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Blockchain and Decentralized Finance: Assessment of Risks, Opportunities, and Innovative Monetary Systems

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Abstract

This PhD thesis examines risks, opportunities and socio-technical innovation in blockchain-based financial systems, combining network analysis, empirical market data, and institutional analysis. As the crypto ecosystem and decentralized financial infrastructures continue to expand and interact with traditional monetary systems, understanding how risk propagates across assets, platforms, and institutional designs has become increasingly important for market participants and policymakers. The first two chapters focus on systemic risk in crypto assets (cryptocurrencies and stablecoins) using a network-based approach. The first paper analyzes major crypto assets and constructs dynamic networks based on return co-movements to study the evolution of interconnectedness and contagion risk over time. Network centrality measures (degree, closeness, betweenness, and eigenvector) are used to identify systemically important nodes (cryptocurrencies and stablecoins) and to assess how these measures affect their systemic risk contributions, particularly during market stress episodes. Results showed that the systemic risk contribution of crypto assets decreases over time as their connectedness in the system increases. This impact is more pronounced for cryptocurrencies than for centrally issued, managed, and governed stablecoins. Our findings suggest that pure network interconnectedness plays a diminished role in tail risk propagation in the crypto market.

The second paper extends this framework to token pairs traded on centralized and decentralized exchanges (CEXs and DEXs), allowing for a comparison of market structure and risk transmission across trading platforms. By incorporating data from CEXs and DEXs, this chapter highlights differences in network topology and the role of liquidity concentration in shaping systemic risk. Results showed that centrality values significantly impact systemic risk contribution of token pairs listed on centralized exchanges. Conversely, insignificant results were found for all token pairs traded on decentralized exchanges. The token pairs on centralized exchanges exhibited a negative association with centrality values, consistent with the findings reported in the first paper. These findings imply that systemic risk in cryptocurrency markets is not solely driven by interconnectedness, but by how that interconnectedness is structured. In particular, the negative relationship between centrality and systemic risk suggests that higher network integration, supported by transparency and decentralized architectures, may enhance risk sharing and reduce systemic vulnerability. These results highlight the potential of blockchain based financial systems to contribute to more resilient, efficient, and inclusive financial ecosystems, while also offering new insights for the design of risk management and regulatory frameworks.

The third paper shifts the focus from market level risk to protocol level risk management in leading Decentralized Finance (DeFi) lending platforms. It examines the determinants of liquidation events and evaluates the effectiveness of protocol design features as risk management tools. Exploiting the transition from earlier to newer protocol versions across different blockchain layers, the empirical analysis employs panel fixed effect regression models to assess how changes in risk control measures

affect liquidation dynamics and protocol's performance. The findings emphasize that protocol level design choices play a critical role in mitigating risk beyond asset price volatility alone. The architectural evolution from v2 to v3, characterized by granular risk parameters, isolation modes, and enhanced risk management mechanisms has systematically improved protocol resilience, with liquidations in v3 serving as positive signals of stability rather than distress.

The fourth paper broadens the scope of the thesis by examining blockchain based complementary currencies in comparison with traditional complementary currency systems, with a particular focus on their potential role in universal basic income schemes. It investigates the socio-technical evolution of Complementary Currencies for Basic Income using a data-driven approach to different case studies (Fiat and Blockchain based models). It highlights how technological choices influence scalability, transparency, and risk exposure in social and monetary innovations by employing mix method approach. Finally, based on the trade-offs of each system, a hybrid model for UBI is proposed for financial inclusion and poverty elimination.

Taken together, the four papers provide an integrated perspective on risks and opportunities in emerging financial ecosystems, spanning asset markets, trading infrastructure, decentralized protocols, and alternative monetary arrangements. Overall, the results suggest that the core features of blockchain based markets, e.g., decentralization, transparency, accessibility, low transaction costs and automated risk management, are not merely technological innovations but may serve as mechanisms for improving system resilience and inclusive financial architectures. This thesis also contributes to the literature by demonstrating how network structures and institutional design jointly shape systemic risk and resilience in DeFi, offering insights relevant for researchers, protocol designers, and policymakers navigating the evolving digital financial landscape.

Key words

Decentralized Finance; Systemic Risk; Monetary Innovation; Network Analysis

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SUMMARY

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Glossary

Term	Definition
Crypto Assets	Crypto-assets are a digital representation of value or rights which are built using distributed ledger technology or similar technology.
Native Cryptocurrencies	Native assets built on a particular blockchain which can be utilized, traded and used as a store of value.
Stablecoins	Stablecoins are cryptocurrencies which are fixed to a specific value and backed by fiat money, usually the US dollar or the euro.
DeFi	Decentralized finance (DeFi) involves those financial instruments and institutions which do not rely on centralized intermediaries.
Proof of work	Proof of work is a type of consensus mechanism in which one party proves to the other that a certain amount of computation effort is expended.
Proof of Stake	Proof of Stake is a type of consensus mechanism in which validators are chosen based on their holdings of a specific cryptocurrency.
CEX	A centralized exchange (CEX) is an online platform operated by a single company that acts as an intermediary for buying, selling, and trading cryptocurrencies.
DEX	A decentralized exchange (DEX) is a peer-to-peer (P2P) marketplace that uses smart contracts to facilitate the buying, selling, and trading of cryptocurrencies directly between users' non-custodial wallets.
AMM	An automated market maker (AMM) is a DeFi protocol that uses algorithms to price and trade crypto assets without an order book.
Oracle	Oracles is a third-party service that connects blockchains to external systems, enabling smart contracts to execute, based on real world inputs and outputs.
Blockchain Layer 1	A blockchain Layer 1 (L1) is the foundational base-layer architecture, such as Bitcoin or Ethereum that operates independently to process, validate, and finalize transactions on its own network.
Blockchain Layer 2	A blockchain Layer 2 (L2) is a secondary protocol or framework built on top of an existing blockchain (Layer 1) to improve transaction speed and reduce fees.
Complementary Currencies	A complementary currency is an alternative currency created by non-bank actors that works alongside the national currency to achieve desired objectives.
Universal Basic Income	Universal basic income is a policy in which all individuals in a society receive a regular, unconditional cash payment from the government, regardless of income, employment status, or wealth.

1. Introduction and Motivation

The 2008 global financial crisis marked a significant turning point in the understanding of the architecture and mechanism of traditional financial systems as it became evident that instability not only originates from the collapse of individual institutions, but from the complex interconnection among them. This understanding redirected scholarly and regulatory attention to systemic risk, a phenomena based on network dynamics and systemic interactions that convert isolated shocks into widespread crises. The inefficiencies of the traditional architecture and mechanism to monitor and manage financial linkages and risks were exposed amid the financial crises.

During the same time in late 2008, Bitcoin whitepaper was published that offered a conceptual and technical vision of an alternative to centralized financial systems built on blockchain technology, characterized by decentralization, cryptographic trust, and distributed consensus. Blockchain store data across numerous nodes within a network and all nodes possessed same copy of data, indicating that if a node became inactive for some reason, the data would remain accessible from another node, and the network would only fail if all nodes were to fail simultaneously. The data is recorded in interconnected blocks, like a chain, thus the term blockchain, as illustrated in Figure 1. Blockchain technology appeared as a viable solution to the problems posed by traditional centralized system.

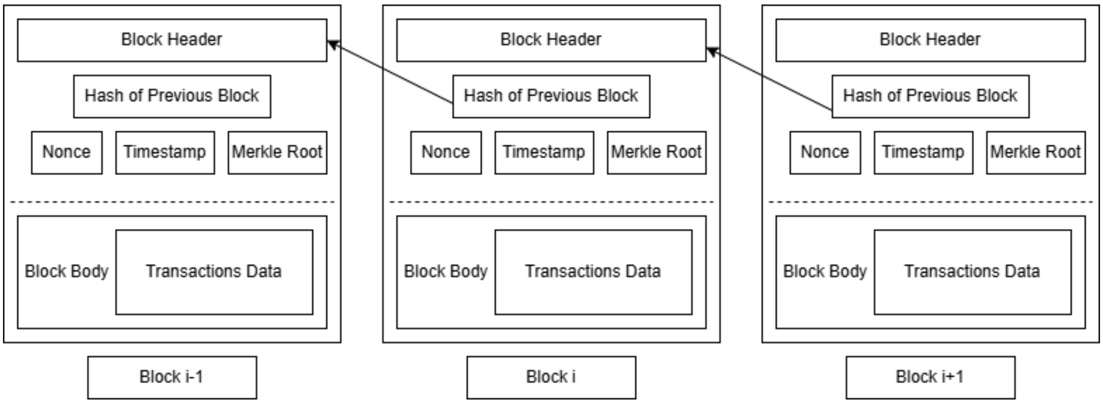

Fig 1. Structure of a Blockchain

Over the following decade, blockchain and distributed ledger technologies showed unprecedented growth by introducing novel financial assets, institutions and services. This transformation produced a fast growing digital financial ecosystem that today operates parallel to traditional markets. Crypto assets, stablecoins, centralized and decentralized exchanges, automated lending protocols, collateralized debt positions, and blockchain-based currencies all contribute to a new constellation of financial interactions. The current market cap and trading volume of the crypto market has reached a new limit of 4 trillion dollar and 138.43 billion dollar, respectively as shown in the Figure 2 as on December 1, 2025. This DeFi ecosystem is composed of various categories including lending, staking, exchanges, gaming, and others. Among these, the DeFi lending market holds the highest total value locked (TVL), reaching approximately 70 billion dollars as of December 1, 2025.

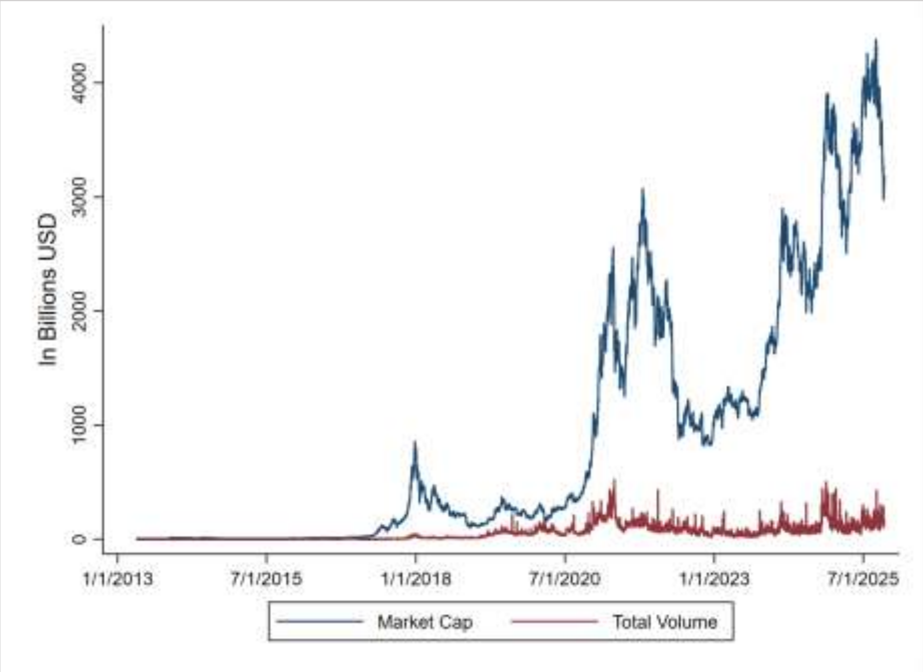

Fig 2. Market Cap and Trading Volume of Crypto Market (source: coinmarketcap)

Blockchain technology offers novel features that address some of the issues in traditional financial system. These features include the transparency of transactions, the automatic governance, and the elimination of intermediaries to reduce incidents of single points of failure. However, it also brought new set of risks that resulted in the collapse of many crypto assets and markets causing huge losses in recent years. Cryptocurrency markets, are characterized by severe volatility, fragmented liquidity, and deep interconnectivity. This interconnectedness is driven by cross collateralization, smart contracts vulnerabilities, oracle dependencies, and bridging infrastructures. Amid rapid growth of DeFi and their increased integration with the traditional economy, understanding and managing the emergence, propagation, and amplification of associated risks is crucial. While systemic risk in traditional finance is extensively studied, empirical studies regarding systemic risk in cryptocurrency markets is still limited. This makes the research on risks in decentralized ecosystems not just important, but also necessary and thus this sets the context of the motivation behind our research.

In this thesis we investigate how interconnectivity, market structure, and technology design influence risk in the decentralized systems by analyzing several core dimensions of risks. This include dynamic structure of interconnections in crypto assets and markets, and their contribution to systemic vulnerability, the behavior of token pairs and liquidity channels in different crypto exchanges, the determinants and consequences of automatic liquidations in decentralized lending markets, and lastly the broader socio-economic implications of blockchain based complementary currencies for public welfare. The research output consists of four papers (two published conference proceedings and two currently under review in peer-reviewed journals) which contribute to the existing literature and advances our understanding of how risk is generated, transmitted, and mitigated within the evolving landscape of DeFi.

The escalating growth of crypto assets and markets in recent years has raised serious concerns about the systemic importance and nature of crypto institutions and assets. The existing research has confirmed the correlation and patterns of co-explosive behaviour among crypto assets. Despite growing literature, no study is available that provides empirical investigation into the role of dynamic network effects and its contribution to the systemic risk in crypto markets.

So our first paper is an empirical investigation of the network properties of crypto assets including volatile cryptocurrencies and stablecoins, and their impact on systemic risk. Systemic risk refers to the potential for the insolvency or default of a financial intermediary to impact other market participants, leading to their failure as defined by the Bank for International Settlements (BIS, 2014). For empirical evaluation we have selected leading crypto assets with highest market cap covering almost 86 percent of entire crypto market cap. In order to quantify their network effect we have used minimum spanning tree (MST) method to observe the network properties of cryptocurrencies. From MST different centrality metrics are extracted such as, degree centrality, Betweenness centrality, closeness centrality, and eigenvector centrality indicating the local importance of the nodes in the network. For the measurement of systemic risk we have employed traditional measure ΔCoVaR that provides time varying systemic risk contribution of individual assets during the periods of crises. Lastly to establish a relationship between centrality metrics and systemic risk contribution we specify OLS regression model, where the independent variable include different centrality metrics, and the dependent variable consists of the systemic risk measure the ΔCoVaR.

Findings indicate that the native cryptocurrency at the core of our minimum spanning tree and with the highest centrality values is Ether, and is also found to be the highest risk contributor when the cryptocurrency market is distressed. On the contrary, the stablecoin found at the periphery of the minimum spanning tree is USDT, and also to be the least systemic risk contributor, according to CoVaR analysis. The periphery nodes are least impacted by the changes in the prices of central nodes and, therefore, can act as a safe haven for crypto investors. Furthermore, regression analysis shows the impact of varying dynamics of network topologies of crypto assets and their systemic risk contribution over time. Our findings also reveal that the impact of interconnectedness on systemic risk is not static, but evolves as network structures change as the crypto markets exhibit lower tail risk propagation through network structures. Results show that the systemic risk contribution of cryptocurrencies decreases with the increase in their interconnections in the crypto ecosystem, as demonstrated by a negative relationship with each centrality measure, but in the case of stablecoins, only degree centrality showed a significant negative relationship. The results suggest that systemic risk in crypto is less about network position and more about liquidity fragility. High-centrality assets may actually stabilize markets by distributing liquidity across fragmented pools, while tail risks emerge from non-network channels including excessive leverage, shared dependence on key external components (e.g., oracles manipulation and stablecoins run), and liquidity fragmentation across chains, and correlated trading behavior during stress events as observed in recent crypto market crashes. These findings suggest that the crypto users, investors and regulators should give priority to monitoring the non-network structural channels. Furthermore, macroprudential policies should be formulated to oversee the systemic risks stemming from the growing exposure to stablecoins.

The second paper is an extension of our first research findings as it employs the same empirical framework to investigate whether market structure (centralized or decentralized) has any impact on the systemic risk in crypto exchanges. We selected top token pairs that are exchanged on major centralized exchanges like Binance and Coinbase, and a major decentralized exchange, Uniswap. This allows the study to assess how the underlying market architecture centralized order books versus decentralized liquidity pools shapes the structure and intensity of interconnectedness within crypto exchanges. For this purpose, we have selected highly traded token pairs to quantify the impact of their interconnections on their systemic risk contribution while also taking into account the structure and size of the crypto exchanges. We have analyzed four token pairs that include two volatile token pairs BTC and ETH traded against USDT, one decentralized stablecoin DAI, and one centralized stablecoin USDC traded against USDT. The data is taken for the period of January 2021 to December 2023. Initially we ran the MST method to derive centrality metrics and then ΔCoVaR method was used to measure their systemic risk contribution and lastly, a simple OLS regression was run between eachcentrality metric and ΔCoVaR for all token pairs.

The findings reveal that ETH/USDT pair plays a central role in DeFi and applications, primarily within the crypto-native ecosystem creating systemic application dependencies. Consequently, ETH serves as a hierarchical reference node for most other assets and sustains this function over time, although it has seen a decline in centrality during periods of volatility. Therefore, high ΔCoVaR in unconditional results suggests that ETH's highest systemic risk contribution on Uniswap, followed by Binance and Coinbase, is internal to the crypto market, where it is used as a foundational asset on which much of the infrastructure depends. Bitcoin on the other hand, is often viewed as a store of value and is more closely correlated with traditional financial markets, especially in recent years. The fact that BTC's systemic risk contribution is highest on Binance, followed by Coinbase in conditional results with SPX and VIX, indicates that macroeconomic conditions and external financial factors influence its risk profile more. The research outcome reveals how macro-market conditions affect BTC more strongly than ETH on centralized exchanges. These results confirms that CEX tokens are a more serious concern for financial stability than DEX tokens because of the huge rise in the spillover effects from CEX tokens to other assets. These results also emphasize that Binance and Coinbase are systemically important financial institutions based on highest centrality values and systemic risk contribution and could generate systemic concerns, considering their prominent role in the global stablecoin market.

Significant regression results between centrality values of all token pairs and their systemic risk contribution on all exchanges confirmed that on centralized exchanges, size and interconnectedness are the main factors that make them systematically important and impact their risk management. All token pairs on Binance have exhibited a significant negative relationship with their centrality values, which means with the growth in the exchange's volume and increased interconnection, the systemic risk contribution of decentralized assets i.e. BTC and ETH and centralized stablecoin USDC tends to decrease except for the DAI token pair, which exhibited significant positive relationship. For Coinbase, only ETH and DAI exhibited a significant relationship. Contrarily, on Uniswap, which is a decentralized platform, insignificant regression results were found for all token pairs which suggests that the decentralized nature of liquidity provision through automated market makers (AMMs) might make the concept of centrality less relevant for systemic risk. Risk in decentralized systems may be more distributed across the network and less dependent on the prominence of individual tokens or pairs in terms of network interconnectedness. These interpretations offer a thorough examination of the risk patterns within crypto markets based on their structure and governance (centralized or decentralized). Financial regulators and policymakers may formulate new regulations by taking into account the unique characteristics of stablecoins and volatile cryptocurrencies, as well as the relevant risk factors identified on centralized and decentralized exchanges.

Across Chapters 2 and 3, a consistent negative relationship emerges between network centrality and systemic risk contribution. While traditional financial network models often associate higher centrality with greater systemic importance, the observed pattern suggests a more nuanced dynamic in crypto markets. One interpretation is liquidity deepening. As leading exchanges and major crypto assets accumulate trading volume and capital, their increased centrality reflects liquidity concentration rather than fragility. Deep liquidity pools may act as shock absorbers, dampening volatility spillovers and reducing marginal systemic impact. A second explanation concerns diversification in maturing markets during the sample period (2020–2024). These years witnessed significant maturation including increased institutional adoption, crypto assets regulations, and significant correlations with traditional assets. As the market matured, the largest and most central assets, particularly BTC and ETH, evolved from speculative instruments toward recognized asset classes in diversified portfolios. Their returns become less driven by idiosyncratic crypto-specific shocks and more sensitive to macro-financial conditions (as confirmed by the conditional ΔCoVaR results with SPX, MSCI and VIX in Chapter 1 and 2). This shift reduces their contribution to systemic risk, even as their network centrality grows. The negative coefficient thus captures a decoupling effect: centrality increases, but the nature of the risk being transmitted from crypto idiosyncratic to macro systematic conditions.

Finally, the negative correlation also reflect structural evolution in market architecture. Improvements in exchange infrastructure, automated market maker design, cross-chain liquidity integration, and enhanced risk management mechanisms may transform central nodes into stabilizing hubs rather than systemic amplifiers. This interpretation aligns with classical finance theory, where liquidity acts as a shock absorber. In the context of ΔCoVaR, which measures an asset's contribution to tail risk, highly liquid assets are better able to withstand selling pressure without propagating losses to connected nodes. The negative coefficient thus captures a 'liquidity buffer' effect, that the centrality on CEXs reflects not just interconnectedness, but also the depth of the market for that asset, which mitigates its systemic impact during stress. The regime dependent results in Chapter 2, where network topology shifted dramatically during the 2022 crises, with stablecoins assuming central roles further support this interpretation. The market's response to stress was seen in the shifting of stablecoins to central positions from periphery, reflecting a market maturation process to manage risks.

Taken together, the results suggest that the relationship between centrality and systemic risk in crypto markets may evolve over time, shifting from fragility driven topology in early stages to liquidity supported resilience in more mature phases. This finding contributes to the broader literature on financial network stability by highlighting the endogenous transformation of network structure in crypto markets.

