and finance by incorporating data on cryptocurrency transactions. The findings indicate a complex interplay, supporting some hypotheses while rejecting others, providing a nuanced understanding of the dynamics at play. In this section, we summarize the conclusion of hypotheses starting from the accepted hypotheses, draw insights from the rejected hypotheses as well as provide recommendations for future research.

Frist, hypothesis 1a suggested a correlation between a country's trade volume and the volume of cryptocurrency transactions. This hypothesis was supported, indicating that countries with higher trade volumes tend to engage more in cryptocurrency transactions, likely due to the increased demand for alternative transaction methods in bustling trade environments. Hypothesis 1b found a significant correlation between a country's imports and the volume of cryptocurrency exports. This finding underscores the role of cryptocurrencies in facilitating international trade, particularly in circumventing traditional banking and currency conversion costs. Hypothesis 3b and Hypothesis 8 highlighted the increasing complexity of cryptocurrency networks over time and their correlation with countries holding capital account deficits. These findings suggest that cryptocurrencies offer an alternative financial pathway for countries experiencing traditional financial constraints. Hypothesis 9 affirmed that trade openness correlates positively with cryptocurrency centrality, illustrating that open trade policies tend to align with greater acceptance and integration of cryptocurrency transactions within national economies.

Second, the rejected hypotheses also yield significant insights. Hypothesis 2, which posited that economic and political instabilities lead to an increase in cryptocurrency transactions, was not supported. This suggests that while cryptocurrencies are often viewed as safe havens, other factors such as regulatory environments or technological adoption rates may play more critical roles. Hypothesis 5, concerning the overlap in centrality between trade and cryptocurrency networks, and Hypothesis 6, regarding the influence of stringent trade regulations, were also rejected. These findings highlight the distinct nature of cryptocurrency networks, which appear to operate under different dynamics than traditional trade networks. Hypothesis 10's rejection, which looked at the correlation between higher World Governance Indicators (WGI) scores and cryptocurrency centrality, implies that governance quality does not necessarily predict the centrality in cryptocurrency networks. This could indicate the decentralized and borderless nature of cryptocurrencies, which operate independently of national governance structures.

Future research could broaden the scope by including additional variables such as other major cryptocurrencies, more economic indicators, and extensive trade data. Comparative studies across different political regimes or economic blocs could deepen our understanding of how various governance structures influence the dynamics between trade and cryptocurrency flows. Expanding the list of countries and the time frame considered would also enrich the analysis of these dynamics under different governance conditions. Exploring the impact of global technological diffusion and innovation, as well as the interplay between monetary policies and cryptocurrency adoption, could also provide valuable insights into the evolving landscape of digital finance. Through these expanded avenues of research, we can continue to unravel the complex interactions between international trade and cryptocurrency movements, paving the way for more informed policy-making and strategic economic planning in the era of digital currency.

APPENDIX A

LIST OF BACKBONE EXTRACTION METHODS

Category	Method	Network		Filter		Parameters
		Weighted	Unweighted	Type	Scope	
Statistical	Disparity	✓	✗	Edges	Local	Alpha (significance level)
	Noise Corrected	✓	✗	Edges	Local	Alpha (significance level)
	Marginal Likelihood	✓	✗	Edges	Local	Alpha (significance level)
	Enhanced Configuration Model	✓	✗	Edges	Local	Alpha (significance level)
	Locally Adaptive Network Sparsification	✓	✗	Edges	Local	Alpha (significance level)
	Multiple Linkage Analysis	✓	✗	Edges	Local	–
Structural	Global threshold	✓	✗	Edges	Global	Threshold
	Maximum Spanning Tree	✓	✗	Edges	Global	–
	Doubly Stochastic	✓	✗	Edges	Local	Threshold
	High Salience Skeleton	✓	✗	Edges	Global	Threshold
	h-Backbone	✓	✗	Edges	Global	–
	Metric Distance Backbone	✓	✗	Edges	Global	–
	Ultrametric Distance Backbone	✓	✗	Edges	Global	–
	Planar Maximally Filtered Graph	✓	✗	Edges	Global	–
	Modularity Backbone	✓	✗	Nodes	Global	Threshold
	Primary Linkage Analysis	✓	✗	Edges	Local	–
	Global Sparsification	✓	✓	Edges	Local	Threshold
	Edge Betweenness	✓	✓	Edges	Global	Threshold
	Node Degree	✓	✓	Nodes	Global	Threshold
Hybrid	Globally and Locally Adaptive Backbone	✓	✓	Edges	Local & Global	c (involvement parameter) Alpha (significance level)