We further expand our risk analysis to DeFi lending markets that have the highest TVL among various categories of DeFi ecosystem. While the second study emphasizes the influence of centralized and decentralized exchange architectures on interdependencies within token pair networks, this paper focuses on the operation of decentralized lending markets, where risk is managed through automated, smart contract based mechanisms rather than traditional risk management mechanism. It investigates how effective these automated risk-management processes are in practice by empirically analysing patterns of liquidation activity relative to the total value locked (TVL) and total revenue of leading lending protocols. By examining how liquidation triggers respond to market movements and liquidity conditions, this paper evaluates whether automated mechanisms succeed in containing liquidation risk or whether they generate additional stress within the system. In this way, the third study provides an evidence based assessment of the robustness of automated risk management which is a defining feature of decentralized lending. Liquidation risk, which occurs when collateral value falls below the minimal collateralization requirement, is the key risk in DeFi lending. It mostly affects borrowers, but it can also hurt lenders, liquidity providers, and protocols amid extreme market volatility. Market data-driven research on DeFi lending protocol and liquidation risk is still limited. In particular, our analysis reveals that no prior research has examined the performance and automated liquidity risk management of lending protocol versions v2 and v3, nor the comparative impacts of deployment on L1 and L2 blockchains.

To cover this gap, we have compared the top lending protocols, Aave and Compound, utilizing most recent data by employing a fixed effects panel regression model to assess their cross-version and cross-chain performance against liquidation risk. We have used TVL and total revenue as proxies for protocol performance that are regressed against liquidations and relevant control variables. Our results indicate that v3 of lending protocols exhibit more efficient risk management, especially on L2 blockchains, suggesting that the improved design of v3, along with the scalability and reduced transaction costs of L2, strengthens the protocols resilience against liquidation risk. Our results also reveal a divergence in user preferences, with institutional users prefer L1 blockchain for its liquidity and ecosystem robustness, whilst retail customers choose L2 blockchain due to its cost-effectiveness and faster execution during liquidation events.

The final paper investigates the risks and opportunities associated with blockchain based complementary currencies for universal basic income (UBI). In recent years many blockchain based UBI projects were launched globally, with the aim to enhance financial inclusion, support local economies, and facilitate cooperative value exchange. But they also brought about unique risks, which include vulnerabilities in governance, technology dependencies, operational limits, and challenges in terms of long term sustainability. To investigate the risks and opportunities in decentralized UBI models, we carried out a qualitative examination of blockchain based UBI projects (Circles and GoodDollar). We examined that how the transition from fiat based traditional systems to digital decentralized systems has influenced the efficiency, affordability, scalability, user empowerment, and the nature of impact of different UBI models. For this purpose, we performed a comparative analysis of three UBI models, including both traditional frameworks (GiveDirectly as a benchmark) and blockchain based systems (Circles and GoodDollar) by using a data driven mixed method approach. We combined the onchain transaction and user data of blockchain based UBI projects with the previous empirical studies and impact evaluation reports and presented our findings through an Impact Assessment MATRIX (IAM). The IAM was proposed by (Place et al., 2015; Palace, 2018) designed specifically to assess performance of complementary currencies across different dimensions by employing multiple criteria. This approach provides a multidimensional view of how technology changes the way UBI is designed and delivered in comparison with traditional UBI model.

Our findings reveal that, GiveDirectly project has many shown positive outcomes for key development indicators such as health, education, and financial stability. The offline payment delivery system via mobile money (M-Pesa) made accessibility and local acceptance easy and convenient. However, its long-term viability is still limited by high operating costs, reliance on centralised middlemen, and the need for continuous funding. Circles, on the other hand, has shown positive outcomes for building and fostering social trust, reciprocity, and financial independence in local networks. However, in Circles version 1, the participation rate declined after reaching its initial peak due to structural fragilities. Even though Circles 2.0 added better features, recent data shows that user engagement has been slowly going down over time. This shows how the difficulties in the engagement of people involved in decentralised spaces. GoodDollar transaction and user activity data show that the platform after reaching its initial peak, is facing a decline in the number of new claimers and active participants on both the Celo and Fuse blockchains. But positive outcomes are observed in various social trust and cohesion criteria. Blockchain based solution though address the issues of traditional UBI model but also introduce new set of risks that hinder their scalability and wide adoption. Based on the trade offs of both systems , we suggest a hybrid blockchain-based UBI framework, that addresses the existing issues and can lead to a more sustainable, apolitical and fair UBI ecosystem.

The subsequent sections of the doctoral thesis are structured as follows. Chapter 2, 3, 4, and 5 presents the first, second, third and fourth research paper, respectively. Each research paper is organized as follows. Section 1 presents the introduction, section 2 addresses the literature review, section 3 presents the data and methodology, and section 4 presents the primary results and findings. Lastly, section 5 finishes and outlines several policy implications.

Chapter 2

Systemic Risk in Crypto Assets: A Time-Varying Network and CoVaR Approach

(Iftikhar E. & Beccalli E.)

(Under Review in International Review of Economics and Finance)

Abstract

Decentralized blockchain ledger technology emerged as a viable solution to the “too connected to fail” problem after 2008 financial crisis, driven by the interdependencies in the financial system. However, because of recent crypto crashes and growing concerns over systemic fragility, this study investigates the effectiveness of blockchain-based crypto market by providing first longitudinal empirical evidence on the dynamic changes in crypto market interconnectedness and its influence on the systemic risk contribution over time by analyzing leading cryptocurrencies and stablecoins for the period of April 2020 to December 2024. By integrating time-varying network analysis with conditional Value-at-Risk (CoVaR), we reveal that crypto assets with highest centrality values (capturing their relative importance and interconnectedness in the network) are associated with greater systemic risk contributions; however, the relationship is not static but evolves with market structure shifts. The regression results show that the systemic risk contribution of crypto assets decreases over time with an increase in their connectedness in the system. This impact is more pronounced for cryptocurrencies than for centrally issued, managed, and governed stablecoins. Our findings suggest that pure network interconnectedness plays a diminished role in tail risk propagation in the crypto market. This temporal dimension offers new insights into evolving structural fragility of crypto markets and emphasizes the need to broaden systemic risk assessment frameworks by incorporating non-network-based structural channels such as stablecoin runs, leverage concentration, smart contract exploits, and external oracle failures that operate independently of direct interconnectedness and might play a more significant role in crypto market disruptions.

1. Introduction

In recent years, the growth of crypto assets has been very volatile. The total market capitalization of crypto assets was almost $3 trillion in November 2021 before dropping to less than $1 trillion in July 2022, and recently, it peaked at $220.58 billion with a market cap of 3.7 trillion on December 17, 2024. As the crypto ecosystem is expanding with the continuous influx of new crypto assets, it is becoming more integrated and interdependent and has created a network of 'systemically important crypto institutions' in the crypto ecosystem. These deregulated interdependencies have shown poor risk management and are often involved in market misconduct, a lack of transparency, inadequate risk management, and market malpractice (Arner et al., 2023).

The COVID-19 pandemic and different crypto crashes in currencies and exchanges severely affected the prices of crypto assets and caused volatility and uncertainty in the past few years (Hong & Yoon, 2022; Almeida et al., 2022). Analyzing the interconnectedness and systemic risk of crypto assets is crucial for determining how the network position and role of specific financial assets change following unexpected events like crises or bubbles. It is confirmed from previous studies that the contagion channels among cryptocurrencies are amplified during times of crisis because of increased integration and interdependence (e.g., Akhtaruzzaman et al., 2022; Arner et al., 2023; Bruhn & Dietmar, 2022). Thus, due to high price volatility, prior literature has identified the presence of price bubbles in the crypto market, characterized by co-explosive price movements and increased risk for investors in crypto assets. Stablecoins, fixed to a specific value and backed by fiat money (US dollar or Euro), are often used as a tool to mitigate price volatility in crypto markets. While the financial system has many potential benefits from global stablecoins, new risks are also emerging for monetary policy and financial stability (Group, 2019) as the credibility of stablecoins became a question when the ecosystems of Luna and Terra failed (Briola et al., 2023). The situation worsens when there is a lack of understanding about the market participants and the crypto ecosystem, and a lack of framework to understand the interconnectivity of services and entities in the system (Arner et al., 2023).

This overview of the current state of the crypto market sets the context for our study on the systemic risk and interdependencies of crypto assets and stablecoins. Existing literature has predominantly focused on static network representations to identify systemically important nodes in crypto markets and assess risk propagation. However, these approaches often overlook the dynamic nature of network structures and their temporal interaction with systemic risk. To address this gap, our study integrates a time series analysis of evolving network topologies with systemic risk metrics, offering a more granular understanding of how structural changes affect tail risk contributions over time.

Our study contributes to three key areas: systemic interconnectedness, risk assessment, and dynamic integration between interconnectedness and risk. Firstly, we delve into the interconnectedness of crypto assets, and track changes in their network topologies over time using network analysis based on the minimum spanning tree (MST). Secondly, we employ the conditional value at risk (CoVaR) methodology to measure risk in isolation, spillover effects, and the systemic risk contribution of these crypto assets. Lastly, we use regression analysis to explore the temporal relationship between the connectedness of crypto assets and their contribution to systemic risk, using their centrality and conditional ΔCoVaR values.

Our findings reveal that Ether among native cryptocurrencies is the most central and influential node from 2020-2024. Correspondingly, Ether is the highest systemic risk contributor according to the CoVaR analysis. USDT appears as a peripheral node and contributes the least to systemic risk. The MST weight calculated for each year from 2020 to 2024 reveals that the weight was lowest for 2022, in which many significant crypto crashes occurred. Furthermore, regression results indicate a significant negative relationship between the interconnection of crypto assets and their contribution to systemic risk with a stronger impact for native cryptocurrencies than stablecoins which suggests that high centrality assets may actually stabilize markets by distributing liquidity across fragmented pools. These results highlight that in decentralized crypto markets, systemic transmission of tail risk may depend less on network position and more on other non-network channels such as liquidity shocks, leverage cascades, stablecoin vulnerabilities, and smart contract exploitation that operate independently of direct interconnectedness, and imply the need for alternative risk models tailored to crypto’s unique market structure.

The remainder of the study is arranged as follows: Section 2 presents the relevant literature in this field and how our research adds to it. In Section 3, we present data, and in Section 4, we discuss the empirical methodology used in our study. Section 5 interprets the relevant empirical findings and discusses the corresponding results. Section 6 concludes the research findings.

2. Literature Review

The cryptocurrency market offers many potential investment opportunities but poses a greater risk for investors (Dasman, 2021). Studies investigating the uncertainty and risks in the cryptocurrency market have confirmed the presence of crypto bubbles in the crypto ecosystem

(Corbet et al., 2018; Bouri et al., 2019; Borri, 2019). During crises, the cryptocurrency market has exhibited co-explosivity in prices and returns, indicating a synchronized pattern of extreme movements across different cryptocurrencies. Numerous studies have investigated the co-explosivity dynamics among leading cryptocurrencies, employing various methodologies. Agosto and Cafferata (2020) confirmed the presence of high interdependence among cryptocurrencies and a significant relationship between cryptocurrencies' co-explosivity using a unit root testing approach. A research study by Ahelegbey et al. (2021) aimed to determine the relationship among crypto assets during turbulent times. Their investigation suggested the presence of extreme risks and a noteworthy positive correlation among the cryptocurrency tail risks. Akhtaruzzaman et al. (2022) also provided evidence of increased transmission channels of contagious shocks during the pandemic by employing a value-at-risk approach. However, the dynamics of systemic risk contribution of each asset over time with the changes in their network topologies and influence in the system has not been studied so far. So, this study seeks to close these gaps as it aims to provide insights into time varying network structures and their impact on risk characteristics of crypto assets.

Various methodologies are used to measure contagion or systemic risk in financial markets, including mathematical, statistical, econometric, network analysis, and predictive analysis tools (Denkowska & Wanat, 2020). The growing interconnections and interdependence of the cryptocurrency market require an interdisciplinary approach to study the structure and dynamics of the cryptocurrency market for the measurement of systemic risk. The existing literature on systemic risk measurement constitutes two main strands (Borri, 2012). The first, known as network modelling, looks into the overall loss distribution of all market participants during a specified period. In contrast, the second strand, known as the micro-evidence approach, examines the individual contributions of institutions to systemic risk (López-Espinosa et al., 2012). Our research uses a hybrid approach, employing network modelling and a micro-evidence approach for a holistic analysis.

Financial network models have four major types depending upon what their edges represent in a network, i.e., cross-shareholding, correlation, liabilities, and Granger causality (Tomeczek, 2021). For our study, we have adopted a correlation-based network, as according to Hong and Yoon (2022), correlation coefficients show how currencies work together in new and volatile markets. The methodology of an MST analysis of correlation networks in the cryptocurrency market is taken from multiple previous studies (Liang et al., 2018; Frances et al., 2018; Giudici & Polinesi, 2021; Burnie, 2018). By building a network using MST in which certain nodes communicate and influence one another, it becomes easy to analyze the level of cooperation amongst cryptocurrencies and the identification of those nodes that have a more significant impact on price fluctuations and market activity overall (Frances et al., 2018). MST analysis is useful for assessing systemic risk and building portfolios (Onnela et al., 2003). Furthermore, the impact of a crisis on the dynamics of a stock market can also be evaluated by examining the combined weight of an MST and the rapid changes in network structure. MSTs usually contract during stressful or high-volatility periods, causing a reduction in MST's total weight. Economists, investors, and regulators can all benefit from MST graphs, weights, and centrality values (Tomeczek, 2022).

The micro evidence approach offers different measures to analyze the marginal contribution of each institution to systemic risk. CoVaR is one of the notable proposals in literature (Lin et al., 2018) developed by Adrain and Brunnermeier (2011) in their paper, in which co stands for conditional, contagion, or co-movement, highlighting the systemic aspect of their risk assessment. CoVaR is based on the value at risk (VaR) conditioned on the institutional distress. Additionally, they proposed a metric called ΔCoVaR, which is the difference between an institution's CoVaR in a distressed state and the same metric in a median state, to quantify how much a single institution contributes to systemic risk. Previous research has confirmed the importance of CoVaR analysis as a useful method for examining the contribution of different entities to systemic risk and risk spillover in the cryptocurrency market (Likitratcharoen et al., 2018; Borri, 2019; Almeida et al., 2022; Waltz et al., 2022). Lastly, a simple linear regression analysis is performed to determine if a statistically significant relationship exists between the varying levels of interconnection of crypto assets and their contribution to systemic risk. Regression analysis is the most frequently used method to determine the relationship between dependent and independent variables (Sarstedt et al., 2019) in cryptocurrency markets (Akbulaev et al., 2020; Yatsyk, 2020; Gil-Alana et al., 2020; Baranovskyi et al., 2023

The hybrid approach adopted in this study introduces three key extensions. First, the use of the Minimum Spanning Tree (MST) provides a parsimonious representation of the most relevant dependencies, avoiding the noise inherent in dense correlation networks. Second, systemic risk is explicitly quantified using ΔCoVaR, allowing for the assessment of each node's marginal contribution to tail risk. Third, and most importantly, both network topology and systemic risk measures are allowed to evolve over time, enabling a dynamic analysis of the relationship between interconnectedness and systemic risk.

This integrated and time-varying framework provides insights that cannot be captured in static network analyses, particularly regarding how the role of central nodes changes across different market conditions.

3. Data

The data for the daily adjusted closing prices of 7 native cryptocurrencies and 2 stablecoins has been collected from the webpage www.coinmarketcap.com, which has been extensively used in many studies (Yi et al., 2018; Francés et al., 2018; Liang et al., 2018; Hasan et al., 2022) for the period of April 4, 2020, to December 31, 2024. The selected timeframe covers the periods of growth in the cryptocurrency market and includes events of major crises in the crypto ecosystem and the traditional finance including the COVID-19 market shock, the 2022 monetary tightening cycle, Terra-Luna collapse, the failure of major crypto lending platforms, and the FTX collapse. Thus, it aligns with our objective of analysing network topologies under varying market conditions. The chosen cryptocurrencies and stablecoins have the highest market capitalization, which covers more than 86% of the total market capitalization.

Those stablecoins that are pegged to the dollar (USDT and USDC) are included in our analysis. The returns of the SP500 Index, the CBOE VIX volatility index, and the market capitalization of cryptocurrencies are chosen as state variables which represent market condition of crypto ecosystem and the traditional financial market. Data for returns of the SP500 index and the CBOE volatility index has been collected from the LSEG workspace. Data for the market capitalization of cryptocurrencies has been collected from www.coinmarketcap.com. These variables represent trends and expectations, and business cycles. The total daily observations are 1726. The price data is transformed into log return values in percentage form to study correlations.[1] The returns of cryptocurrencies and stablecoins are shown in Figure 1 and Figure 2, respectively and the summary statistics of our data are presented in Table 1.

Table 1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
BTC	1,726	0.001508	0.031857	-0.17252	0.176026
ETH	1,726	0.001772	0.041307	-0.3052	0.219406
XRP	1,726	0.001385	0.054596	-0.54955	0.544472
BNB	1,726	0.002281	0.044508	-0.38395	0.552656
SOL	1,726	0.003067	0.067164	-0.54817	0.384486

[1] $r_i(t) = \ln P_i(t) - \ln P_i(t-1)$

DOGE	1,726	0.002942	0.074406	-0.50707	1.479104
ADA	1,726	0.001879	0.04954	-0.28251	0.269196
USDC	1,726	3.25E-07	0.002429	-0.02849	0.028665
USDT	1,726	-1.89E-06	0.002137	-0.01973	0.017314

Notes: This table presents the summary statistics of all crypto assets included in our dataset.

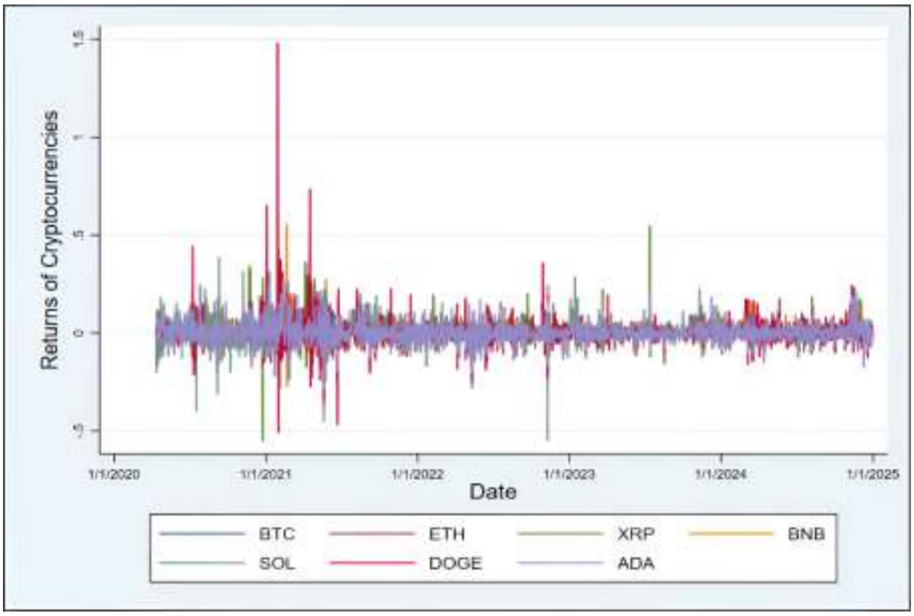

Fig 1. Returns of Cryptocurrencies (2020-2024)

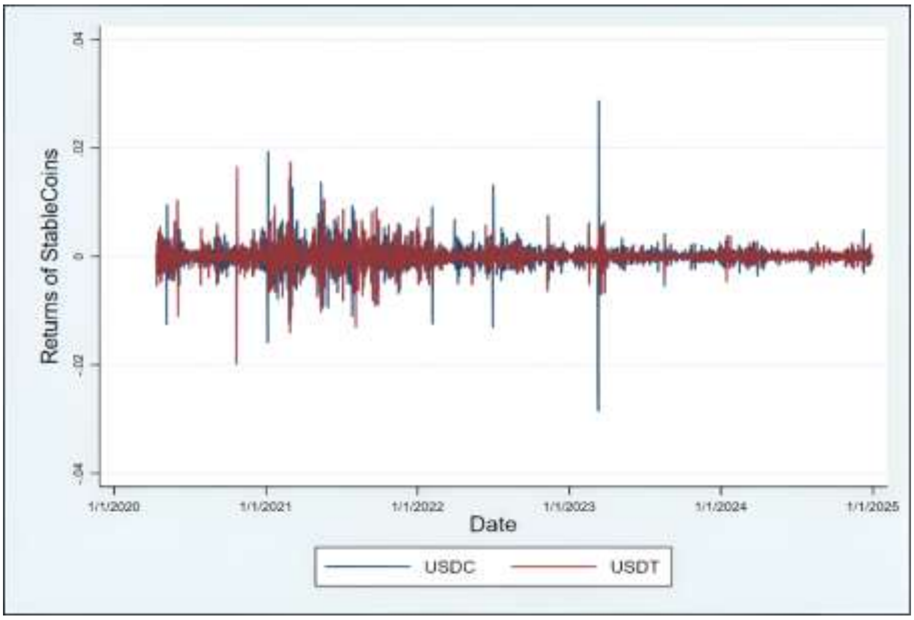

Fig 2. Returns of Stablecoins (2020-2024)

4. Methodology

4.1 MST Analysis for the measurement of interconnectedness

Mantegna (1999) originally proposed the MST approach for examining the topology of financial markets. Creating the matrix of correlations between the daily returns of all the cryptocurrencies under study is the first step in building the "Minimum Spanning Tree" (MST). This yields the coefficients of the Pearson correlations between each pair of currencies, *i* and *j*, which are defined as:

$$C_{ij} = \frac{n(\sum r_i r_j) - (\sum r_i)(\sum r_j)}{\sqrt{[n\sum r_i^2 - (\sum r_i)^2]\,[n\sum r_i^2 - (\sum r_i)^2]}} \tag{1}$$

A correlation matrix is obtained:

$$C = \begin{bmatrix} C_{11} & \cdots & C_{1N} \\ \vdots & \ddots & \vdots \\ C_{N1} & \cdots & C_{NN} \end{bmatrix} \tag{2}$$

N is the total number of currencies (36 in our study), and C_ij values range between -1 and 1.

The elements of the correlation matrix C_ij can be converted into distances, according to Mantegna and Stanley (1999), to create a distance matrix where

$$d_{ij} = \sqrt{2(1 - C_{ij}})\tag{3}$$

The value ranges from 0 to 2, so the distance will be short if the correlation is high among cryptocurrencies. To construct an MST, we combine nodes N (which are the native cryptocurrencies and stablecoins) with links N–1, and thus, the total of all the distances of the links is the smallest. So, the most relevant data will be taken out of the correlation matrix using the N–1 linkages. We have created the MST that employs the Kruskal algorithm (1956) by following Mantegna and Stanley (1999) and Stanley and Mantegna (2000). We employed the following steps for creating the MST graph: First, using the distance matrix, we selected N (N – 1) / 2 elements in ascending order, then chose the cryptocurrency pair with the shortest distance and included the link to the graph. After that, we added the link to the next pair of cryptocurrencies with the smallest distance between them. The exact process is repeated until all the currencies are linked in the MST graph.

While MST captures the strongest connections within the cryptocurrency network, alternative network constructions may also be considered. For example, full correlation networks, threshold based graphs, or partial correlation networks would generate denser structures that retain a larger set of pairwise relationships. Similarly, alternative dependence measures could also capture nonlinear interconnections more explicitly. A denser network, such as a threshold correlation graph (where edges are retained if correlations exceed a specified value) or a Planar Maximally Filtered Graph (PMFG), would retain more connections and might produce higher centrality values for nodes that are moderately correlated with many others. For our research, using such alternatives could potentially amplify the centrality of stablecoins, which exhibit low but broad based correlations across many assets. Alternative dependence structures, such as tail-dependence matrices derived from copula models or rank correlations, could capture non-linear co-movements that intensify during crisis periods. If such measures were employed, the centrality of assets like BTC and ETH during the 2022 crises might appear even more pronounced. Therefore, the choice of MST in this study is motivated by its ability to filter noisy correlations and highlight the most significant and meaningful linkages while preserving interpretability and comparability across assets.

For our network construction, different centrality measures were collected from MST, indicating various aspects of cryptocurrencies' interconnectedness. These four centrality measures include degree centrality, betweenness centrality, closeness centrality, and eigenvector centrality.

4.1.1 Degree centrality

Degree centrality counts the number of edges a node is linked to in a network. It is the primary centrality metric and could be regarded as the instant risk circulating through the network that a node can contract.

$$\text{Degree centrality of Node } (i) = \text{Total number of edges connected to node } (i) \tag{4}$$

4.1.2 Closeness centrality

The distance of a node from another node in the network is calculated by its closeness centrality. This centrality metric shows a node's level of impact within a network. Its closeness to other nodes in the network is demonstrated by its closeness centrality.

Centrality and closeness could be determined as

$$\text{Closeness Centrality (i)} = \frac{N-1}{\sum_{j=1}^{N} d(i,j)} \tag{5}$$

While N is the total number of nodes in the graph, and *d (i, j)* is the shortest path between node *i* and node (*j*). While $\sum_{j=1}^{N} d(i,j)$ denotes the total of the shortest distances between node (i) and all other nodes (j) in the network.

4.1.3 Betweenness centrality

The shortest distance between two nodes is measured by betweenness centrality. It detects the nodes that serve as links between various nodes. The node with a high betweenness centrality can significantly influence the information flow in the network. It displays the most significant vertex that joins several vertex pairs.

$$\text{Betweenness Centrality} = a_0 + \sum_{\mathrm{s \neq v \neq t}} \frac{\sigma \mathrm{st(v)}}{\sigma \mathrm{st}} \tag{6}$$

Whereas $\Sigma\mathrm{st}$ is the total number of shortest paths from node (s) to node (*v*), and $\sigma\mathrm{st(v)}$ is the total number of shortest paths from node (s) to node (t) that pass through node (v).

4.1.4 Eigenvector centrality

Another term for eigenvector centrality is Broncich's centrality. It calculates a node's connections within its local network. The node with the highest eigenvector value is the most powerful, and its power originates from its relationships with other strong or weak nodes.

$$\text{Eigenvector Centrality (v)} = \frac{1}{\lambda} \sum_{j=1}^{n} \alpha\, j, v\ (centrality\ j) \tag{7}$$

4.2 CoVaR for the Measurement of Systemic Risk

Adrian and Brunnermeier (2011) introduced CoVaR, one of the systemic risk measures. According to the definition, CoVaR is the VaR of a financial system conditional on various institutions experiencing distress. In this context, "distress" is an institution falling below its

1%-VaR level. VaR is the maximum loss that can occur with a given probability during a given time frame.

$$VaR_a(L) = \{l: \Pr(L > l) \leq 1 - a\} \tag{8}$$

It is the smallest loss *l* for which the probability of a future loss L greater than loss *l* is equal to or less than 1 - a. As demonstrated in this study, CoVaR can also be used to analyze the risk exposure of one entity to another, such as the systemic risk contribution of a corporation to a financial system (or market).

$$\Delta\mathrm{CoVaR}_q^{J|i} = \mathrm{CoVaR}_q^{J|X^i=VaR_q^i} - \mathrm{CoVaR}_q^{J|X^i=VaR_{Median}^i} \tag{9}$$

ΔCoVaR is defined as CoVaR conditional on the institution *(i),* which is under distress (at its 1%-VaR), minus the CoVaR that is conditional on the institution *(i),* which is in its median state (at its 50%-VaR). Unconditional CoVaR and ΔCoVaR are estimated for 9 crypto assets, including native cryptocurrencies and stablecoins, which yield CoVaR values that stay constant across time. A time-varying ΔCoVaR analysis is also performed to check the robustness of our results by including the state variables (the SP500 index, the CBOE Volatility Index, and the market cap of the crypto market), which serve as proxies for traditional and crypto market trends. When discussing CoVaR in this article, CCM is the cryptocurrency market, and *i* indicate specific cryptocurrencies' returns. The derivation of equations for the estimation of unconditional and conditional VaR, CoVaR, and ΔCoVaR is given in Appendix A.

4.3 Relationship between interconnectedness and contribution to systemic risk

The conditional time-varying values are then regressed against centrality values calculated from MST analysis. The frequency of observations is reduced to 57 months, and the results still hold validity and align with the results generated from the high-frequency data of daily observations. Linear regression is employed to predict the dependent variable y, which in our research is the conditional time-varying ΔCoVaR values, and the independent variables include centrality values (Degree, Closeness, Betweenness, and Eigenvector) calculated from MST analysis.

$$\Delta CoVaR_i = \beta_o + \beta_1 Centrality\, Values_i + \varepsilon \tag{10}$$

5. Research Findings and Discussion

5.1 Results of MST analysis

MST based centrality values were calculated for individual years and the entire period of 2020-2024, which shows that centrality values of crypto assets kept changing each year in response to specific events in that year. The position of most central and peripheral nodes was also shifted; however, the MST calculated for the entire period 2020-2024 shows that ETH is the most influential cryptocurrency, with the highest values for all centrality measures, given in Table 2.

Table 2. MST centrality values (2020-2024)

Variables	Degree	Betweenness	Closeness	Eigenvector	Index
BTC	3	17	0.0714	0.1784	5.06245
ETH	4	21	0.0769	0.2225	6.32485
USDT	1	0	0.0385	0.0441	0.27065
XRP	1	0	0.04	0.055	0.27375
BNB	1	0	0.05	0.099	0.28725
SOL	1	0	0.05	0.099	0.28725
DOGE	1	0	0.0476	0.0794	0.28175
USDC	2	7	0.0526	0.099	2.2879
ADA	2	7	0.0556	0.1235	2.294775

Notes: This table presents a summary of native cryptocurrencies and stablecoins that have the highest and lowest centrality values. These centrality values are calculated from the MST graph and constitute four centrality measures (Degree, Betweenness, Closeness, Eigenvector and Index of all centrality values). Detailed results are reported in Appendix B.

As the cryptocurrency market matured and boomed in 2021, several currencies exceeded the market leader, Bitcoin. The returns on ETH increased to 399.2% due to the development of DeFi 2.0 protocols, making ETH the most influential and central cryptocurrency in 2021 (Kumar et al., 2022; Katsiampa et al., 2022). In 2022, even though ETH lost 66% of its value from the start to the end of the year, as it transitioned from proof of work to proof of stake and market crash triggered by the FTX exchange's collapse caused a severe hit to the price of ETH, but it remained the most prominent cryptocurrency in 2022 and observed an 85% increase in market cap in 2023. Many decentralized applications run on the Ethereum blockchain, making ETH the most central, popular, and influential node in the cryptocurrency network (Ciaian et al., 2018; Francés et al., 2018). USDT was found to be the peripheral node with the smallest centrality values throughout the period, which shows that USDT is least affected by changes in cryptocurrency prices and thus can provide hedging against volatile currencies and bear the properties of a safe haven during turbulent times. MST plot for each year and the entire period is shown in Figure 3 and detailed MST centrality values calculated for each year are reported in Appendix B, Table 1.

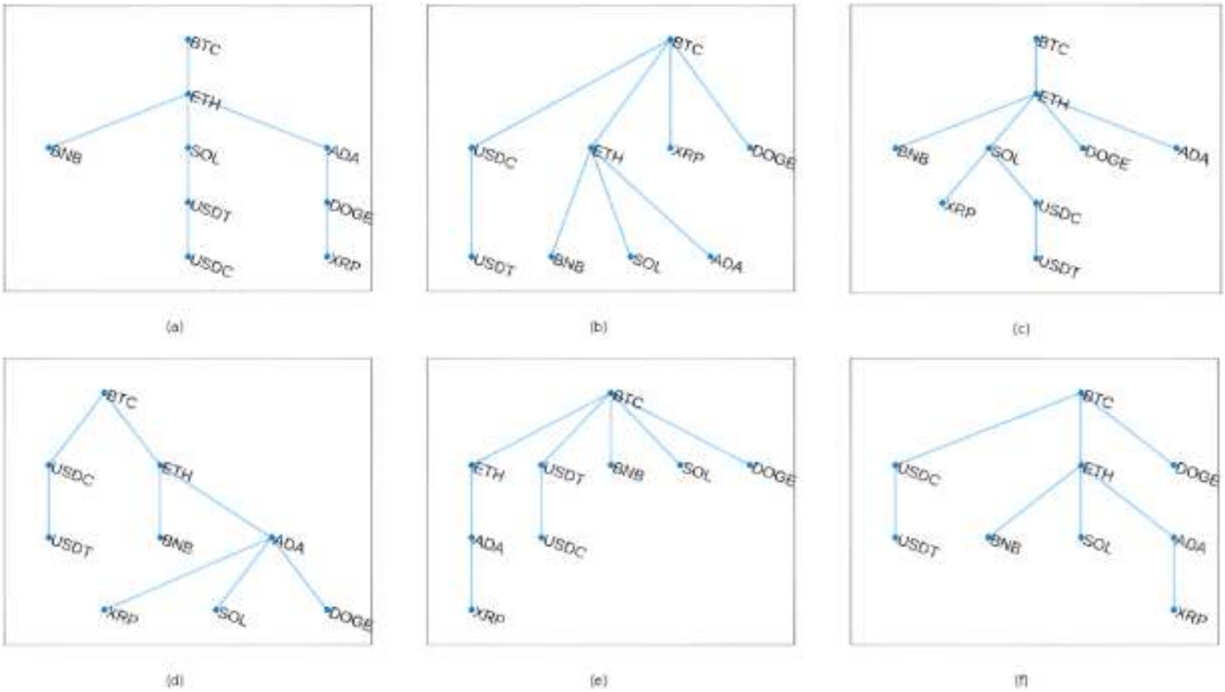

Fig 3. Minimum Spanning Tree for each year 2020, 2021, 2022, 2023, 2024, and for the entire period 2020 – 2024 labelled as (a), (b), (c), (d), (e), and (f), respectively.

5.2 MST Weight

MST weight represents the co-movement of prices of crypto assets, which becomes weak during crises (Frances et al., 2018). The MST weight calculated for each year is presented in Table 3.

Table 3. MST weight for each year (2020-2024)

Year	MST Weight
2020	2.8988
2021	3.5077
2022	2.5514
2023	4.137
2024	3.8432

Notes: This table presents the MST weight calculated for each year from 2020 to 2024. MST weight shows the strength of the connections in the MST graph. During crises, these connections become weak, and as a result, the weight of the MST graph is reduced.

MST 2022 has a weight of 2.5514, the smallest of all MST weights, which suggests the weak connection among market participants and the emergence of specific nodes during periods of crisis (Tomeczek, 2022) as the same year observed two major crypto crashes i.e., Terra-Luna collapse and FTX collapse. The high MST weight in 2023 shows a market recovery.

5.3 Results of CoVaR Analysis

The summary results of unconditional estimates of ΔCoVaR values are given in Table 4 (Panel A). The systemic risk contribution is highest for ETH in unconditional results at different quantile levels, i.e. 0.01, 0.05, and 0.10. Our results align with the results generated by previous studies, such as Chen et al. (2024), who analyzed the risk-connectedness of five cryptocurrencies (BTC, ETH, ADA, LTC, and BNB) during periods of extreme events and showed that Ether leads in risk spillover at all order moments. Extreme tail risk in BTC, ETH, LTC, and XRP was also found in the ΔCoVaR analysis conducted by Borri (2019), and all cryptocurrencies were found to be highly correlated both conditionally and unconditionally.

Table 4. Unconditional and Conditional ΔCoVaR Results (2020-2024)

	Panel A. Unconditional ΔCoVaR			**Panel B. Conditional ΔCoVaR**		
Nodes	**At 0.01**	**At 0.05**	**At 0.10**	**At 0.01**	**At 0.05**	**At 0.10**
BTC	-0.0724	-0.0387	-0.0679	-0.07595	-0.03807	-0.02506
ETH	-0.0762	-0.0400	-0.0728	-0.07281	-0.03898	-0.02693
USDT	-0.0172	-0.0005	-0.0012	-0.00066	-0.00164	-0.00019
XRP	-0.0469	-0.0283	-0.0550	-0.0454	-0.02714	-0.01842
BNB	-0.0489	-0.0319	-0.0582	-0.05207	-0.02956	-0.02102
SOL	-0.0510	-0.0295	-0.0544	-0.05068	-0.03015	-0.02236
DOGE	-0.0355	-0.0223	-0.0505	-0.03197	-0.02322	-0.01683
USDC	-0.0199	-0.0059	-0.0061	-0.0216	-0.00562	-0.00092
ADA	-0.0539	-0.0323	-0.0595	-0.05331	-0.03304	-0.0239

Notes: This table summarises the estimates for unconditional and conditional ΔCoVaR calculated for different quantiles, i.e. 1%, 5%, and 10%, for 2020 to 2024. Detailed results of VaR, CoVaR, and ΔCoVaR for native cryptocurrencies and stablecoins are given in Appendix B.

Conversely, USDT has the lowest systemic risk contribution in CoVaR analysis at all quantile levels, i.e. 0.01, 0.05, and 0.10. Similar results were produced by the research conducted by Wang et al. (2020), who investigated stablecoins by using time-varying copula models for mixed cryptocurrency-stable coin portfolios. They discovered that USDT shows the best characteristics of a strong hedge for risk diversification. Another research by Xie et al. (2021)

showed that USDT's status as a safe haven before, during, and after the pandemic. Furthermore, when USDT is added to the portfolio, it outperforms the naked portfolio and the portfolio backed by traditional assets, i.e., gold. Research conducted by Baur and Hoang (2021) provided evidence for the safe haven properties of stablecoins, specifically USDT. Stablecoin USDT, in response to the extreme price volatility and negative returns of Bitcoin, behaves positively and thus offers investors security and protection, lowering overall risk in the cryptocurrency market. The results confirm that during 2020-2024, ETH appear to have the highest centrality values and correspondingly has the highest systemic risk contribution at different quantiles. Conversely, USDT, which has the lowest centrality values, contribute the least to the systemic risk at different quantiles.

5.4 Robustness check and Extension of CoVaR Analysis

To check the robustness of the results of CoVaR analysis, time-varying ΔCoVaR analysis was performed by including state variables. Conditional estimates are time-varying and capture the aspect of time in the analysis. The summary results of conditional estimates of ΔCoVaR for all cryptocurrencies and stablecoins are presented in Table 4 (Panel B), which shows that BTC has the highest systemic risk contribution at 0.01 and at 0.05 and 0.10, ETH has the highest systemic risk contribution. USDT is found to be the least systemic risk contributor at all quantile levels. These results confirm our unconditional results discussed in Section 5.2 and also align with the studies which confirm that BTC and ETH as net transmitters of risk in the cryptocurrency market (Bruhn and Dietmar, 2022; Hasan et al., 2021; Koutmos, 2018; Mensi et al., 2021).

5.5 Results of Regression Analysis

To ascertain the temporal relationship between the interconnectedness and systemic risk contribution, we employed linear regression between centrality values (betweenness, closeness, degree, and eigenvector) and time-varying ΔCoVaR values. The summary results regression analysis for native cryptocurrencies are reported in Table 5, which show that a significant negative relationship exists between each centrality value and the ΔCoVaR values of cryptocurrencies. The coefficient value of regression between betweenness and ΔCoVaR is -.001 with 0.028$R^2\ value$, -0.599 with 0.023 $R^2\ value$ for closeness, -.007 with 0.025 $R^2\ value$ for degree centrality, and -0.14 with 0.025 $R^2\ value$ for eigenvector indicating decrease in systemic risk with increase in centrality metrics. The regression results for stablecoins are reported in Table 6, which also indicates the presence of a negative and significant relationship between ΔCoVaR and the degree centrality value. The relationship with closeness and eigenvector is found to be insignificant. The coefficient value for degree is -0.002, with .007$R^2\ value$. A Wald test was conducted to assess the joint significance of the model coefficients. The results confirmed a significant negative relationship between centrality and systemic risk contribution for native cryptocurrencies. For stablecoins, however, only degree centrality exhibited a significant negative association.

Table 5. Regression Results for Cryptocurrencies and Stablecoins

tDCoVaR	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
Native Cryptocurrencies	-.007***	-.599***	-.001***	-.14***
	(0.002)	(0.195)	(0.00)	(0.044)
Adj-R square	0.025	0.023	0.028	0.025
Stablecoins	-.002***	-0.067	0.00***	-0.01
	(0.001	(0.045)	(0.00)	(0.011)
Adj-R square	0.063	0.020	0.067	0.007

**** p<.01, ** p<.05, * p<.1*

Notes: This table shows estimates of regression analysis, which is performed on time-varying ΔCoVaR values (dependent variable) and centrality values (independent variable) of native Cryptocurrencies and Stablecoins.

5.6 Endogeneity, Reverse Causality and Temporal dynamics

A central consideration in this study is the potential for endogeneity, particularly reverse causality, between centrality measures and systemic risk contribution (ΔCoVaR). To empirically assess the presence of reverse causality, additional robustness tests were conducted. First, Granger causality tests were implemented to examine the direction of predictive relationships between centrality and ΔCoVaR. Second, lagged centrality measures were employed to mitigate simultaneity between network position and systemic risk contribution and to assess their temporal dynamics. Specifically, for each t, ΔCoVaR was regressed on centrality values from $t-1$ and $t-2$, controlling for the same state variables as in the main specification. The results for reverse causality and lagged regression are reported in Appendix C. The Granger Causality test showed no evidence of reverse causality and at the same time, lagged regression specifications reveal marginally significant effects, particularly at the first lag, indicating limited short term temporal dependence. Taken together, these findings suggest that the relationship between centrality and systemic risk is primarily contemporaneous, with limited predictive power.

5.7 Discussion

Contradicting views are found in the literature regarding the causes of risk and contagion behaviour of financial assets and institutions, and how their network structure impacts them. Freixas et al. (2000) state that a more integrated network structure makes the system more resilient to any bank's insolvency. For instance, Allen and Gale (2000) contend that in a financial network with a greater density of connections, a bank's losses in trouble are distributed among multiple nodes, lessening the effect of adverse shocks on specific institutions in the remainder of the framework. However, some researchers have argued that the more interconnected and concentrated a network is, the more it is vulnerable to contagions and shocks (Blume et al., 2011). Both views hold in the case of our research results. The native cryptocurrency at the core of our minimum spanning tree and with the highest centrality values is Ether, and is also found to be the highest risk contributor when the cryptocurrency market is distressed. On the contrary, the stablecoin found at the periphery of the minimum spanning tree, such as USDT, is the least systemic risk contributor, according to CoVaR analysis. These periphery nodes are least impacted by the changes in the prices of central nodes and, therefore, can act as a safe haven for crypto investors.