APPENDIX B

LIST OF COUNTRIES INCLUDED IN THE 'EU' CLUSTER

Code	Bitcoin Data	DOTS Data	BOP Data
EUN	Austria	Y	Y
	Croatia	Y	Y
	Cyprus	Y	Y
	Czech Republic	Y	Y
	Denmark	Y	Y
	Estonia	Y	Y
	Finland	Y	Y
	France	Y	Y
	Germany	Y	Y
	Hungary	Y	Y
	Ireland	Y	Y
	Italy	Y	Y
	Latvia	Y	Y
	Lithuania	Y	Y
	Malta	Y	Y
	Netherlands	Y	Y
	Poland	Y	Y
	Portugal	Y	Y
	Romania	Y	Y
	Slovak Republic	Y	Y
	Slovenia	Y	Y
	Spain	Y	Y
	Sweden	Y	Y

APPENDIX C

LIST OF COUNTRIES INCLUDED IN THE 'OTHERS' CLUSTER

Code	Bitcoin Data	DOTS Data	BOP Data
OTH	Antigua and Barbuda	Y	Y
	Azerbaijan	Y	Y
	Bahamas	Y	Y
	Belarus	Y	Y
	Belize	Y	Y
	Chile	Y	Y
	Comoros	Y	Y
	Costa Rica	Y	Y
	Dominica	Y	Y
	El Salvador	Y	Y
	Gibraltar	Y	N
	Iran	Y	N
	Israel	Y	Y
	Kazakhstan	Y	Y
	Macao	Y	Y
	Malaysia	Y	Y
	Marshall Islands	Y	Y
	Mongolia	Y	Y
	New Zealand	Y	Y
	Niger	Y	Y
	Nigeria	Y	Y
	Norway	Y	Y
	Pakistan	Y	Y
	Philippines	Y	Y
	Saint Kitts and Nevis	Y	Y
	Saint Vincent and the Grenadines	Y	Y
	Samoa	Y	Y
	Switzerland	Y	Y
	Syrian Arab Republic	Y	N
	Taiwan	N	N
	Thailand	Y	Y
	Ukraine	Y	Y
	United Arab Emirates	Y	N
	Vanuatu	Y	Y
	Venezuela	Y	Y
	Vietnam	Y	Y
	Zimbabwe	Y	Y

APPENDIX D

THRESHOLDING VALUES USED FOR BACKBONE EXTRACTION

Network	Year	Optimal Thresholding Value	Number of Edges Left in the Network
BTC	2015	0.027399999999999956	197/400
	2016	0.047	200/400
	2017	0.029400000000000003	258/400
	2018	0.08514080000000405	212/400
	2019	0.0366	214/400
	2020	0.05397000000000122	205/400
	2021	0.016310799999998155	228/400
DOT	2015	0.022500000000000003	334/378
	2016	0.026000000000000002	329/378
	2017	0.020399999999999998	339/378
	2018	0.020409999999999984	331/378
	2019	0.019700000000000002	335/378
	2020	0.015399999999999968	332/378
	2021	0.012289999999999907	335/378