Regression analysis shows the impact of varying dynamics of network topologies of crypto assets and their systemic risk contribution over time. Results show that the systemic risk contribution of cryptocurrencies decreases with the increase in their interconnections in the crypto ecosystem, as demonstrated by a negative relationship with each centrality measure, but in the case of stablecoins, only degree centrality showed a significant negative relationship. The results suggest that systemic risk in crypto is less about network position and more about liquidity fragility. High-centrality assets may actually stabilize markets by distributing liquidity across fragmented pools, while tail risks emerge from non-network channels including excessive leverage, shared dependence on key external components (e.g., oracles manipulation and stablecoins run), and liquidity fragmentation across chains, and correlated trading behavior during stress events as observed in recent crypto market crashes.

Significant regression results confirm that the network position is a meaningful correlate of systemic importance. However, the direction of this negative relationship inidcates deeper interpretation of the underlying causal mechanisms. Accordingly, the negative coefficient does not imply that central assets are risk free, but rather that their marginal systemic contribution relative to normal conditions may be mitigated by liquidity depth and structural integration. Several factors may explain this pattern such as liquidity distribution effect. As highly central tokens, such as BTC and ETH are the deepest and most liquid markets. In a well-functioning financial market, deep liquidity acts as a shock absorber reducing the marginal systemic impact of individual assets. Thus, centrality may proxy for liquidity resilience, which reduces the asset's contribution to systemic risk, even as its importance to the network grows. Another contributing reason is crypto market maturation. The sample period (Apr 2020 – Dec 2024) captures a phase of significant maturation for major cryptocurrencies like BTC and ETH. As these assets have become more integrated into traditional finance and adopted by institutional investors, their return distributions have exhibited lower idiosyncratic crypto shocks and greater sensitivity to macro financial variables (as seen in the conditional results with SPX, MSCI and VIX). This maturation process means that while crypto assets remains central, their systemic risk contribution may have declined relative to earlier periods. Furthermore, endogenous network growth of large crypto assets occurs due to their perceived stability and utility. This creates a self-reinforcing cycle where the most successful assets become more central because they are perceived as safer and less risky as their systemic relevance grows, potentially diffusing their risk contribution.

The supplementary analysis of reverse causality and lag structures yields additional insights that deepen the interpretation of the main findings. The absence of reverse causality reflect the relatively slow moving nature of network structure compared to short-term fluctuations in systemic risk. While ΔCoVaR captures time-varying risk contributions, centrality measures reflect the structural position of assets within the network, which evolves more gradually. As a result, changes in systemic risk do not immediately translate into shifts in network centrality.

5.8 Limitations

While the regression framework models centrality as an explanatory variable for systemic risk contribution, it is important to acknowledge the limits of causal identification. Centrality and systemic risk may be jointly determined by underlying market conditions, trading intensity, or volatility shocks as supported by additional empirical analysis. Additionally, reverse causality may arise if systemically important assets attract higher trading volumes and stronger co-movements, thereby increasing their network centrality. The results thus provide, evidence of association rather than definitive causal effects.

6. Conclusions

These results have important theoretical and practical implications. The network analysis and CoVaR results reveal that crypto assets with highest centrality values are associated with highest systemic risk contribution. However, after incorporating a time series dimension into network-based systemic risk analysis, this study advances current understanding of risk propagation in crypto markets. Our findings reveal that the impact of interconnectedness on systemic risk is not static, but evolves as network structures change as the crypto markets exhibit lower tail risk propagation through network structures. However, this does not eliminate systemic vulnerabilities instead, it shifts them toward liquidity dependencies, leverage amplification, oracle failures and smart contracts exploitation. Liquidity dependencies can amplify shocks when participants rely on common liquidity pools, potentially triggering rapid asset sell-offs. Oracle failures may introduce incorrect price signals, resulting in mispriced collateral and subsequent losses. Depegging events and stablecoin runs can generate severe systemic disruptions. Finally, vulnerabilities in smart contracts can be exploited to generate sudden and severe losses, undermining confidence and triggering broader market disruptions. While these channels do not arise directly from network topology, they can interact with and magnify network based contagion, highlighting the multi-layered nature of systemic risk in decentralized finance. These findings suggest that regulators and market participants should prioritize monitoring these non-network structural channels even in the absence of tightly coupled network effects.

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Appendix A

A.1 Estimation of VaR, CoVaR, and ΔCoVaR

ΔCoVaR is calculated as the 1% CoVaR minus the 50% CoVaR. Adrian and Brunnermeier (2011) propose referring to $\Delta\mathrm{CoVaR}_q^{J|i}$ where i is the definition of the financial system as "exposure CoVaR" since it quantifies an institution's vulnerability to systemic financial events. The $\Delta\mathrm{CoVaR}_q^{J|i}$ metric is interesting because it can assist with determining the most critical enterprises in terms of being most at risk during financial crises. CoVaR methodology is implemented using the quantile regression (QR) method (Koenker and Bassett, 1978). The base of QR is the minimization of the absolute value of the sum of the residuals, weighted asymmetrically through the quantile dependent on whether they are positive or negative.

A.2 Unconditional estimation of VaR, CoVaR, and ΔCoVaR

The QR approach makes it simple to estimate CoVaR. To obtain $CoVaR^{CCM|i}$ we need to calculate 1% and 50%-VaR of cryptocurrency returns i, for i = 1, 2,…, 36, QR is run of *i*'s returns on a constant only, (with q=1% and q=50%) for median state VaR:

$$X_q^i = \alpha_q^i + \varepsilon_q^i \tag{A.1}$$

$$VaR_q^i = \hat{a}_q^i \tag{A.2}$$

Similarly, for the system,

$$X_q^{system} = \alpha_q^{system} + \varepsilon_q^{system} \tag{A.3}$$

$$VaR_q^{system} = \hat{a}_q^{system} \tag{A.4}$$

In order to get the $CoVaR^{CCM|i}$, we (quantile) regress the cryptosystem's returns on a constant and on the returns of cryptocurrency i:

$$X_q^{CCM|i} = \alpha_q^i + \beta_q^i X^i + \varepsilon_q^i \tag{A.5}$$

After getting the coefficients of α and β from QR, we construct $CoVaR^{CCM|i}$, by putting them together with VaR_q^i,

$$CoVaR_q^{CCM|X^i=VaR_q^i} = VaR_q^{CCM} | VaR_q^i = \hat{a}_q^i + \hat{\beta}_q^i VaR_q^i \tag{A.6}$$

and further, construct ΔCoVaR

$$\Delta CoVaR_{q=1\%}^{CCM|i} = \hat{\beta}_{q=1\%}^i \ (VaR_{q=1\%}^i - VaR_{q=50\%}^i) \tag{A.7}$$

A.3 Conditional estimation of VaR, CoVaR, and ΔCoVaR

Unconditional estimation is incorporated with additional macro variables to get more refined ΔCoVaR values.

Then QR is run for all cryptocurrency returns (i = 36) for quantile q=1% and q=50%. This will yield time-varying 50%-VaR and 1%-VaR series, conditioned on the vector M's macro variables.

$$X_t^i(q) = \alpha_q^i + \beta_q^i M_t + \varepsilon_t^i \tag{A.8}$$

Using estimates of α and β, we can generate a conditional VaR series for i,

$$VaR_t^i(q) = \hat{\alpha}_q^i + \hat{\beta}_q^i M_t \tag{A.9}$$

Time-varying cryptosystem VaR series is also generated in the same way,

$$X_t^{system}(q) = \alpha_q^{system} + \beta_q^{system} M_t + \varepsilon_t^{system}$$

(A.10)

$$VaR_t^{system}(q) = \hat{\alpha}_q^{system} + \hat{\beta}_q^{system} M_t \tag{A.11}$$

For calculating CoVaR and ΔCoVaR, the following regressions for q=1% and q=50% are run,

$$X_t^{system|i}(q) = \alpha_q^{system|i} + \beta_{q,1}^{system|i} X_t^i + \beta_{q,2}^{system|i} M_t + \varepsilon_t^{system|i} \tag{A.12}$$

$$CoVaR_t^i(q) = \hat{\alpha}_0^{system|i} + \hat{\beta}_{q,1}^{system|i} VaR_t^i(q) + \hat{\beta}_{q,2}^{system|i} M_t \tag{A.13}$$

Where X_t^i, are the cryptocurrency returns i. Each cryptocurrency's systemic risk contribution is estimated as follows:

$$\Delta CoVaR_t^i(q) = CoVaR_t^i(q) - CoVaR_t^i(q = 50\%) \tag{A.14}$$

$$\Delta CoVaR_t^{system}(q) = CoVaR_t^{system}(q) - CoVaR_t^{system}(q = 50\%) \tag{A.15}$$

Thus, this approach calculates the time-varying risk contribution of each cryptocurrency to overall market systemic risk in times of distress.

Appendix B

Table B.1 Detailed results of MST Centrality Values for each year (April 2020-December 2024)

MST 2020				
Variables	Degree	Betweenness	Closeness	Eigenvector
BTC	1	0	0.0476	0.1083
ETH	4	22	0.0714	0.2356
USDT	2	7	0.0455	0.0862
XRP	1	0	0.0345	0.0396
BNB	1	0	0.0476	0.1083
SOL	2	12	0.0588	0.148
DOGE	2	7	0.0455	0.0862
USDC	1	0	0.0345	0.0396
ADA	2	12	0.0588	0.148
MST 2021				
Variables	Degree	Betweenness	Closeness	Eigenvector
BTC	4	21	0.0833	0.209
ETH	4	18	0.0769	0.1992
USDT	1	0	0.0417	0.047
XRP	1	0	0.0526	0.0895
BNB	1	0	0.05	0.0853
SOL	1	0	0.05	0.0853
DOGE	1	0	0.0526	0.0895
USDC	2	7	0.0588	0.1097
ADA	1	0	0.05	0.0853
MST 2022				
Variables	Degree	Betweenness	Closeness	Eigenvector
BTC	1	0	0.0526	0.1009
ETH	5	22	0.0833	0.2398
USDT	1	0	0.04	0.0357
XRP	1	0	0.05	0.0699
BNB	1	0	0.0526	0.1009
SOL	3	17	0.0769	0.1661
DOGE	1	0	0.0526	0.1009
USDC	2	7	0.0556	0.0849
ADA	1	0	0.0526	0.1009
MST 2023				
Variables	Degree	Betweenness	Closeness	Eigenvector
BTC	2	12	0.0588	0.1147
ETH	3	19	0.0714	0.1893
USDT	1	0	0.0345	0.0293
XRP	1	0	0.0455	0.099
BNB	1	0	0.0476	0.0854
SOL	1	0	0.0455	0.099
DOGE	1	0	0.0455	0.099
USDC	2	7	0.0455	0.065
ADA	4	18	0.0667	0.2194
MST 2024				
Variables	Degree	Betweenness	Closeness	Eigenvector

BTC	5	24	0.0833	0.2516
ETH	2	12	0.0667	0.1378
USDT	2	7	0.0588	0.131
XRP	1	0	0.037	0.0306
BNB	1	0	0.0526	0.1072
SOL	1	0	0.0526	0.1072
DOGE	1	0	0.0526	0.1072
USDC	1	0	0.0417	0.0558
ADA	2	7	0.05	0.0717

Notes: Degree measures the local importance of a node, while closeness, eigenvector and betweenness measure the systemic importance of a node.

Table B.2 Detailed results of unconditional VaR, CoVaR, and DCoVaR for native cryptocurrencies and stablecoins at 1%, 5%, and 10%

Panel A. Results at 0.01			
\`x'	VaR	CoVaR	DCoVaR
BTC	-0.0900	-0.1183	-0.0724
ETH	-0.1167	-0.1194	-0.0762
USDT	-0.0065	-0.1100	-0.0172
XRP	-0.1315	-0.1008	-0.0469
BNB	-0.1102	-0.1001	-0.0489
SOL	-0.1656	-0.1093	-0.0510
DOGE	-0.1563	-0.1001	-0.0355
USDC	-0.0067	-0.1117	-0.0199
ADA	-0.1245	-0.1045	-0.0539
Panel B. Results at 0.05			
\`x'	VaR	CoVaR	DCoVaR
BTC	-0.0498	-0.0616	-0.0387
ETH	-0.0638	-0.0605	-0.0400
USDT	-0.0030	-0.0477	-0.0005
XRP	-0.0719	-0.0594	-0.0283
BNB	-0.0614	-0.0593	-0.0319
SOL	-0.0925	-0.0610	-0.0295
DOGE	-0.0811	-0.0572	-0.0223
USDC	-0.0029	-0.0525	-0.0059
ADA	-0.0734	-0.0567	-0.0323
Panel C. Results at 0.10			
\`x'	VaR	CoVaR	DCoVaR
BTC	-0.0900	-0.0841	-0.0679
ETH	-0.1167	-0.0869	-0.0728
USDT	-0.0065	-0.0337	-0.0012
XRP	-0.1315	-0.0758	-0.0550
BNB	-0.1102	-0.0782	-0.0582
SOL	-0.1656	-0.0764	-0.0544
DOGE	-0.1563	-0.0729	-0.0505
USDC	-0.0067	-0.0389	-0.0061
ADA	-0.1245	-0.0762	-0.0595

Table B.3 Detailed results of conditional VaR, CoVaR, and DCoVaR for native cryptocurrencies and stablecoins at 1%, 5%, and 10%

Panel A. Results at 0.01

Variable	Obs	Mean	Std.Dev	Min	Max
tVaR_BTC	1726	-0.08636	0.016628	-0.1341	-0.05525
tCoVaR_BTC	1726	-0.11785	0.024302	-0.20763	-0.07191
tDCoVaR_BTC	1726	-0.07595	0.014673	-0.11948	-0.04859
tVaR_ETH	1726	-0.11304	0.031072	-0.20426	-0.0545
tCoVaR_ETH	1726	-0.11611	0.022556	-0.1912	-0.07209
tDCoVaR_ETH	1726	-0.07281	0.018953	-0.12583	-0.03772
tVaR_USDT	1726	-0.00667	0.002267	-0.01313	-0.00244
tCoVaR_USDT	1726	-0.08303	0.01825	-0.17476	-0.01275
tDCoVaR_USDT	1726	-0.00066	0.000224	-0.0013	-0.00024
tVaR_XRP	1726	-0.135	0.035841	-0.352	-0.02344
tCoVaR_XRP	1726	-0.10042	0.019126	-0.21226	-0.03885
tDCoVaR_XRP	1726	-0.0454	0.012112	-0.11825	-0.00897
tVaR_BNB	1726	-0.10933	0.020809	-0.20735	-0.02361
tCoVaR_BNB	1726	-0.10589	0.024137	-0.25103	-0.02622
tDCoVaR_BNB	1726	-0.05207	0.009396	-0.10027	-0.01177
tVaR_SOL	1726	-0.156	0.041342	-0.36256	-0.07352
tCoVaR_SOL	1726	-0.10567	0.020518	-0.21985	-0.05974
tDCoVaR_SOL	1726	-0.05068	0.013138	-0.11774	-0.02465
tVaR_DOGE	1726	-0.15577	0.029801	-0.25286	-0.09676
tCoVaR_DOGE	1726	-0.09722	0.020471	-0.20094	-0.03604
tDCoVaR_DOGE	1726	-0.03197	0.005897	-0.05234	-0.02021
tVaR_USDC	1726	-0.00713	0.003039	-0.01655	-0.00098
tCoVaR_USDC	1726	-0.10632	0.028014	-0.21597	-0.02325
tDCoVaR_USDC	1726	-0.0216	0.009286	-0.0503	-0.00291
tVaR_ADA	1726	-0.12271	0.02068	-0.22119	-0.00318
tCoVaR_ADA	1726	-0.1031	0.021445	-0.20536	-0.02053
tDCoVaR_ADA	1726	-0.05331	0.008323	-0.1003	0

Panel B. Results at 0.05

Variable	Obs	Mean	Std.Dev	Min	Max
tVaR_BTC	1726	-0.04914	0.011405	-0.08878	-0.02709
tCoVaR_BTC	1726	-0.06077	0.009835	-0.08795	-0.04228
tDCoVaR_BTC	1726	-0.03807	0.007966	-0.0648	-0.02302
tVaR_ETH	1726	-0.06201	0.01402	-0.10586	-0.03491
tCoVaR_ETH	1726	-0.06008	0.009342	-0.08811	-0.04177
tDCoVaR_ETH	1726	-0.03898	0.007669	-0.06077	-0.02441
tVaR_USDT	1726	-0.00298	0.000965	-0.00851	-0.00109
tCoVaR_USDT	1726	-0.04566	0.008786	-0.07839	-0.02195
tDCoVaR_USDT	1726	-0.00164	0.000533	-0.00471	-0.0006
tVaR_XRP	1726	-0.07182	0.009021	-0.09979	-0.05306
tCoVaR_XRP	1726	-0.05744	0.006716	-0.07856	-0.04437
tDCoVaR_XRP	1726	-0.02714	0.003026	-0.03611	-0.02093
tVaR_BNB	1726	-0.05667	0.00686	-0.08199	-0.04245

tCoVaR_BNB	1726	-0.05711	0.006984	-0.08422	-0.04346
tDCoVaR_BNB	1726	-0.02956	0.003179	-0.04474	-0.02299
tVaR_SOL	1726	-0.09102	0.020956	-0.15473	-0.05282
tCoVaR_SOL	1726	-0.06162	0.012675	-0.1011	-0.03856
tDCoVaR_SOL	1726	-0.03015	0.006134	-0.0489	-0.01907
tVaR_DOGE	1726	-0.08146	0.011242	-0.115	-0.06076
tCoVaR_DOGE	1726	-0.05619	0.010407	-0.08711	-0.03733
tDCoVaR_DOGE	1726	-0.02322	0.002931	-0.0322	-0.01781
tVaR_USDC	1726	-0.00288	0.000741	-0.00506	-0.00152
tCoVaR_USDC	1726	-0.05143	0.010085	-0.08512	-0.03235
tDCoVaR_USDC	1726	-0.00562	0.001525	-0.01011	-0.00287
tVaR_ADA	1726	-0.07388	0.010586	-0.10363	-0.0548
tCoVaR_ADA	1726	-0.05867	0.008465	-0.08363	-0.04336
tDCoVaR_ADA	1726	-0.03304	0.004185	-0.04576	-0.02537

Panel C. Results at 0.10

Variable	Obs	Mean	Std. Dev.	Min	Max
tVaR_BTC	1726	-0.03266	0.006647	-0.05522	-0.0205
tCoVaR_BTC	1726	-0.04541	0.005692	-0.06325	-0.03413
tDCoVaR_BTC	1726	-0.02506	0.003931	-0.03847	-0.01771
tVaR_ETH	1726	-0.04299	0.010884	-0.07882	-0.02278
tCoVaR_ETH	1726	-0.05049	0.006262	-0.07061	-0.03837
tDCoVaR_ETH	1726	-0.02693	0.005296	-0.04407	-0.01674
tVaR_USDT	1726	-0.00191	0.000503	-0.00345	-0.001
tCoVaR_USDT	1726	-0.10356	0.003406	-0.12449	-0.09677
tDCoVaR_USDT	1726	-0.00019	5.04E-05	-0.00035	-1E-04
tVaR_XRP	1726	-0.04702	0.00689	-0.07019	-0.03401
tCoVaR_XRP	1726	-0.06586	0.003979	-0.07911	-0.05832
tDCoVaR_XRP	1726	-0.01842	0.00231	-0.02711	-0.01401
tVaR_BNB	1726	-0.0397	0.006996	-0.06207	-0.0262
tCoVaR_BNB	1726	-0.05034	0.006214	-0.06715	-0.0388
tDCoVaR_BNB	1726	-0.02102	0.002703	-0.02922	-0.01578
tVaR_SOL	1726	-0.06784	0.016799	-0.11746	-0.0374
tCoVaR_SOL	1726	-0.06147	0.008155	-0.08916	-0.04667
tDCoVaR_SOL	1726	-0.02236	0.004584	-0.03637	-0.01398
tVaR_DOGE	1726	-0.05499	0.006638	-0.0779	-0.03817
tCoVaR_DOGE	1726	-0.07888	0.003905	-0.09349	-0.07164
tDCoVaR_DOGE	1726	-0.01683	0.001583	-0.02216	-0.01261
tVaR_USDC	1726	-0.00215	0.000523	-0.00368	-0.00121
tCoVaR_USDC	1726	-0.10013	0.003572	-0.12305	-0.09292
tDCoVaR_USDC	1726	-0.00092	0.000241	-0.00163	-0.00048
tVaR_ADA	1726	-0.05038	0.009885	-0.08353	-0.03165
tCoVaR_ADA	1726	-0.05956	0.005994	-0.08873	-0.04812
tDCoVaR_ADA	1726	-0.0239	0.00338	-0.03687	-0.01765

Appendix C

Table C.1 Regression Results of lagged centrality values and tDCoVaR

tDCoVaR	Degree Centrality	Closeness Centrality	Betweenness Centrality	Eigenvector Centrality
Lag 1	-0.004* (0.002)	-0.358* (0.195)	-0.001** (0.001)	-0.073* (0.044)
Adj-R square	0.013	0.021	0.012	0.011
Lag 2	-0.004 (0.002)	-0.289 (0.195)	-0.001* (0.001)	-0.064 (0.044)
Adj-R square	0.013	0.021	0.012	0.011

**** p<.01, ** p<.05, * p<.1*

Notes: This table shows estimates of regression analysis, which is performed on time-varying ΔCoVaR values (dependent variable) and lagged centrality values (independent variable) of all crypto assets.

Table C.2 Results of Granger Causality Tests (Dumitrescu–Hurlin)

Panel A: Does Centrality → Systemic Risk (tDCoVaR)

Direction	**Variable**	**Lags**	**Z-bar**	**p-value**
Centrality → ΔCoVaR	Degree	1	0.2367	0.8129
	Degree	2	-0.6365	0.5245
	Closeness	1	0.0815	0.9351
	Closeness	2	-0.6740	0.5003
	Betweenness	1	-0.4656	0.6415
	Betweenness	2	-1.0984	0.2720
	Eigenvector	1	0.8106	0.4176
	Eigenvector	2	0.5289	0.5969

Panel B: Does Systemic Risk (tDCoVaR) → Centrality? (Reverse Causality)

Direction	**Variable**	**Lags**	**Z-bar**	**p-value**
ΔCoVaR → Centrality	Degree	1	-1.0605	0.2889
	Degree	2	0.1905	0.8489
	Closeness	1	-0.6595	0.5096
	Closeness	2	0.4697	0.6386
	Betweenness	1	-0.5988	0.5493
	Betweenness	2	-0.1870	0.8517
	Eigenvector	1	-0.4355	0.6632
	Eigenvector	2	0.8804	0.3786

Notes: This table reports Dumitrescu–Hurlin panel Granger causality tests examining the predictive relationship between network centrality measures and systemic risk (tDCoVaR) across nodes. Results are reported for lag lengths of 1 and 2. Across all specifications, p-values are above conventional significance levels, indicating that the null hypothesis cannot be rejected in either direction.

Chapter 3

Systemic Risk Assessment in CEXs and DEXs: An Application of a Tail Dependence-Based MST and CoVaR Approach

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Abstract

This research provides empirical evidence on whether decentralization offered by blockchain technology can mitigate the problem of "too connected to fail" in crypto ecosystem by comparing centralized and decentralized exchanges. The Minimum Spanning Tree measures changes in network topologies of crypto token pairs across crypto exchanges during normal and crisis periods, and Conditional Value at Risk (ΔCoVaR) is employed to investigate their systemic risk contribution. Finally, regression analysis is performed to ascertain the link between centrality values and systemic risk contribution. Results showed that centrality values (capturing the relative importance and interconnectedness of tokens in the network) significantly impact systemic risk contribution of those token pairs listed on centralized exchanges. Conversely, insignificant results were found for all token pairs traded on decentralized exchanges. This confirms that decentralized mechanism mitigates systemic risk propagation arising from returns interconnectedness among crypto assets and institutions. However, other factors such as liquidity, smart contract vulnerabilities, and regulatory compliance might affect risk characteristics of decentralized assets and platforms.

1. Introduction

Centralized exchanges and decentralized exchanges are the main actors of the digital financial ecosystem that facilitated the adoption of blockchain technology (Yousaf et al., 2023). The first foundation for trading cryptocurrencies against conventional fiat currencies was built by centralized exchanges such as the notorious Mt. Gox. Although important for the market's inception, these platforms have exhibited indications of operational limitations, regulatory oversight, and security vulnerabilities (Hägele, 2024; Lucey et al., 2022). Public data indicate that hackers have withdrawn billions of dollars from major trading platforms such as Bitfinex and Binance in the last few years (Steven, 2019). To counter the inherent problems of centralized exchanges, the concept of decentralized exchanges emerged (Lo & Medda, 2021). The fundamental principle of DEX is to create peer-to-peer, reliable systems enabling traders to exchange on-chain assets independently without any intermediation (Angeris & Chitra, 2020) while maintaining ownership and control of their private keys and cryptocurrencies (Dai, 2020). Trading volume on centralized and decentralized exchanges peaked in May 2021 and escalated by over sevenfold within the next six months. Following the launch of UniswapV3, a highly successful decentralized exchange (Hägele, 2024) DEXs experienced a disproportionately significant rise in their trading volume share compared to their centralized counterparts (Yousaf et al., 2023). Despite rapid progress, DEXs have also demonstrated substantial hazards and vulnerabilities over time. Due to trustlessness and anonymity, DEXs are increasingly favoured for selling stolen cryptocurrencies (Aspris et al., 2021). Also, inefficient price mechanisms, hacker attacks, prolonged execution time, and smart contract vulnerabilities have caused huge losses for investors and traders (Krishnamachari et al., 2021; Barbon & Ranaldo, 2021).

The current discussions over whether the vulnerabilities of quickly expanding digital platforms constitute a danger to the global financial system's stability have been fueled by the recent collapses of crypto assets and exchanges such as Mt. Gox in 2014, QuadrigaCX in 2019, and FTX in 2022. Due to the growing interconnectedness and complex operations in heterogeneous contexts, CEXs and DEXs present significant too-connected-to-fail concerns, which can spread financial risks across DeFi and traditional finance (Dell'Erba, 2024). Our study contributes to the decentralized solutions for systemic risk management by providing empirical evidence for the “too connected to fail” theory in the crypto-ecosystem. It quantifies the interconnectedness of crypto tokens across CEXs and DEXs by using centrality measures of Minimum Spanning

Tree (MST), which are then regressed against ΔCoVaR values, which measure the systemic risk contribution of the same token pairs.

Our MST findings indicate that BTC/USDT on Binance is the most central and prominent token pair, and DAI/USDT on Uniswap is the least central/peripheral token pair. Correspondingly, CoVaR analysis reveals that the same BTC/USDT pair on Binance is the highest risk-contributing pair, and DAI/USDT on Binance is the least risk-contributing pair. Regression results confirmed that centrality measures have a significant role in the systemic risk contribution of token pairs traded on centralized exchanges. Conversely, insignificant results were found for all token pairs traded on the decentralized exchange. Our research has important implications for portfolio diversification, legislation, regulation, and investment. The subsequent sections of this study are organized as follows: Section 2 describes the relevant literature and how our research contributes. Section 3 offers the data, whereas Section 4 outlines our empirical methodologies. Section 5 discusses relevant empirical findings and results. Section 6 summarizes the research findings.

2. Literature Review

Cryptocurrency exchanges are among the most widely used platforms for trading and holding cryptocurrencies (Fantazzini & Calabrese, 2021). Decentralized and centralized exchanges have coexisted for years, with investors using both, based on their preferences for security, trust, cost, liquidity, and risk (Nummelin, 2022). Recent cryptocurrency collapses, including Terra Luna and FTX, created widespread uncertainty among crypto investors (Yaffe-Bellany, 2022) and raised significant concerns among regulators about exchanges' capacity to safeguard their clients from liquidity limitations and volatility surges (Yousaf et al., 2023). Multiple studies have examined the risk dynamics among prominent cryptocurrency assets and exchanges, utilizing diverse methodologies, and their combined results consistently confirm the co-explosivity pattern, particularly prevalent during financial crises (Yousaf et al., 2023; Fantazzini & Calabrese, 2021; Likitratcharoen et al., 2018; Borri, 2019; Almeida et al., 2022; Waltz et al., 2022). Over the years, integration and interdependence among crypto exchanges and assets have grown extensively, raising serious concerns about systemic risk in the crypto ecosystem. (Nguyen et al., 2023; Serena et al., 2022) utilized complex network theory to examine the interaction patterns among cryptocurrencies and demonstrated that all cryptocurrency transaction graphs display small-world characteristics, wherein two nodes are typically linked by a minimal number of hops, and neighbouring nodes frequently connected to the same adjacent nodes, displaying disproportionate influence in the network.

The increasing linkages and interconnectedness within the cryptocurrency market necessitate an interdisciplinary approach to analyze its structure and dynamics for the assessment of systemic risk. Consequently, our research utilizes a hybrid methodology, employing network modelling to compute multiple centrality metrics from the MST analysis that measure interconnections and co-movements among nodes. The method for conducting an MST analysis of correlation networks within the cryptocurrency market is derived from several prior research studies (Liang et al., 2018; Francés et al., 2018; Giudici & Polinesi, 2021; Burnie, 2018). To estimate the marginal risk contribution of each asset or institution to systemic risk, the micro-evidence technique ΔCoVaR is utilized, as it is the most commonly adopted method that enables the assessment of overall risk distribution throughout the system. A study by (Dičpinigaitienė & Novickytė, 2018) on a systematic literature analysis of systemic risk measuring methodologies indicated that the predominant systemic risk metrics are the Delta conditional value-at-risk (Δ CoVaR) and the conditional value-at-risk (CoVaR). Lastly, a simple regression analysis is performed to establish a relationship between dynamic centrality measures and ΔCoVaR.

Research on the spread of contagion networks and systemic risk in the crypto ecosystem is currently limited, particularly regarding the effects of changes in network connection under normal and volatile conditions. Moreover, there is a lack of research on the increasing interrelations between cryptocurrencies and stablecoins in the context of managing and distributing systemic risk across centralized exchanges and decentralized exchanges. So, this study seeks to close these gaps as it aims to provide insights into how interconnectedness has changed over time and how those changes have affected the risk characteristics of digital institutions (CEXs and DEXS) and digital assets.

3. Data

The OHLCV (Open, High, Low, Close, and Volume) data for two centralized exchanges, i.e., Binance and Coinbase, is derived from the Ethereum blockchain using the web portal https://www.cryptocompare.com/ from July 2021 to December 2023. The OHLCV data for decentralized exchange, i.e., Uniswap, is derived from the Ethereum blockchain using BitQuery integration through their open API https://bitquery.io/products/dex. This dataset includes prices, volume of non-stable and stable token pairs, and trading volume of crypto exchanges. The selected timeframe covers the periods of growth in the cryptocurrency market and includes events of major crypto and real-world crises including the COVID-19 market shock, the 2022 monetary tightening cycle, Terra-Luna collapse, the failure of major crypto lending platforms, and the FTX collapse. Thus, it aligns with our objective of analyzing network topologies under varying market conditions. The chosen crypto exchanges have the highest trading volume and number of trading pairs. The chosen non-stable and stable pairs have the highest trading volume. The SP500 Index, the CBOE VIX volatility index, and the cryptocurrency market's fear and greed index (FIG) are selected as state variables. Data regarding SP500 index and the CBOE volatility index has been collected from the LSEG workspace, while data for the FIG index has been obtained from https://alternative.me/crypto/fear-and-greed-index/. These factors signify investor attitudes, patterns, expectations, and financial cycles. The cumulative daily observations amount to 908. The price data is transformed into log return values in percentage form to study correlations. Table 1 presents names, codes, and summaries of returns for all non-stable and stable pairs.

Table 1. Summary Statistics

Exchange	Coin	Code	Obs.	Mean	Std.D	Min	Max
Binance	Bitcoin	BNBTC	908	0.00024	0.030	-0.167	0.135
Coinbase	Bitcoin	CBBTC	908	0.00024	0.030	-0.167	0.135
Uniswap	Bitcoin	UNWBTC	908	0.00031	0.215	-3.581	3.557
Binance	Ether	BNETH	908	-0.00002	0.037	-0.191	0.166
Coinbase	Ether	CBETH	908	-0.00002	0.037	-0.193	0.166
Uniswap	Ether	UNWETH	908	0.00003	0.035	-0.158	0.154
Binance	DAI	BNDAI	908	0.0000	0.001	-0.032	0.022
Coinbase	DAI	CBDAI	908	0.0000	0.001	-0.030	0.024
Uniswap	DAI	UNDAI	908	0.00002	0.023	-0.459	0.462
Binance	USDC	BNUSDC	908	0.0000	0.001	-0.042	0.026
Coinbase	USDC	CBUSDC	908	0.0000	0.001	-0.036	0.023
Uniswap	USDC	UNUSDC	908	0.0000	0.012	-0.237	0.236

4. Methodology

4.1 MST Analysis for the measurement of interconnectedness

The positions of individuals in a network lead to the identification of institutions that are too connected to fail (Gofman, 2017). By building a network using MST in which certain nodes communicate and influence one another, it becomes easy to analyze the level of cooperation amongst cryptocurrencies and the identification of those nodes that have a more significant impact on price fluctuations and market activity overall (Francés et al., 2018). (Mantegna & Stanley, 1999) originally proposed the MST approach for examining the topology of financial markets. Firstly the correlation matrix of the daily returns for all token pairs is created which generates the coefficients of the Pearson correlations for each token pair, denoted as i and j, which are defined as follows:

$$C_{ij} = \frac{n(\sum r_i r_j) - (\sum r_i)(\sum r_j)}{\sqrt{[n\sum r_i^2 - (\sum r_i)^2]\,[n\sum r_i^2 - (\sum r_i)^2]}} \tag{1}$$

A correlation matrix is obtained:

$$C = \begin{bmatrix} C_{11} & \cdots & C_{1N} \\ \vdots & \ddots & \vdots \\ C_{N1} & \cdots & C_{NN} \end{bmatrix} \tag{2}$$

N represents the number of token pairs (12 in our research), and the values of C_ij vary from -1 to 1. The correlation coefficient serves as a useful tool for examining relationships among cryptocurrencies; however, it overlooks topological elements by failing to position connections within a metric space. To counter this issue the components of the correlation matrix C_ij are transformed into distances, utilizing the Kruskal technique as established by (Mantegna & Stanley, 1999; Stanley & Mantegna, 2000) to generate a distance matrix:

$$d_{ij} = \sqrt{2(1 - C_{ij}} \tag{3}$$

The value varies from 0 to 2, indicating that a high correlation among cryptocurrencies will result in a short distance. Where dij varies from '0' to '2', with '0' signifying total dissimilarity and '2' denoting similarity between two elements, this method ensures that the resultant distance matrix adheres to the fundamental characteristics of a metric $dij \geq 0$, $dij = 0$ when $i = j$, and $dij = dji$. We employed the subsequent techniques to construct the MST graph: We began by using the distance matrix to choose N (N – 1) / 2 elements in ascending order. Following this, we chose the token pair exhibiting the smallest distance and integrated the corresponding link into the graph. Subsequently, we integrated the link to the subsequent pair of tokens that demonstrated the minimal distance between them. The process is repeated until every currency is linked within the MST graph. Then centrality metrics were derived from the MST, illustrating the various dimensions of interconnectivity within cryptocurrencies.

Degree centrality measures the number of direct links of one node to other nodes within a network. It can be interpreted as the direct risk that a node may encounter across the network. Closeness, betweenness, and eigenvector centrality indicate the systemic importance and influence of nodes by quantifying their positions in the network. The proximity of one node to another within the network is assessed through its closeness centrality. Betweenness centrality measures the shortest path connecting two nodes. It identifies the nodes that function as connections between different nodes. A node with elevated betweenness centrality can substantially affect the information flow inside the network. Eigenvector centrality is alternatively known as Broncich's centrality. The node having the highest eigenvector centrality is identified as highly influential, as its strength is derived from its connections to both strong and weak nodes.

4.2 CoVaR for the Measurement of Systemic Risk

(Adrian & Brunnermeier, 2011) proposed CoVaR, a systemic risk metric, defined as the Value at Risk (VaR) of a financial system, conditional upon the distress of individual institutions. In this context, "distress" refers to an underperforming institution relative to its 1%-Value at Risk (VaR) threshold. Value at Risk (VaR) is the maximum potential loss that may be incurred with a specified probability over a defined period.

$$VaR_a(L) = \{l : \Pr(L > l) \leq 1 - a\} \tag{4}$$

This study demonstrates that CoVaR can be utilised to evaluate the susceptibility of one entity to another, particularly regarding the marginal contribution of an asset or institution to a financial system.

$$\Delta \mathrm{CoVaR}_q^{J|i} = \mathrm{CoVaR}_q^{J|X^i = VaR_q^i} - \mathrm{CoVaR}_q^{J|X^i = VaR_{Median}^i} \tag{5}$$

ΔCoVaR refers to the CoVaR conditional on an entity *(i)* in distress (at its 1%-VaR) minus the CoVaR conditional on an entity *(i)* in its median state (at its 50%-VaR). Unconditional CoVaR and ΔCoVaR are computed for cryptocurrency token pairs, resulting in CoVaR values that remain constant throughout time. A time-varying CoVaR analysis is conducted to assess the robustness of our findings by incorporating state variables which act as proxies for short-term risks and sentiments in both traditional and crypto markets.

4.3 Relationship between Centrality Metrics and Systemic Risk Contribution

The ΔCoVaR values are then subjected to regression analysis with respect to different centrality values. The use of weekly observations decreases the frequency of data; however, the results continue to be valid and align with those obtained from high-frequency daily data. Regression analysis is utilized to estimate the dependent variable y, the conditional ΔCoVaR values, with a range of independent variables such as centrality metrics (Degree, Closeness, Betweenness, and Eigenvector). The relationship is defined by the following equation.

$$\Delta CoVaR \ = \ \beta_o + \ \beta_1 Centrality\, Values + \varepsilon \tag{6}$$

5. Research Findings and Discussion

5.1 Results of MST analysis

Table 2 of the MST analysis presents the centrality values of all token pairs calculated for each year individually and for the entire period.

Table 2. Results of MST Analysis

Panel A: MST Centrality Values 2021

Nodes	Betweenness	Closeness	Degree	Eigenvector	Index
BNBTC	10	0.022	2	0.057	3.02
CBBTC	18	0.026	2	0.092	5.03
UNWBTC	18	0.026	2	0.092	5.03
BNETH	0	0.024	1	0.065	0.27
CBETH	31	0.031	3	0.135	8.54
UNWETH	10	0.022	2	0.057	3.02
BNDAI	31	0.031	3	0.135	8.54
CBDAI	0	0.024	1	0.065	0.27
UNDAI	0	0.018	1	0.027	0.26
BNUSDC	30	0.033	2	0.124	8.04
CBUSDC	30	0.033	2	0.124	8.04
UNUSDC	0	0.018	1	0.027	0.26

Panel B: MST Centrality Values 2022

Nodes	Betweenness	Closeness	Degree	Eigenvector	Index
BNBTC	10	0.026	2	0.054	3.020
CBBTC	26	0.032	3	0.095	7.282

UNWBTC	0	0.023	1	0.054	0.269
BNETH	0	0.020	1	0.024	0.261
CBETH	0	0.024	1	0.043	0.267
UNWETH	19	0.030	3	0.119	5.537
BNDAI	31	0.037	3	0.155	8.548
CBDAI	0	0.027	1	0.070	0.274
UNDAI	0	0.023	1	0.054	0.269
BNUSDC	35	0.040	3	0.152	9.548
CBUSDC	28	0.037	2	0.112	7.537
UNUSDC	0	0.029	1	0.069	0.274

Panel C: MST Centrality Values 2023

Nodes	Betweenness	Closeness	Degree	Eigenvector	Index
BNBTC	30	0.036	2	0.136	8.043
CBBTC	28	0.033	2	0.085	7.530
UNWBTC	0	0.017	1	0.008	0.256
BNETH	24	0.029	2	0.053	6.521
CBETH	18	0.025	2	0.032	5.014
UNWETH	10	0.021	2	0.018	3.010
BNDAI	0	0.026	1	0.097	0.281
CBDAI	0	0.022	1	0.055	0.269
UNDAI	0	0.022	1	0.055	0.269
BNUSDC	10	0.028	2	0.122	3.037
CBUSDC	38	0.036	4	0.216	10.563
UNUSDC	10	0.028	2	0.122	3.037

Panel D: MST Centrality Values 2021 - 2023

Nodes	Betweenness	Closeness	Degree	Eigenvector	Index
BNBTC	36	0.036	3	0.16	9.80
CBBTC	18	0.029	2	0.10	5.03
UNWBTC	0	0.022	1	0.05	0.27
BNETH	0	0.019	1	0.03	0.26
CBETH	10	0.024	2	0.06	3.02
UNWETH	10	0.028	2	0.10	3.03
BNDAI	0	0.023	1	0.05	0.27
CBDAI	30	0.036	2	0.13	8.04
UNDAI	0	0.019	1	0.03	0.26
BNUSDC	28	0.033	2	0.11	7.54
CBUSDC	26	0.029	3	0.11	7.29
UNUSDC	10	0.024	2	0.07	3.02

5.1.1 MST 2021. For MST 2021, ETH on Coinbase and DAI on Binance have the highest centrality values as shown in Figure 1, panel (a). In 2021, the cryptocurrency market boomed, reaching its peak. ETH, in particular, saw a significant increase in returns, rising by 399.02% due to the development of the DeFi 2.0 protocol and the accelerated use of smart contracts, NFTSs, and other DeFi assets on the Ethereum blockchain (Katsiampa et al., 2022; Qin et al., 2021). ETH's influential role in the cryptocurrency market is also confirmed by various studies (Katsiampa et al., 2022; Kumar et al., 2022). Additionally, the collateral reserves for DAI stablecoins in 2021 were primarily on-chain assets, with ETH holding the highest reserves. So since January 2021, DAI has shown increasing stability and had the highest betweenness centrality, meaning it acted as a bridge between different token pairs on the Binance protocol, playing a critical role in DeFi activities and cross-platform trades (Oefele et al., 2024), while DAI/USDT and USDC/USDT on Uniswap has the lowest centrality values.