APPENDIX E

GEPHI PARAMETERS FOR NETWORK AND NODE METRICS

Type	Gephi Metric	Settings	Network Metrics	Node Metrics
Network Overview	Avg. Weighted Degree (Dong and Wong 1987)	N/A	• Avg. Weighted Degree	• Weighted in-degree • Weighted out-degree • Weighted Degree
	Network Diameter (Brandes 2001) (Freeman 1977) (Marchiori and Latora 2000) (Hage and Harary 1995)	• Directed • Not normalized	• Diameter • Radius • Avg. Path Len.	• Closeness Centrality • Har. Closeness Centrality • Betweenness Centrality • Eccentricity
	Graph Density (Goldberg 1984)	• Directed	• Density	N/A
Community Detection	Modularity (Lambiotte et al. 2008)	• Randomized with Edge weights • Resolution: 0.35	• Modularity • Modularity with resolution • Number of Communities	• Modularity Class
	Statistical Inference (Peixoto 2019; Zhang and Peixoto 2020)	N/A	• Description Length • Number of Communities	• Cluster • Inferred Class
Node Overview	Eigenvector Centrality (Bonacich 1972)	• Directed • Number of Iterations: 100	N/A	• Eigenvector Centrality
	HITS (Kleinberg 1999)	• Directed • Epsilon: Default	N/A	• Authority Distribution • Hubs Distribution
	PageRank (Page et al. 1999)	• Probability (p): 0.85 • Epsilon: 0.001 • Directed With Edge Weights	N/A	• PageRank • PageRanking (derivative)
	Louvain/Leiden Algorithms (Blondel et al. 2008) (Traag et al. 2019)	• Louvain & Leiden Algorithms / Modularity • With Edge Weights • Resolution: 1.2	N/A	• Louvain Cluster • Leiden Cluster

APPENDIX F

PYTHON CODE USED FOR BACKBONING USING DISPARITY FILTER

```
import os
import backboning
import pandas as pd
import numpy as np
import networkx as nx

# Get the directory of the script
script_directory = os.path.dirname(os.path.abspath(__file__))

previous_connectivity_status = None

for x in np.arange(0, 1, 0.0001):
    y = str(x)

    data_table = pd.read_csv("2015.csv", encoding='cp1252')
    table_df = backboning.disparity_filter(data_table, undirected=False)

    bb_vespignani = backboning.thresholding(table_df, x)

    # Convert the DataFrame to a NetworkX graph
    G = nx.from_pandas_edgelist(bb_vespignani, source='src', target='trg',
create_using=nx.DiGraph())

    # Check if the network is fully connected.
        # nx.is_strongly_connected(G) - A directed graph is strongly connected if
and only if every vertex in the graph is reachable from every other vertex.
        # nx.is_weakly_connected(G) -
https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.a
lgorithms.components.is_weakly_connected.html#networkx.algorithms.components.is_wea
kly_connected

    is_fully_connected = nx.is_strongly_connected(G)
    if is_fully_connected:
        connectivity_status = "FullyConnected"
    else:
        connectivity_status = "NotFullyConnected"

    print(f"Connectivity status (DF Backbone) for threshold {x}:
{connectivity_status}")

    print("DF Backbone:")
    print(bb_vespignani)

    # Break the loop if the network is no longer fully connected
    if previous_connectivity_status == "FullyConnected" and not is_fully_connected:
        print("Network is no longer fully connected. Stopping the loop.")
        break
    previous_connectivity_status = connectivity_status

    # Construct the output file path
    output_filename = os.path.join(script_directory,
f"df{y}_{connectivity_status}.csv")

    # Export as CSV
    bb_vespignani.to_csv(output_filename, index=False)

    print(f"Backboning result exported to: {output_filename}")
```