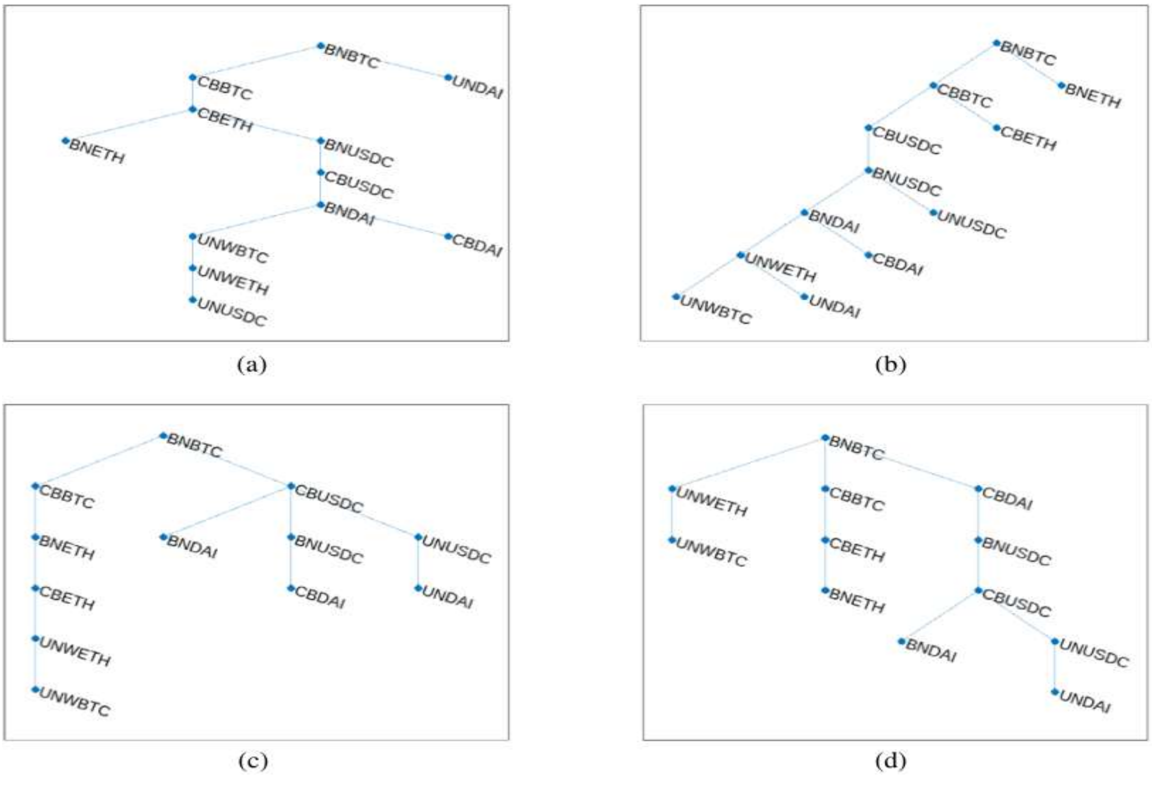

Fig. 1. Minimum Spanning Tree for each year 2021, 2022, 2023 and the entire period 2021-2023, labelled as a, b, c, and d respectively.

5.1.2 MST 2022. For MST 2022, DAI and USDC on Binance demonstrated the highest centrality values, as illustrated in Figure 1, panel (b). In 2022, the previously observed upward trend of cryptocurrency experienced a reversal, as the market cap of many crypto assets significantly declined. During the market volatility triggered by the Terra/Luna failure, around $450 billion and $200 billion due to FTX collapse were erased in 2022 (Cornelli et al., 2023). Crashes caused traders and investors to exit volatile assets and seek stable assets like USDC, thus making it a net beneficiary (Esparcia et al., 2022). (Allen et al., 2024) found an increase in DAI net issuance and minting activity in crisis periods relative to non-crisis periods. In contrast, ETH on Coinbase and Binance, and wBTC and DAI on Uniswap have the lowest centrality values.

5.1.3 MST 2023. In 2023, Coinbase saw significant volumes of USDC trades, supported by its deep connections with the fiat world and regulatory backing as shown in Figure 1, panel (c). Furthermore, wBTC on Uniswap has the lowest centrality values, which suggests reduced trading volumes and diminishing role due to the focus on DeFi-specific tokens and the dominance of stablecoins, as USDC is the preferred asset for trading and liquidity provision. (Hernandez Cruz et al., 2024) confirmed that liquidity tends to diminish during periods of market stress on Uniswap compared to centralized exchanges for Wrapped Bitcoin (wBTC), DAI, and Wrapped Ether (wETH) pairs.

5.1.4 MST 2021 – 2023. BTC on Binance has the highest centrality values for the MST of 2021-2023, holding the highest degree and eigenvector centrality as shown in Figure 1, panel (d). This highlights BTC's persistent role as a leading asset for liquidity and trading. Binance, as the largest exchange, has continued to dominate BTC trading volumes, especially as it solidified its market position globally.

Additionally, DAI on Coinbase also showed high centrality values. In 2023, the transition from stablecoin to real-world assets (RWA) collateral has heightened DAI reliance on Coinbase, which acts as an exchange agent for three of the four largest RWAs. ETH has the lowest centrality values on Coinbase, which means it is least impacted by the price changes in BTC. DAI on Uniswap also saw low centrality, likely due to the preference for other stablecoins like USDC in decentralized exchanges.

The temporal analysis of MSTs across 2021, 2022, and 2023 (as presented in Figure 1 and Table 2) reveals evidence of regime dependence, where network topologies undergo structural breaks during crisis periods. This dynamic behavior indicates that interconnectedness is not a static property but evolves with market conditions. During the bull market of 2021 (Panel A), the network was centred around by growth oriented assets like ETH, reflecting a regime where market participants were focused on DeFi and NFT driven returns. The Terra Luna collapse and subsequent FTX crisis in 2022 (Panel B) triggered a significant structural break. The network topology shifted dramatically, and stablecoins (DAI and USDC on Binance) attained the central positions in the network. By 2023 (Panel C), the network began to gain stability, but with a new structure where USDC on Coinbase an exchange with regulatory clarity became highly central. This post-crisis regime reflects a market shifting towards regulatory safety and real world asset connectivity. This analysis confirms that systemic risk in the crypto ecosystem is not only about the level of interconnectedness but also about how the network's architecture and its central nodes reconfigure in response to different types of systemic shocks.

5.2 Empirical findings of the CoVaR approach

The findings are organized as follows: Table 3 presents the results from the unconditional estimates for VaR, CoVaR, and ΔCoVaR across all token pairs. ΔCoVaR values are the highest for wETH at Uniswap at the 1% levels for unconditional outcomes. Our results align with those of (Heimbach et al., 2022) who analysed the risk and returns of three different categories of token pairs selected based on the highest total value locked and liquidity. The results showed that liquidity positions in the pair consisting of wETH and USDC experienced more extreme volatility in their daily returns and also exhibited higher risk compared to the normal pair. ΔCoVaR values for wETH at Uniswap were found to be consistently highest even at 5%, and 10% levels in our results.

Table 3. Results of CoVaR Analysis

Token Pairs	**Conditional Results**			**Unconditional Results**		
x	VaR	CoVaR	DCoVaR	VaR	CoVaR	DCoVaR
BNBTC	-0.093	-0.053	-0.033	-0.083	-0.049	-0.032
CBBTC	-0.094	-0.052	-0.032	-0.083	-0.049	-0.032
UNWBTC	-0.120	-0.050	-0.011	-0.186	-0.052	-0.018
BNETH	-0.116	-0.055	-0.029	-0.101	-0.053	-0.030
CBETH	-0.117	-0.055	-0.030	-0.099	-0.052	-0.030
UNWETH	-0.107	-0.078	-0.040	-0.091	-0.065	-0.029
BNDAI	-0.001	-0.040	0.001	-0.001	-0.038	0.002
CBDAI	-0.001	-0.043	-0.001	-0.001	-0.043	-0.003
UNDAI	-0.017	-0.044	-0.0031	-0.018	-0.042	-0.003
BNUSDC	-0.001	-0.040	0.0009	-0.001	-0.039	0.001
CBUSDC	-0.001	-0.041	0.0011	-0.001	-0.038	0.001
UNUSDC	-0.009	-0.040	0.0008	-0.009	-0.043	-0.003

5.3 Robustness check

We performed a time-varying ΔCoVaR analysis to evaluate the robustness of CoVaR, integrating lagged state variables to capture the dynamic risk responses influenced by broader macroeconomic conditions. The findings indicate that ΔCoVaR for BTC on Binance exhibited the highest values at 1%. Table 3 presents conditional results for VaR, CoVaR, and ΔCoVaR for all token pairs. These results are consistent with the conclusions drawn by (Kirste et al., 2024), identifying Binance as the primary market for BTC and Coinbase as the secondary market. According to (Alexander et al., 2022), Binance's tether-margined contracts serve as the primary sources of volatility, particularly during the hours of Western market activity. In contrast, Uniswap demonstrates a low level of systemic risk, aligning with the results produced by (Alves, 2023). Our conditional findings indicate that Binance is a significant channel for systemic risk, whereas Uniswap exhibits a more isolated risk profile, enhancing the comprehension of risk propagation within cryptocurrency markets. The risk shift from ETH to BTC in unconditional and conditional results suggests the need to take into account broader market conditions including real-world variables and events. ΔCoVaR values for BTC at Binance were also found to be highest at 5%, and at 10% ETH at Coinbase has the highest values in our results.

5.4 Empirical results on the relationship between systemic risk and interconnections

We performed simple linear regression focusing on centrality values (betweenness, closeness, degree, and eigenvector) with time-varying ΔCoVaR values. Table 4 presents the outcomes of regression results of all token pairs on all exchanges. It indicates a substantial negative correlation between each centrality value and the ΔCoVaR values of Bitcoin, Ether, and USDC on Binance. On Coinbase, ETH and DAI exhibited a negative relation with closeness centrality and on Uniswap, all token pairs showed insignificant results.

Table 4. Results of Regression Analysis

Token Pairs	Closeness	Betweenness	Degree	Eigenvector
BNBTC	-0.158*** (0.054)	-0.00008** (0)	-0.001*** (0)	-0.019** (0.008)
BNETH	-0.179*** (0.053)	0	0	-0.02** (.008)
BNUSDC	0	-0.000014*** (0)	-0.00024*** (0)	-0.003** (0.001)
BNDAI	0	0	0	0

CBBTC	-0.004 (0.063)	0	0	0.011 (0.01)
CBETH	-0.158*** (0.053)	0	0	-0.011 (0.008)
CBUSDC	-0.004 (0.004)	0	0	-0.001 (0.001)
CBDAI	-0.037** (0.016)	0	0	-0.003 (0.002)
UNWBTC	-0.017 (0.046)	0	0	0
UNWETH	-0.017 (0.046)	0	0	0
UNUSDC	0.006 (0.005)	0	0	0
UNDAI	0.001 (0)	0	0	0

**** p<.01, ** p<.05, * p<.1*

The significant negative relationship for ETH and DAI, alongside insignificant results for BTC and USDC, reflect the distinct user base and regulatory architecture of the exchange. Coinbase is a preferred choice for institutional and retail investors from the traditional financial system and for these users, assets like ETH and DAI may carry different risk perceptions. The insignificance for BTC and USDC on Coinbase suggests that for these assets, network centrality does not strongly predict systemic risk, potentially because their risk profiles are already heavily influenced by external macro factors rather than internal exchange dynamics. Furthermore, the complete absence of significant relationships on Uniswap reinforces that in a decentralized, AMM-based exchange, the mechanisms linking network position to systemic risk are fundamentally different. On Uniswap, risk is distributed across liquidity pools and governed by algorithm rather than concentrated in a few centrally cleared pairs. This finding suggests that decentralization, in its current form, disrupts the 'too connected to fail' dynamic but introduces new kind of risks such as smart contract vulnerabilities and oracle failures.

5.5 Discussion

ETH plays a central role in DeFi and applications, primarily within the crypto-native ecosystem (Burnie, 2018; Hicks, 2023) creating systemic application dependencies (Röckener, 2024). Ether, is the second most popular altcoin, and it has more connections than any other currency

(Burnie, 2018). Consequently, ETH serves as a hierarchical reference node for most other assets and sustains this function over time, although it has seen a decline in centrality during periods of volatility. Therefore, high ΔCoVaR in unconditional results suggests that ETH's highest systemic risk contribution on Uniswap, followed by Binance and Coinbase, is internal to the crypto market, where it is used as a foundational asset on which much of the infrastructure depends. These results align with the results produced by (Dell'Erba, 2023; Lin, 2019) who regard DEX tokens as more risky due to low liquidity and high complexity. BTC, on the other hand, is often viewed as a store of value and is more closely correlated with traditional financial markets, especially in recent years. The fact that BTC's systemic risk contribution is highest on Binance, followed by Coinbase in conditional results with SPX and VIX, indicates that macroeconomic conditions and external financial factors influence its risk profile more. The research outcome reveals how macro-market conditions affect BTC more strongly than ETH on CEXs. These results align with the results produced by (Aspris et al., 2021) which confirms that CEX tokens are a more serious danger to financial stability than DEX tokens because of the huge rise in the spillover effects from CEX tokens to other assets. (Dell'Erba, 2023) also confirmed that Binance and Coinbase are systemically important financial institutions based on highest centrality values and systemic risk contribution and could generate systemic concerns, considering their prominent role in the global stablecoin market.

(Allen & Gale, 2000) argue that in a financial network characterized by a higher density of connections, a bank's losses during difficult times are spread across multiple nodes, thereby reducing the impact of negative shocks on particular institutions within the overall system. Some researchers have contended that a network's interconnectedness and concentration can increase its susceptibility to contagions and shocks (Blume et al., 2011). Both perspectives are valid in light of our research findings. Significant regression results between centrality values of all token pairs and their systemic risk contribution on all exchanges confirmed that on centralized exchanges, size and interconnectedness are the main factors that make them systematically important and impact their risk management, i.e. mitigation or amplification. All token pairs on Binance have exhibited a significant negative relationship with their centrality values, which means with the growth in the exchange's volume and increased interconnection, the systemic risk contribution of decentralized assets i.e. BTC and ETH and centralized stablecoin USDC tends to decrease except for the DAI token pair, which exhibited significant positive relationship. For Coinbase, only ETH and DAI exhibited a significant relationship. Contrarily, on Uniswap, which is a decentralized platform, insignificant regression results were found for all token pairs.

No relationship was found between centrality values and ΔCoVaR for any token pair on Uniswap, which suggests that the decentralized nature of liquidity provision through AMMs might make the concept of centrality less relevant for systemic risk. Risk in decentralized systems may be more distributed across the network and less dependent on the prominence of individual tokens or pairs in terms of network interconnectedness. These interpretations reflect how network structure and exchange type (centralized vs. decentralized) impact systemic risk and asset interconnectivity differently, providing an in-depth analysis of the risk patterns within crypto markets.

The divergent systemic risk contributions of token pairs across Binance, Coinbase, and Uniswap can be attributed to three fundamental structural differences. First, the liquidity concentration is a main differentiator. On Binance, the world's largest CEX by volume, liquidity is highly concentrated in a few dominant pairs like BTC/USDT. This concentration amplifies their centrality (as seen in Table 2, Panel D) and, consequently, their systemic risk contribution, as a shock to these pairs can propagate through the entire exchange ecosystem. Coinbase exhibits a different liquidity profile, with significant volume in BTC and ETH but also a significant role for regulated stablecoins like USDC, particularly following the 2022 crises. This reflects its deep integration with traditional finance. In contrast, on Uniswap, liquidity is distributed across numerous pools by individual liquidity providers. While pairs like wETH/USDC have high TVL, this liquidity is not "concentrated" in a network centrality sense but rather fragmented across many automated pools. The insignificant regression results for Uniswap directly suggest that in a decentralized exchange, an asset's liquidity share does not translate into the same kind of systemic influence as a concentrated order book does.Second, the governance and operational structure is critical as Binance and Coinbase act as central counterparties, managing order books and this centralization directly impacts asset risk. The significant relationship between centrality and risk on these platforms captures this institutional layer. Uniswap, governed by a decentralized community and code, removes this institutional intermediary. Risk on Uniswap is therefore more idiosyncratic tied to the specific smart contract or the dynamics of its liquidity pools rather than a function of its interconnectedness within a broader exchange network.

Finally, the technical distinction between CEXs and DEXs is critical. In CEXs, price discovery and trade execution are centralized processes. A large shock to a highly central pair can instantly disrupt the order book creating a direct channel for systemic contagion. In a DEX, trades are executed against a liquidity pool algorithmically. While this prevents the systemic risk arising from interconnectedness, it introduces new set of risks, such as slippage in volatile markets or the exploitation of smart contract vulnerabilities. The insignificant relationship between centrality and systemic risk on Uniswap confirms that the channels of risk propagation are fundamentally different in a DEX.

6. Conclusions

This research investigates systemic risk in the crypto ecosystem by taking into account the three biggest crypto exchanges Binance (Centralized), Coinbase (Centralized), and Uniswap (decentralized) and four highly traded token pairs across all three exchanges i.e., BTC, ETH, DAI, and USDC. Our results provide that those token pairs which have the highest centrality values are the ones contributing the highest to systemic risk, confirming the significant relationship between interconnectedness and systemic risk. Furthermore, regression results confirm that systemic risk contribution appears to be decreasing for decentralized cryptocurrencies across CEXs, and no significant relationship was found for any token pair traded on decentralized exchanges making the role of interconnectedness irrelevant in DEXs. These results confirm the notion of "too connected to fail" as increased integration helps dissipate the systemic risk across the system in CEXs for decentralized cryptocurrencies. Binance appears as a as a highly central and dominant node in the network, reflecting its high trading volume, liquidity, and user activity compared to others. Uniswap, a decentralized exchange based on AMMs, emerged as a solution to counter the risks posed by centralized platforms. However, it has brought another set of risks, such as low liquidity, complex interface, and smart contract vulnerabilities. In terms of liquidity, Uniswap relies on fragmented liquidity pools and is exposed to impermanent loss, resulting in lower depth and higher slippage for large trades compared to highly liquid centralized exchanges. Also, its interface presents a significantly steeper learning curve, as users must manage private keys, understand gas fees, and execute token approvals, understanding slippage tolerance, shifting the operational burden onto individuals relative to the simplified custodial experience of centralized platforms. Finally, technical vulnerabilities embedded in smart contracts of DEXs, expose users to exploits such as re-entrancy attacks and flash. Future research could extend this analysis by investigating DEX specific risks interaction with network structure that may provide deeper insights into the mechanisms of systemic risk transmission in decentralized finance.

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Chapter 4

Automated Risk Management Mechanisms in DeFi Lending Protocols: A Crosschain Comparative Analysis of Aave and Compound

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Abstract

Blockchain-based decentralised lending is a rapidly growing and evolving alternative to traditional lending, but it poses new risks. To mitigate these risks, lending protocols have integrated automated risk management tools into their smart contracts. However, the effectiveness of the latest risk management features introduced in the most recent versions of these lending protocols is understudied. To close this gap, we use a panel regression fixed effects model to empirically analyse the cross-version (v2 and v3) and cross-chain (L1 and L2) effectiveness of liquidation mechanisms, measured through TVL and total revenue as proxies for performance of the two most popular lending protocols, Aave and Compound, during the period Jan 2021 to Dec 2024. Our analysis reveals that liquidation events in v3 of both protocols lead to an increase in total value locked and total revenue, with stronger impact on the L2 blockchain compared to L1. In contrast, liquidations in v2 have an insignificant impact, which indicates that the most recent v3 protocols have better risk management than the earlier v2 protocols. We also show that L1 blockchains are the preferred choice among large investors for their robust liquidity and ecosystem depth, while L2 blockchains are more popular among retail investors for their lower fees and faster execution. Index Terms—Blockchain, DeFi, Lending, Risk Management

1. Introduction

Decentralised finance (DeFi) is a new and rapidly growing financial system built on blockchain technology and smart contracts. It offers more transparent, accessible, interoperable, secure, open, and peer-to-peer financial transactions (Kaplan et al., 2023) by replacing centralised intermediaries (Bertucci et al, 2024; Sun et al., 2022). These transactions are often more profitable than traditional financial systems (Sick, 2023) due to the low borrowing cost and high-return investments in crypto assets, even during a recession in traditional markets (Kuzenkov, 2023). Smart contracts can be programmed for a wide array of functions, replicating traditional financial services (Harvey et al., 2021; Werner et al., 2022) such as lending, cryptocurrency exchange, asset management (Sun et al., 2022) and insurance services (Huber & Treytl, 2022). The market size of DeFi, measured by the total value locked (TVL), has increased substantially over the last few years, peaking at USD $179bn on 17 Dec 2024, as shown in Fig. 1. Among the various categories of DeFi protocols, lending is the largest, with nearly $75bn TVL as of 31 Dec 2024 (source: DeFiLlama).

Fig 1. DeFi TVL 2020-2025 (Data Source: The Graph).

However, despite its potential, DeFi faces significant risks, including regulatory concerns, scalability issues, liquidity risk, oracle risk, credit risk, and smart contract vulnerabilities (Huber & Treytl, 2022). The nascent ecosystem of DeFi also raises concerns about its stability and the lack of consumer protection mechanisms (Kuzenkov, 2023). These risks also manifest in DeFi lending markets, with the potential to cause considerable losses to participants and protocols. In DeFi lending, especially, the main risk is the liquidation risk (Qin et al., 2021) which occurs when the value of the collateral falls below the minimum collateralization threshold. Although liquidation risk primarily affects the borrower, it can also negatively affect lenders, liquidity providers, and protocols during black swan events of extreme market volatility (Gogol et al., 2024). Analyzing the health and stability of lending protocols in response to liquidation risk is therefore crucial to understanding the automated risk management offered by different protocols, so that investors and policymakers can make informed decisions.

To our knowledge, market data-driven research on liquidation risk management in DeFi lending protocols remains limited. In particular, we find that no previous studies have compared the performance and automated liquidity risk management of lending protocol versions v2 and v3, or the comparative effects of deployment on L1 and L2 blockchains. Of the available studies in the literature, their findings indicate that liquidation events can decrease the TVL of lending protocols (Sun et al., 2022; Luo et al., 2024) however, these works are limited to only earlier versions of the protocols (v1 and v2), which are deployed exclusively on L1 blockchains. Further investigation of risk management strategies used in the most recent version v3, deployed on both L1 and L2 blockchains, is still lacking. In this work, we compare the top lending protocols, Aave and Compound, using recent data covering the period Jan 2021 to Dec 2024. We apply a panel regression fixed effects model to discover fresh insights into cross-version and cross-chain performance, as well as liquidation risk management. We use TVL and total revenue (TR) as proxies for protocol stability, regressed on liquidations-related and risk-related variables.

Our findings reveal that v3 lending protocols have better risk management, particularly when deployed on L2 blockchains. Unlike the v2 protocols deployed on L1, where liquidations have no significant effect on revenue, v3 protocols—especially on L2—exhibit a positive relationship between liquidations and TVL, and a positive relationship between liquidations and TR. This suggests that the enhanced design of v3, combined with the scalability and lower transaction costs of L2, strengthens the resilience of the protocol during market stress. The results also point to a split in user preferences, such that institutional users gravitate toward L1 for its liquidity and ecosystem depth, while retail users prefer L2 for its cost efficiency. The remainder of this study is arranged as follows: Section II presents an introduction to the DeFi lending market and discusses the relevant literature in this field and how our research contributes to it. In Section III, we present our data collection process. In Section IV, we discuss the empirical methodology used in our study. Section V interprets the relevant empirical findings and discusses the corresponding results. Finally, Section VI concludes.

2. Background

2.1 Evolution of DeFi lending Market, Protocols, and Advanced Risk Management
Decentralised lending refers to the practice of lending and borrowing facilitated directly through blockchain technology and smart contracts (Cornelli et al., 2024) thereby bypassing traditional centralised intermediaries. According to Heimbach & Huang (2024), decentralised lending platforms have emerged as a cornerstone, facilitating collateralised borrowing activities on an economically significant scale (Chiu et al., 2023) facilitating liquidity provision (Bhoyar et al., 2024) and allowing users to earn interest on their crypto holdings or borrow funds.

Lending and borrowing activities via DeFi lending protocols typically operate as shown in Fig. 2. Lenders with excess funds provide assets to a lending smart contract. These assets are mostly in the form of stablecoins, e.g., USDT. Borrowers then provide collateral, mostly in the form of volatile coins, such as bitcoin, to borrow stablecoins. To access the service, borrowers pay a fee in the form of an interest payment, which is then passed on to lenders as a reward. The borrow rate of interest is set dynamically by a pre-defined function of crypto demand and supply (Bertucci et al., 2024). This fluctuating rate protects the protocol against the run risk (Lehar & Parlour, 2022).

Fig 2. DeFi lending mechanism.

Due to the anonymity of borrowers and lenders and the volatile nature of the crypto market, the DeFi lending platform relies heavily on over-collateralised loans, which means that the amount of debt the borrowers can take on is typically lower than the value of the collateral deposited (Qin et al., 2021; Bertomeu et al., 2024). The protocol ensures that enough collateral is locked over time and liquidation serves as a safety mechanism to reduce the risks of default (Mittal, 2023). If the collateral depreciates below a liquidation threshold, the borrow position is designated as ‘under-collateralised’ and the collateral can be liquidated by a third party liquidator. On such occasions, liquidators can claim a portion of the borrower’s collateral at a discounted price known as liquidation bonus for liquidators, and liquidation penalty for borrowers to repay the debt, thus reducing the loan-to-value ratio (ratio of loan amount to collateral value) of the borrower’s loan, as shown in Fig. 3.

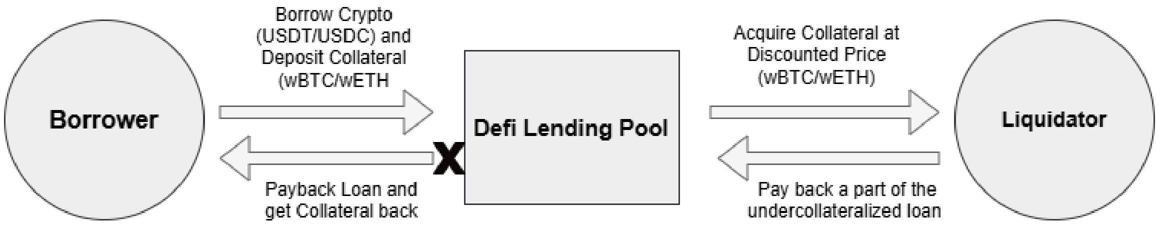

Fig 3. DeFi liquidation mechanism.

However, despite the presence of liquidation mechanisms, defaults can still occur due to sudden drops in collateral value or insufficient incentives for liquidators to act (Bastankhah et al., 2024) which results in reduced capital efficiency and increased collateral illiquidity risk.

Table I summarizes the functionality of Aave and Compound, two of the oldest and most successful DeFi lending platforms. Aave has the highest TVL in the DeFi lending space and is a decentralised open-source platform operating on 11 different blockchains. Compound finance is also among the top five lending protocols and operates on nine different blockchains. Notably, initial versions (i.e., v1, v2) of these protocols only implemented basic risk controls, such as collateral factors and static risk parameters (liquidation threshold, liquidation penalties, borrow/lending rates), whereas upgraded versions (i.e., v3) introduced more sophisticated tools that are explicitly designed to mitigate systemic vulnerabilities. These tools differ from traditional risk management practices (ringfencing, credit exposure limits, and portfolio rebalancing) by being automated, transparent, and enforced via smart contracts. The dynamic risk parameters and targeted mechanisms provide more granular control over asset-specific risk and reduce the likelihood of systemic contagion. These upgraded versions are launched on both L1 and L2 blockchains: L1 blockchains (e.g., Ethereum) denote the base networks that establish the primary consensus processes to achieve decentralization and guarantee primary on-chain activities; while L2 blockchains (e.g., Arbitrum, Optimism) inherit security and decentralization from L1 and increase transaction throughput, offering low transaction fees and faster transactions (Song et al., 2024).

Risk management in lending protocols relies on automated mechanisms like over-collateralisation ratios, governance frameworks, and liquidation triggers to protect participants and maintain stability. However, these measures can be insufficient during periods of high volatility, market congestion, liquidation spirals, and systemic risk. High transaction costs can also reduce their effectiveness in maintaining stability (Lehar & Parlour, 2022; Bertomeu et al., 2024). The latest v3 versions of the protocols address these shortcomings by incorporating advanced risk management features, as shown in Table I; including enhanced liquidation incentives and dynamic collateral requirements, which allow users to adjust their borrowing parameters to match their risk profile, thus mitigating liquidation cascades and improving resilience.

Table I: Feature Comparison: Aave and Compound.

Feature	Aave v1	Aave v2	Aave v3	Compound v1	Compound v2	Compound v3
Year Launched	Jan 2020	Dec 2020	Mar 2022	Sep 2018	May 2019	Aug 2022
Blockchain Layer	L1	L1	L1 & L2	L1	L1	L1 & L2
Collateral Swaps	x	✓	✓	x	x	Not Supported directly
Repayment with Collateral	x	✓	✓	x	x	Not Supported directly
Flashloans	Introduced	Improved	Cross-chain Flashloans	x	x	x
Isolation Mode	x	x	✓	x	x	Isolated Pools
Risk Parameters Customization	Static	Improved	Dynamic, asset - specific	Static	More Flexibility	Asset-specific
Efficiency Mode (eMode)	x	x	✓	x	x	x
Borrow/Supply Caps	x	x	✓	x	x	✓
Oracle Source	Chainlink	Chainlink	Chainlink + CAPO	Centralized OPF	Chainlink	Chainlink + TWAP
Liquidity Portals	x	x	✓	x	x	x

Isolation mode prevents contagion from volatile assets; efficiency mode, optimizes capital utilization for correlated assets; and caps on borrow and supply asset limits, overexposure to risky tokens. Furthermore, the integration of L2 blockchain with v3 protocols has reduced transaction cost and increased throughput, thus facilitating faster and more efficient collateral modifications and immediate liquidation triggers, which mitigates the prospect of delayed or unsuccessful liquidations. As more than 70% of liquidations occur in the absence of any price decline of crypto assets (Moallemi & Patange, 2024), the latest protocols also observe market sentiment and patterns for efficient risk management. These innovations collectively facilitate a more resilient and efficient risk management system (particularly when compared with v2 on L1 blockchain). Our study focuses on investigating those risk parameters that exert a direct impact on the liquidation risk mechanism, such as to loan-to-value ratio, liquidation penalty, and liquidation threshold.

2.2 Existing work on liquidation risks in DeFi lending

Here, we review the relatively limited literature on the evaluation of liquidation risks in DeFi lending protocols. Study by Qin et al. (2021) investigated liquidations in lending protocols by considering the potential to manipulate the existing system and suggested an alternative liquidation mechanism called a “reversible call option”. Another study by Warmuz et al. (2022) also investigated liquidation spirals and recommended changes to existing liquidation mechanisms. In a research by Lehar and Parlour (2022), an inherent systemic fragility was observed in DeFi lending markets, resulting from liquidators selling the collateral during a price drop, leading to a further drop in prices and causing cascading liquidations of other loans. Related to systemic issues, Cohen et al. (2023) highlighted that any incentive for liquidators to act when a loan is in distress would be associated with a subsequent incentive to manipulate prices and cause liquidations of loans.

Previous studies, with a particular focus on the relationship between liquidations and TVL, highlight the negative impact of liquidations on the TVL of the protocols. A Study by Luo et al. (2024) investigated the impact of ETH volatility on TVL of the protocol via liquidations. They performed an empirical and sensitivity analysis using the decline in ETH as a price shock to TVL, while controlling different factors, such as the gas price, the liquidation threshold, and VIX. Their findings showed that TVL is highly unstable during market downturns due to cascading liquidation events. The impact of different risk indicators on the performance of the protocol was also investigated by Sun et al. (2022). They used different performance metrics including TVL and TR and confirmed the negative impact of liquidations on TVL, but found insignificant results for the impact on TR. The key findings of all these studies are summarised in Table II. Note that these studies focused mainly on earlier versions, that is v1 and v2 of the protocols; only the research by Sun et al. (2022) included v3 of the Compound protocol, but within a relatively limited time frame (from protocol launch in Aug 2022, until Jan 2023).

Table II: Summary of prior findings on the impact of liquidations on TVL and revenue in DeFi lending protocols.

Study	Findings	Timeframe	Protocols	Blockchain
Sun et al. (2022)	Liquidations cause a decrease in TVL	Dec 2019 – Jan 2023	Aave v1, Aave v2, Compound v3	Layer 1
Luo et al. (2024)	Liquidations cause a decrease in TVL	Jan 2021 – Mar 2024	Aave v2, MakerDAO, JustLend	Layer 1
Sun et al. (2022)	Insignificant relationship between liquidations and total revenue	Dec 2019 – Jan 2023	Aave v1, Aave v2, Compound v3	Layer 1
Sinyugin (2023)	Mass liquidations can sometimes signal efficient risk management	Descriptive analysis	Aave and Compound	Not specified

Despite a growing body of literature on DeFi risks, existing studies have largely overlooked the effectiveness of evolving risk management mechanisms within lending protocols, particularly in the most recent v3 versions launched on L1 and L2 blockchains. Our study adds to the growing literature that focuses on the efficiency of risk management system in upgraded versions of lending protocols by investigating protocol's advanced features, transaction costs, volatility, and sentiment in crypto and traditional markets.

3. Data Collection

We focus on Aave and Compound in analyzing the performance of risk management in lending protocols. The period of the research ranges from 01 Jan 2021 to 31 Dec 2024, which includes significant events of boom and crises, aligning with our research goals (see Fig. 1). For cross-version comparison, v2 and v3 versions are selected (see Table I for feature descriptions), while v1 was omitted due to its deprecated status. In conducting a cross-chain analysis, we focus on Ethereum as a representative of Layer 1 blockchains and Arbitrum for Layer 2 blockchains, chosen based on their leading TVL during the time period under consideration. The TVL data for the selected protocols is presented in Fig. 4. To include data related to the performances of protocols, we collect the underlying asset data specifically, the daily adjusted closing prices of ETH from webpage *https://coinmarketcap.com/*. Core protocol-level data, including TVL, TR, liquidation volume, withdrawal volume, loan-to-value ratios, liquidation penalties, and liquidation thresholds for each protocol, are obtained from *https://thegraph.com/*. Additionally, borrowing rates for USDC in Aave and Compound are sourced from *https://aavescan.com/*. We also collect gas price data for the Ethereum and Arbitrum blockchains from *https://etherscan.io/* and *https://arbiscan.io/*, respectively, to account for the transaction costs of each layer.

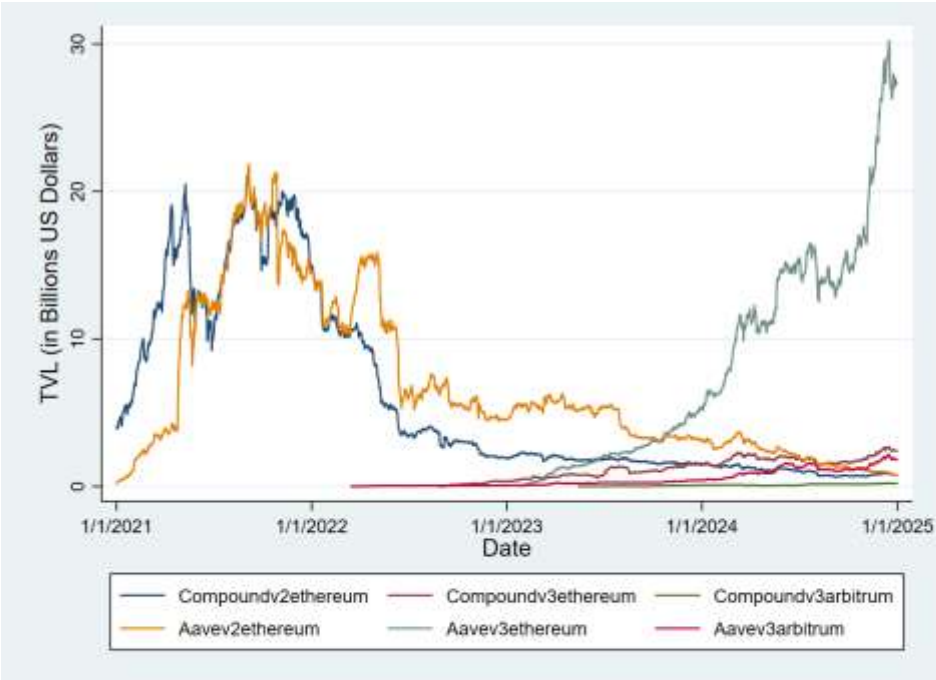

Fig 4. Crosschain TVL of Aave and Compound.

To capture market sentiment, we include the fear and greed index (FGI) of the crypto market, and CBOE volatility index (VIX) from https://alternative.me/crypto/fear-and-greed-index/ and LSEG workspace, respectively. We also define a risk metric in Equation (1), which we call the Default Risk Metric (DRM). The DRM is a composite measure designed to capture the stringency of a lending protocol's risk management framework. It include variables that are directly related to liquidations. A higher DRM value indicates a more stringent risk policy, meaning borrowers face a higher likelihood of liquidation because the protocol maintains tighter collateral requirements and imposes larger penalties upon default. Conversely, a lower DRM reflects a more lenient framework, offering borrowers greater flexibility at the cost of potentially higher protocol exposure to under-collateralized positions. This metric serves as a key control variable in our regression analysis, allowing us to isolate the effect of protocol-level risk stringency on performance outcomes.

$$\text{DRM} = \frac{\text{Loan to Value}}{\text{Liquidation Threshold}} + (1 + \text{Liquidation Penalty}) \quad (1)$$

The final dataset used for further analysis comprises 1456 observations, following the removal of extreme outliers. Summary statistics for these data are reported in Table III.

Table III: Summary Statistics

Variable	Mean	Std. Deviation	Minimum	Maximum
ETH Returns	0.00	0.04	−0.31	0.22
TVL ($bn)	4.46	5.54	0.01	30.21
Total Revenue ($bn)	0.13	5.09	0.00	260.00
Liquidations ($mn)	0.47	5.16	0.00	232.22
Withdrawals ($bn)	0.31	0.88	0.00	25.40
USDC Borrow APR	5.76	7.11	0.71	63.57
Gas Ethereum (ETH)	41.52	52.06	0.00	939.59
Gas Arbitrum (ETH)	3.32	1.43	0.00	4.78
FGI	51.12	20.75	6.00	95.00
VIX	18.44	5.17	11.86	38.57
DRM	7.19	4.92	0.95	11.10

Note: Summary of all variables included in our data from 01 Jan 2021 to 31 Dec 2024, with outliers removed. Raw data consists of daily frequency of 1461 observations. Total revenue had some extreme outliers, driven by large scale liquidations in Aave v3, which generated substantial liquidation fees. These daily observations were removed (5 in total) using a 1% cut-off, resulting in 1456 observations. However, all findings reported in this study are unchanged when analysis is performed on the full data, including outliers.

4. Methodology

Regression analysis is the most common method to determine the relationship between dependent and independent variables in DeFi markets. Many studies (Bertucci et al., 2024; Sun et al., 2022; Cornelli et al., 2024; Lehar & Parlour, 2022; Bertomeu et al., 2024; Bastankhah et al., 2024; Moallemi & Patange, 2025; Abraham, 2024) that have used regression analysis to assess various aspects and risks in DeFi lending markets. In this study, we employ a panel regression model with fixed effects to quantify how liquidations driven by various risk factors affect the performance (proxied by TVL and TR) of DeFi lending protocols. As our dataset spans multiple protocols (Aave and Compound, across v2/v3 and L1/L2 deployments) over time, panel regression analysis is well-suited because it captures both the cross-sectional variation between protocols and the time-series variation within each protocol. This yields a total of 16 distinct entities (2 protocols × 2 versions × 2 chains × time), each observed daily. Panel regression with fixed effects controls for unobserved, time invariant heterogeneity and improves estimation efficiency by leveraging repeated observations over time (Wooldridge, 2010). We employ a fixed effects model with Entity fixed effects that capture time-invariant, unobserved characteristics unique to each protocol, version, and chain combination including protocol specific smart contract architecture, version specific risk parameters, chain specific characteristics, and user base composition. Time fixed effects captures common shocks affecting all entities in a given period e.g. cryptocurrency market cycles (bull or bear), major regulatory announcements, systemic events (Terra Luna collapse, FTX failure), and macroeconomic conditions affecting all lending protocols. The inclusion of both entity and time fixed effects addresses the concern that omitted variables whether constant over time or constant across entities might bias the estimates. The regression model is illustrated in Equation (2).

$$\begin{aligned} Perf_{i,t} = {} & \alpha_i + \beta_1 Liq_{i,t} + \beta_2 Liq_{i,t} Lay_i + \beta_3 Liq_{i,t} Ver_i + \beta_4 Liq_{i,t} Platf_i + \gamma_1 DRM_{i,t} + \\ & \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \\ & \gamma_7 VIX_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

The dependent variable, $Perf_{i,t}$ measures the performance of protocol *i* at time *t*, using either TVL or TR data after logarithmic transformation. Our main explanatory variable is the logged liquidation volume, $Liq_{i,t}$. We include several control variables to account for potential confounding factors. The variable $DRM_{i,t}$ captures the level of default risk associated with protocol *i* at time *t*. Market volatility is represented by $VolETH_{i,t}$ for the collateral asset ETH, $VolGasPri_{i,t}$ for the volatility of gas prices, and $VolUSDCbor_{i,t}$ for the volatility of USDC borrow rate. The volatilities are 7-day rolling standard deviation of the log-returns. Protocol-level activity is measured by $Wd_{i,t}$, which is the logged total withdrawal volume from protocol *i* at time *t*. To control for broader market sentiment, we incorporate FGI_t as a proxy for investor sentiment in the cryptocurrency market and VIX_t for sentiment in the traditional financial market. The sentiment variables are used after logarithmic transformation. By including these controls alongside entity and time fixed effects, we isolate the marginal effect of liquidations on protocol performance from a wide range of confounding factors. These controls mitigate omitted variable bias arising from macro level shocks that simultaneously affect liquidations and protocol performance.