APPENDIX G

DESCRIPTIONS FOR ALL VARIABLES USED IN ANALYSES

Node (Country) Metrics			
Type	Variable Name	Description	Source
Bitcoin Transfer Statistics	BTC_Sent	Refers to the total value of Bitcoin exports in USD. The valuation is calculated in USD according to the Bitcoin exchange rate on the day and hour of each transaction.	(Crystal Blockchain 2021)
	BTC_Recv	Refers to the total value of Bitcoin imports in USD. The valuation is calculated in USD according to the Bitcoin exchange rate on the day and hour of each transaction.	
	BTC_Net	Net value of Bitcoin imports in USD: $= \text{BTC}_{\text{Recv}} - \text{BTC}_{\text{Sent}}$	
Direction of Trade Statistics	Exports	Value of Export of goods in USD acquired from the Direction of Trade database: “Goods, Value of Exports, Free on board (FOB), US Dollars (TXG_FOB_USD)”.	(International Monetary Fund 2023b)
	Imports	Direction of Trade (Imports) - Derivative of the Direction of Trade, Exports - calculated by inverting the direction of trade in the same dataset.	
	NetTrade	Net value of exports in USD: $= \text{Exports} - \text{Imports}$	
Financial Metrics (Balance of Payment Statistics)	NetGoods	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Goods”	(International Monetary Fund 2023a)
	GoodsCredit	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Goods > Credit”	
	GoodsDebit	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Goods > Debit”	
	NetServices	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Services”	
	ServCred	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Services > Credit”	
	ServDeb	Value in USD acquired from “Balance of Payments > Current Account > Goods & Services > Services > Debit”	
	CapAcc	Value in USD acquired from “Balance of Payments > Capital Account”	
	CapTransCred	Value in USD acquired from “Balance of Payments > Capital Account > Capital Transfers, Credit”	
	CapTransDebt	Value in USD acquired from “Balance of Payments > Capital Account > Capital Transfers, Debit”	
	NetFinAcc	Value in USD acquired from “Balance of Payments > Financial Account”	
	NetPortInv	Value in USD acquired from “Balance of Payments > Financial Account > Portfolio Investments”	
	NetFinAsset	Value in USD acquired from “Balance of Payments > Financial Account > Portfolio Investments > Net Acquisition of Financial Assets”	
	NetLiab	Value in USD acquired from “Balance of Payments > Financial Account > Portfolio Investments > Net Incurrence of Liabilities”	
Governance Indicators	Continent	The continent where the country is located.	
	RealGDP	Constant Price GDP ($)	(World Bank 2024)
	CapitalCtrl	Countries classified as “Open” typically impose capital controls on fewer than 10 percent of their transaction subcategories throughout the sample period, and never experience years where controls affect more than 20 percent of these subcategories. On the contrast, countries classified as “Wall” tend to impose capital controls on more than 70 percent of their transaction subcategories throughout the sample period, and never experience years where controls affect less than 60 percent of these subcategories. Countries labeled as “Gate” do not fall into either the Walls or Open categories.	(Klein 2012)
	Legal	Binary value of whether or not a country banned cryptocurrencies for transactions.	(*Legality of cryptocurrency*

	BankBan	Binary value of whether or not a country banned its institutions to carry out any cryptocurrency-related transactions.	*by country or Territory* 2024)
	GreyList	Binary value of whether or not a country is listed under the jurisdictions with increased monitoring in terms of strategic deficiencies in their regimes to counter money laundering, terrorist financing, and proliferation financing.	(Financial Action Task Force (FATF) 2024)
	Accountablty	The Voice and Accountability Index measures citizens' perceptions of their capacity to engage in choosing their government. It includes the freedom of expression, the freedom of association, and the freedom of the media. The scale for estimating governance performance ranges from -2.5, indicating weak governance, to 2.5, indicating strong governance.	(Kaufmann and Kraay 2023)
	Stability	The Political Stability and Absence of Violence/Terrorism index assesses the probability that a government will be destabilized or overthrown through unconstitutional or violent methods, such as political violence or terrorism. The governance performance is evaluated on a scale that ranges from -2.5, indicating weak stability, to 2.5, indicating strong stability.	
	Governance	Government effectiveness measures the quality of public services, the government's ability to develop and execute sensible policies, and the public's respect for state institutions. The quality of governance is rated on a scale from -2.5, indicating weak effectiveness, to 2.5, indicating strong effectiveness.	
	Regulations	Regulatory quality reflects how well people think the government can develop and enforce effective policies and regulations that promote and support private sector growth. Governance performance is measured on a scale from -2.5, representing weak regulatory quality, to 2.5, representing strong regulatory quality	
	RuleLaw	The rule of law involves how much trust citizens place in society's rules and their compliance with them. This specifically includes the quality of contract enforcement, property rights, the police, and the courts, along with the chances of crime and violence occurring. The governance performance is evaluated on a scale from -2.5, indicating weak adherence to the rule of law, to 2.5, indicating strong adherence	
	CorruptCtrl	Control of corruption measures the extent to which public power is used for private gain. This includes all types of corruption, from minor to major, as well as the influence that elites and private interests have over government actions. Governance performance in controlling corruption is rated on a scale from -2.5, indicating weak control, to 2.5, indicating strong control.	
	WGI_AVG	Synthetic calculation based on the arithmetic mean of all governance metrics for a given country.	
	TaxHaven	The Corporate Tax Haven Index provides a ranking of jurisdictions that are deeply involved in assisting multinational corporations in minimizing their corporate income tax payments. A higher ranking reflects how the combination of local laws and the jurisdiction's position in the global economy increases the risk of corporate tax avoidance by multinational corporations.	(Tax Justice Network 2022)
	FinSecrecy	The Financial Secrecy Index assesses countries based on their level of financial secrecy. A higher ranking on the index does not necessarily indicate greater secrecy within a country; rather, it highlights the country's significant role in facilitating the concealment and laundering of money by wealthy individuals and criminals worldwide.	
Centrality Metrics	WinDeg	The weighted in-degree of a node is the sum of weights of all incoming edges to that node. It reflects how much influence or importance other nodes (with their associated weights) have on the focal node. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Newman 2001)
	WoutDeg	The weighted-out degree of a node is calculated by summing up the weights of all its outgoing edges (i.e., connections pointing away from the node). It reflects the total strength of a node's interactions with other nodes. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	
	Wdeg	For a given node, the Weighted Degree is calculated as the sum of the weights assigned to its direct connections. These weights represent the strength of the ties between nodes. In other words, it reflects how influential a node is based on the intensity of its connections. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	
	Eccent	The Eccentricity of a node refers to the maximum distance from that node to all other nodes in the network. Essentially, it measures how far a node is from the farthest other nodes in terms of shortest paths. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Hage and Harary 1995)

	CloseC	Closeness Centrality measures the centrality of a node within a connected graph. Specifically, it quantifies how close a node is to all other nodes in the network. Closeness Centrality focuses on average distances, while Eccentricity looks at the maximum distance. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	
	HarmoC	Harmonic centrality offers an alternative approach to calculating average distances. Instead of summing the distances of a node to all other nodes (as in closeness centrality), harmonic centrality sums the inverse of those distances. This allows to deal with infinite values. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Marchiori and Latora 2000)
	BtwnC	Betweenness centrality is a used to assess the importance of nodes within a network. Specifically, it quantifies the degree to which nodes act as bridges or intermediaries between other nodes. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Page et al. 1999)
	PRScore	PageRank measures the importance of each node (or vertex) within a graph. The underlying assumption is that important nodes are those that have many incoming connections from other important nodes. While PageRank was initially designed for web pages, it can be applied to any type of network. It works best for networks with directed edges (where nodes have specific directions of influence). In our case, in a trade network, influential countries would have higher PageRank values. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Page et al. 1999)
	PRrank	The ranking of countries per year in each main dataset (DOTe, DOTi, BTC) per year based on their PageRank score.	
	EigenC	Eigenvector centrality measures the relative significance of a node within a connected network by assigning scores to each node. This measure is based on the principle that connections to nodes with higher scores have a greater impact on a node's overall centrality than connections to nodes with lower scores..	(Bonacich 1972)
	Auth	The authority value is a concept used in link analysis algorithms. Specifically, it's part of the HITS algorithm (Hyperlink-Induced Topic Search), also known as "hubs and authorities." Authorities represent nodes that are linked by many different hubs. Authority value is computed as the sum of the scaled hub values that point to that page. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Kleinberg 1999)
	Hub	The Hub value is the other metric as part of the HITS algorithm. The underlying assumption is that certain nodes act as hubs—large directories that point to other nodes. A hub value is the sum of the scaled authority values of the nodes it points to. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	
Community Detection Metrics	Sta_Inf	Statistically Inferred Class value refers to the group that each country is assigned to based on statistical inference of assortative community structures, which is a methodology for identifying and analyzing communities within complex network. In essence, in a network, nodes tend to connect with others who are similar to them. Assortative communities are groups of nodes that exhibit this tendency. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Peixoto 2019; Zhang and Peixoto 2020)
	Modul	Modularity assesses the strength of a network's division into communities. It compares the actual number of edges within these communities to the expected number if the edges were randomly distributed.	(Lambiotte, Delvenne, and Barahona 2008)
	Louvain	The Louvain method for community detection is an efficient algorithm used to identify non-overlapping communities within large-scale networks. However, it has a flaw: Louvain algorithm can group nodes into clusters even if they have no link with others in the same clusters. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Blondel et al. 2008)
	Leiden	The Leiden algorithm is a powerful tool for identifying well-connected clusters within large-scale networks. It was developed to address the flaw of Louvain algorithm. It guarantees to find well-connected clusters and does so more efficiently than the Louvain algorithm. However, it is important to note that there are some questions regarding the effectiveness of community detection in network science, which we discuss at later stages of this chapter. Calculated for the three main datasets (DOTe, DOTi, BTC) per year.	(Traag et al. 2019)

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