To capture heterogeneity across blockchain layers, protocol versions, and lending platforms, we introduce three dummy variables. To indicate the blockchain layer, we use $Lay_i \in \{0 = \text{L1}, 1 = \text{L2}\}$; for the protocol version, we use $Ver_i \in \{0 = \text{v2}, 1 = \text{v3}\}$; and for the individual protocol, we use $Platf_i \in \{0 = \text{Compound}, 1 = \text{Aave}\}$. In cross-version and cross-chain analysis, we include the dummy variable Ver_i and Lay_i in the regression models referred to as Model 1 (regression on TVL) and Model 2 (regression on TR). For the analysis of cross-protocol and cross-version effects on performance, we incorporate the dummy variables Ver_i and $Platf_i$, corresponding to Model 3 (regression on TVL) and Model 4 (regression on TR). A comprehensive regression model including all variables is presented in Appendix B. Before conducting the regression analysis, the multicollinearity was assessed using the Variance Inflation Factor (VIF). The VIF values ranged from 1.1 to 2.1, well below the commonly used threshold of 3, indicating that there is no significant multicollinearity among the explanatory variables (see Appendix A for details).

5. Results and Findings

5.1 Cross-version and cross-chain analysis of liquidations

Model 1 in Table IV presents TVL regression results for lending protocols v2 and v3 across Ethereum (L1) and Arbitrum (L2) chains. For v2 lending protocols deployed on the Ethereum blockchain, we find that a 1% increase in liquidations is associated with a 0.01% decrease in TVL for these protocols (i.e., Liq = −0.01). This negative relationship observed in v2 protocols is consistent with previous findings (Sun et al., 2022; Luo et al., 2024) (also see Table II). In contrast, we find that TVL in v3 protocols deployed on L1 and L2 chains has a positive significant relationship with liquidation, with a 1% increase in liquidations associated with a 0.02% increase in TVL on L1 (Liq + Liq:Ver = (−0.01) + 0.03 = 0.02), and a 0.07% increase in TVL on L2 (Liq + Liq:Lay + Liq:Ver = (−0.01)+0.05+0.03 = 0.07). The overall positive relationship on v3 protocols—i.e., an increase in liquidations leads to an increase in TVL is a new finding that has not been reported before. It should be noted that the coefficient Liq:Lay is significantly positive at 0.05, indicating that liquidation has a heterogeneous impact on TVL across different layers under the same version, specifically in v3. This suggests that a 1%

increase in liquidation on Arbitrum is associated with a 0.05% greater increase in TVL compared to Ethereum, highlighting a differentiated response to liquidation activity between the two layers. This is a new finding that has not been reported before.

Model 2 in Table IV presents the regression on TR for protocols v2 and v3 across Ethereum (L1) and Arbitrum (L2) chains. An insignificant coefficient for Liq was found, indicating an insignificant impact of liquidation on TR for the v2 protocols on L1 (Ethereum). This insignificance on TR is consistent with previous findings (Sun et al., 2022) (see Table II, row 3). For v3 deployed on L1 and L2 blockchains, we see that TR is positively related to liquidations, i.e., with 1% increase in liquidation, TR will increase by 0.02% on L1 (Liq + Liq:Ver = 0.00 + 0.02 = 0.02), and 0.11% on L2 (Liq + Liq:Lay + Liq:Ver = 0.00 + 0.09 + 0.02 = 0.11). This is a new finding that has not been reported before. Moreover, we also see that this positive effect is stronger for the Arbitrum-based (L2) protocols, due to a significant coefficient of Liq:Lay.

5.2 Cross-protocol and cross-version analysis of liquidations

Model 3 in Table IV presents the regression on TVL for v2 and v3 versions of Aave and Compound. For Compound v2, as the baseline in Model 3, an insignificant coefficient for Liq was found, so there is no significant relationship between liquidations and TVL. However, for Aave v2, we find that TVL has a statistically significant negative relationship with liquidations, such that a 1% increase in liquidations is associated with a 0.01% decrease in TVR (Liq + Liq:Platf = 0.00 + (−0.01) = −0.01). In contrast, v3 protocols both show a significant positive relationship between liquidations and TVL. For Compound v3, we see that a 1% increase in liquidations leads to a 0.05% increase in TVL (Liq + Liq:Ver = 0.00+0.05 = 0.05); and for Aave v3, we see that a 1% increase in liquidations leads to a 0.04% increase in TVL (Liq + Liq:Ver + Liq:Platf = 0.00 + 0.05 + (−0.01) = 0.04).

Table IV: Cross-Version, Cross-Chain, and Cross-Protocol Regression of TVL and TR on Liquidations

Variable	Model 1	Model 2	Model 3	Model 4
Liq	-0.01***	0.00	0.00	0.00
Liq:Lay	0.05***	0.09***		
Liq:Ver	0.03***	0.02*	0.05***	0.06***
Liq:Platf			-0.01*	0.00
DRM	0.01***	0.01***	0.01***	0.01***
VolETH	-1.90***	-2.23**	-1.94***	-2.25**
VolGasPri	-0.15***	-0.19***	-0.15***	-0.19***

VolUSDCbor	0.02***	0.05***	0.02***	0.05***
Wd	0.40***	0.49***	0.40***	0.49***
FGI	0.08***	0.46***	0.09**	0.48***
VIX	-0.27***	-0.76***	-0.29***	-0.79***
Adj. R-sq	0.61	0.57	0.61	0.56

Note: This table includes estimates of four panel regression models performed on cross-chain, cross-version TVL (Model 1) and TR (Model 2) as dependent variables, regressed against liquidations and relevant control variables. In Model 3 and Model 4, regression estimates of cross-protocol, cross-version analysis are reported, where TVL (Model 3) and TR (Model 4) as dependent variables are regressed against liquidations and relevant control variables. All models are estimated as follows:

Model 1: $TVL_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_2 Liq_{i,t} Lay_i + \beta_3 Liq_{i,t} Ver_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Model 2: $TR_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_2 Liq_{i,t} Lay_i + \beta_3 Liq_{i,t} Ver_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Model 3: $TVL_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_3 Liq_{i,t} Ver_i + \beta_4 Liq_{i,t} Platf_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Model 4: $TR_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_3 Liq_{i,t} Ver_i + \beta_4 Liq_{i,t} Platf_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Asterisks indicate statistical significance of estimates; with $*$ indicating p < 0.10, $**$ indicating p < 0.05, and $***$ indicating p < 0.01.

Model 4 in Table IV reports regression on TR for v2 and v3 versions of Aave and Compound. Significant heterogeneity across versions can be observed. For all v2 protocols, the impact of liquidation on TR is insignificant (see Liq and Liq:Platf, respectively). However, there is a significant positive relationship between liquidation and TR for Compound v3 and Aave v3 protocols, with a 1% increase in liquidations leading to a 0.06% increase in TR (Liq:Ver = 0.06). These results confirm that the v3 protocols have more efficient and robust liquidity risk management than the older v2 protocols. This finding is consistent with the results reported by Sinyugin (2023), which showed that liquidations, in some cases, reflect a protocol's stability against risks.

An important methodological consideration in this study is the potential for endogeneity, particularly reverse causality, between liquidation events and protocol performance (proxied by TVL and TR). While the primary specification in Equation (2) treats liquidations as an exogenous shock affecting protocol performance, theoretical considerations suggest that the relationship may be bidirectional: periods of low TVL or declining revenue may increase the likelihood of liquidation events as collateral values become more volatile and borrower positions approach threshold levels.

To empirically assess the presence and direction of causality, a supplementary analysis was conducted employing a panel Granger causality framework. For each protocol-version-chain combination, lagged values of liquidations were regressed against current TVL, and conversely, lagged values of TVL were regressed against current liquidations, controlling for protocol and time fixed effects. The results reveal a unidirectional causal relationship: past TVL Granger causes liquidations, while past liquidations do not Granger cause TVL. This directional finding indicates that a larger pool of deposited collateral creates greater liquidation exposure and predicts liquidation activity. However, total revenue and liquidations exhibit a bidirectional causal relationship, reflecting a self-reinforcing feedback loop between liquidation fee generation and protocol growth that is a characteristic of the v3 risk management architecture. Results are reported in Appendix C.

5.3 Discussion

Decentralised lending offers innovative opportunities for direct interaction between borrowers and lenders (Harvey et al., 2021), yet it also introduces new risks that lack centralised governance. The liquidation process functions as a risk mitigation strategy; but its effectiveness decreases as risk levels increase and, if implemented too late, it may fail to recover the debt position (Sick, 2023). However, an increased volume of liquidations does not necessarily indicate a risk for a platform; instead, sometimes, it demonstrates the protocol's ability to effectively reduce risk and protect funds within the system. Especially if the functioning of the protocol remains unaffected by significant liquidations (Sinyugin, 2023). The results hold for our research as the regression analyses for version 3 of Aave and Compound on the Ethereum and Arbitrum blockchains exhibit a positive correlation between liquidations and both TVL and TR, reflecting the protocols' stability and health against liquidation risk. However, versions 2 of both platforms do not exhibit this positive correlation. The behavioral divergence between v2 and v3 is likely influenced by a combination of protocol-specific and market-driven factors.

Following the launch of the v3 protocols, substantial user migration was observed from v2 to v3. To smooth this shift, v3 smart contracts were embedded with integrated migration tools, advancing the user migration process. Fig. 5a shows the daily active user count for both the v2 and v3 protocols, indicating a significant transition in user engagement towards v3 protocols during the period Jan 2021 to Dec 2024. This pattern offers a plausible explanation for the increase in TVL in v3 protocols, especially after liquidation events. Instead of reinvesting in v2, borrowers choose to transition to v3, driven by its improved risk management systems and advanced functionalities. The reported increase in TVL and TR on v3 protocols—particularly on the L2 Arbitrum chain during the period of this study can be attributed to this influx of users (see Fig. 5a and Fig. 5c, showing high user activity and high deposit counts on Aave v3 Arbitrum). The increase in engagement from both depositors and borrowers during market stress events such as liquidations highlights the growing preference for the more resilient and user-centric design of the v3 protocols. However, the number of direct deposits and loans on the v3 protocols is significantly higher than migrated deposits and loans (Source: Dune Analytics).

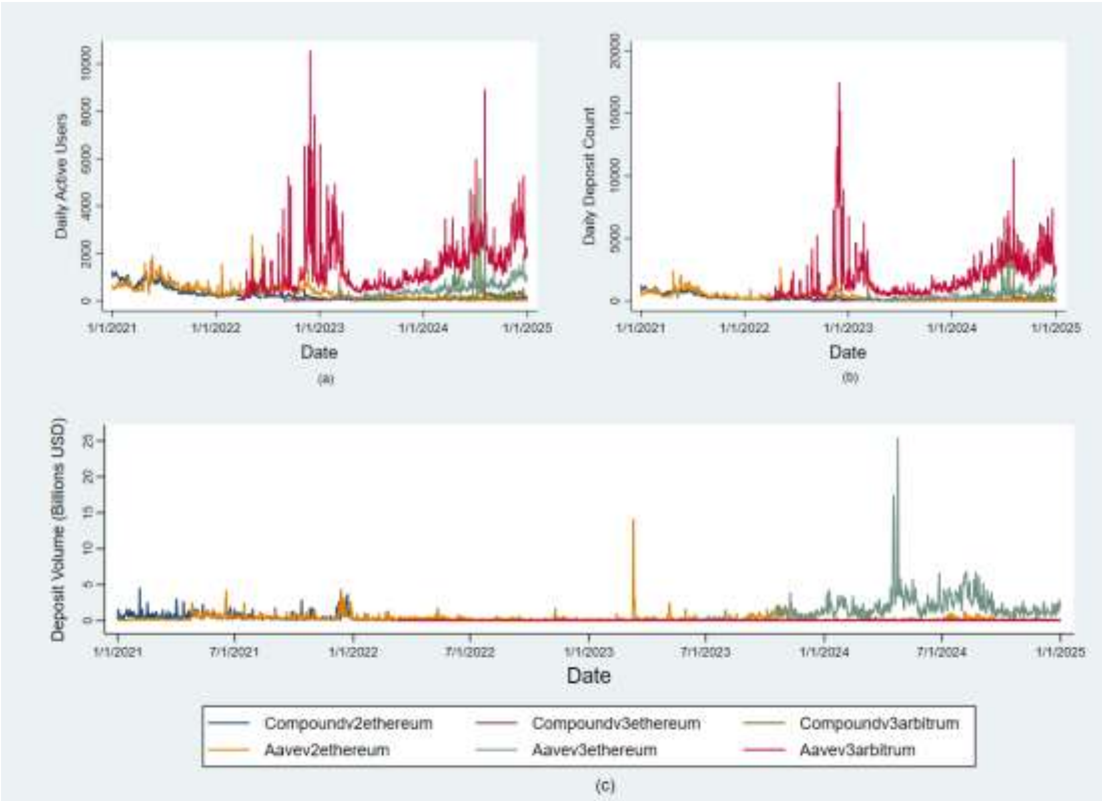

Fig. 5: Usage comparison of lending protocols.

Another contributing reason to the observed increase in TVL after liquidation events, notably in v3 cross-chain lending protocols, is the rebound effect commonly observed in cryptocurrency markets. This phenomenon denotes a rapid recovery in the prices of volatile assets, such as Bitcoin and Ether, after a significant decrease. The rapid increase in asset prices following a liquidation can inflate the TVL as collateral values recover and users restore faith in market conditions. Within the framework of v3 protocols, this rebound effect can amplify TVL growth, intensifying the impact of increased user migration and continued protocol engagement.

Fig. 5b shows that the Ethereum blockchain in v3 lending protocols represents the highest total deposit volume in USD, indicating a substantial capital concentration. In contrast, Fig. 5c illustrates that the Arbitrum chain experiences the highest number of individual deposit transactions. Moreover, Fig. 5b also confirms that the Arbitrum chain has the largest number of active users, indicating a predominantly retail oriented user base. These findings suggest a divergence in user behaviour between chains, with large investors tending to prefer the Ethereum (L1) chain due to its robust liquidity, institutional involvement, and more integrated infrastructure within the DeFi ecosystem; while smaller retail investors primarily use Arbitrum-based (L2) protocols, likely motivated by its reduced transaction fees and faster execution. We have shown that the sensitivity of TVL and TR to liquidation events is significantly greater on the Arbitrum chain compared to Ethereum (see Table IV). This increased responsiveness illustrates the behavioural characteristics of retail investors, who are generally more sensitive to market fluctuations. These observations align with the findings of (Cornelli et al., 2024), which indicate that retail investors are more sensitive to ETH price changes than large investors. Furthermore, the change in the relationship with liquidations on the v2 and v3 protocols can be attributed to the varying methodologies used to execute functions such as collateralisation ratios and interest rate models, leading to significant differences in their robustness, efficiency, and resilience (Sinyugin, 2023). In v3 protocols, liquidations occur with greater frequency; however, they are managed more effectively. Their upgraded mechanism facilitates liquidations without significant depletion of TVL and, in some cases, liquidations can even increase TVL and TR depending on the architecture, mechanism, and governance of the protocols.

Granger causality tests also confirm that TVL temporally precedes liquidation activity, consistent with the mechanism that high TVL generates greater liquidation exposure. This unidirectional causality supports our interpretation that v3 protocols attract capital inflows which, while increasing liquidation frequency, are managed more effectively by the enhanced risk mechanisms. Our panel regression captures contemporaneous correlations specifically, that liquidation events and TVL move together positively within the same period in v3 protocols and the Granger test addresses temporal precedence. The TR results reveal a contrasting and more nuanced dynamic. Unlike TVL, where causality runs from TVL to liquidations, the relationship between TR and liquidations is bidirectional at both lag orders. Liquidation events directly generate protocol revenue through liquidation penalty fees, which are distributed to the protocol treasury, while higher revenue reflecting a thriving, active protocol attracts greater borrowing activity, expanding the pool of positions susceptible to future liquidations. This self-reinforcing cycle is particularly consistent with the v3 architecture, where liquidation incentives are more sophisticated and fee structures are more transparent, making the revenue liquidation feedback more efficient.

The findings of this study carry implications that extend beyond the narrow context of Aave and Compound, offering broader insights into how automated risk management tools shape lending protocol outcomes. Within the DeFi ecosystem, the observed divergence between v2 and v3 protocols underscores that the design of liquidation mechanisms particularly the shift toward more granular, asset-specific risk parameters and dynamic fee structures directly influences protocol resilience during periods of market stress. The positive relationship between liquidations and both total value locked and total revenue in v3 protocols suggests that well-designed risk frameworks can transform liquidation events from destabilizing shocks into mechanisms that reinforce user confidence and protocol stability. This stands in contrast to earlier versions, where liquidations carried no such positive signal. When comparing across protocols, Aave and Compound exhibited similar directional responses within the same version cohort, indicating that the version-level architectural choices (e.g., the introduction of isolation modes, portal functionality, and enhanced oracle mechanisms in v3) may matter more than protocol-specific idiosyncrasies in determining how effectively risk is managed.

Beyond DeFi, the mechanisms driving automated risk management have practical relevance for traditional lending risk management. Traditional financial institutions could implement real time, transparent collateral monitoring by adopting blockchain inspired infrastructure where collateral values are continuously tracked through integrated data feeds instead of periodic manual valuations that can become outdated during rapid market movements. This would enable early warning systems that trigger automated margin calls when collateralization ratios approach predefined thresholds, reducing the lag between risk emergence and risk response. Second, the DeFi model of incentive aligned third party participation for liquidations could be adopted for traditional lending. Incentivised and regulated firms could perform a similar function, keeping non-performing loans from piling up on bank balance sheets. Third, one of the more persistent problems in traditional lending is discretionary forbearance. Smart contract based liquidation thresholds, could reduce this ambiguity by making enforcement conditions explicit and automatic strengthening both borrower discipline and regulatory confidence. Finally, the isolation mechanism seen in v3 protocols where volatile assets are contained within separate lending pools to limit contagion has a clear parallel in traditional banking. Ringfencing high risk loan portfolios in a similar fashion could prevent distress in one segment from spreading into a broader institutional crisis. Thus, the evolution of DeFi lending protocols provides a natural experiment from which both decentralized and traditional financial systems can draw actionable insights.

6. Conclusions

We have investigated the effectiveness of automated risk management strategies during liquidation events and their impact on the performance and stability (measured by TVL and TR) of decentralised lending protocols. For this purpose, we selected the top lending protocols, Aave and Compound, including their old (v2) and upgraded (v3) versions deployed on L1 and L2 blockchains, to assess the effectiveness of prevalent risk management mechanisms. The results suggest that liquidation events in v3 protocols lead to increased TVL and total revenue, with a more pronounced effect on the Arbitrum (L2) blockchain compared to the Ethereum (L1) blockchain. In contrast, for the v2 protocols, liquidations have an insignificant impact on TVL and total revenue. A combination of protocol-specific and market-driven factors is likely to influence the behavioral divergence between v2 and v3.

Beyond the immediate context of Aave and Compound, our findings reveal that the architectural evolution from v2 to v3 characterized by granular risk parameters, isolation modes, and enhanced oracle mechanisms has systematically improved protocol resilience, with liquidations in v3 serving as positive signals of stability rather than distress. This pattern held consistently across both protocols, suggesting that version level design choices outweigh protocol specific differences. These results also offer insights for traditional lending risk management such as implementation of blockchain based real time monitoring of liquidations, role of third parties for managing liquidation events and isolation mechanism to mitigating propagation of systemic risk. Our research has important implications for risk managers, investors, and policy makers. This research could be further extended by investigating the wallet-level behavior of lenders, borrowers, and liquidators during and after liquidation events to assess strategic user actions. Furthermore, an event study could be used to explore the role of specific stablecoins and volatile assets in causing systemic risk or spillover effects, after cascading liquidations or oracle failure. Another avenue of investigation is to explore the total value redeemable (TVR) as a performance measure alternative to TVL, as it has been proposed as a more accurate quantifier of the value stored within a protocol (Luo et al., 2024). In the longer term, our aim is to explore the effects of different risk mechanisms using agent-based simulation modelling (Bullock et al., 2024).

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APPENDIX A

Multicollinearity Test

We test multicollinearity of the variables before conducting regression, using the Variance Inflation Factor (VIF) method. These estimates of VIF fall within the range 1.1 to 2.1, as shown in Table A.1, indicating that there is no presence of multicollinearity between the independent variables.

TABLE A.1: Variance Inflation Factor (VIF) Results

Variable	VIF
Liq	1.25
DRM	1.13
VolETH	1.28
VolGasPri	1.61
VolUSDCbor	1.61

FGI	2.11
VIX	1.84
Wd	1.36

APPENDIX B

Comprehensive Model

Here we have used all variable mentioned in our regression model (see Section IV) to account for cross-version, crosschain and cross-protocol effect on protocol performance (proxied by TVL and TR). Our findings in Table B.2 are consistent with the conclusions we made in Section V. The results show that there is significant heterogeneity between layers and versions, which is consistent with the results of Models 1–4.

TABLE B.1: Cross-Version, Cross-Chain, and Cross-Protocol Regression on TVL and Total Revenue

Variable	Model 5	Model 6
Liq	0.00	0.00
Liq:Lay	0.05***	0.09***
Liq:Ver	0.03***	0.02*
Liq:Platf	-0.01*	0.00
DRM	0.01***	0.01***
VolETH	-1.93**	-2.23**
VolGasPri	-0.15***	-0.19***
VolUSDCbor	0.02***	0.05***
Wd	0.40***	0.49***
FGI	0.08**	0.46***
VIX	-0.27***	-0.76***
Adj. R-sq	0.61	0.57

Note: This table includes estimates of two panel regression models performed on cross-chain, cross-version, cross-protocol TVL (Model 5) and TR (Model 6) as dependent variables, regressed against liquidations and relevant control variables. The models are estimated as follows:

Model 5: $TVL_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_2 Liq_{i,t} Lay_i + \beta_3 Liq_{i,t} Ver_i + \beta_4 Liq_{i,t} Platf_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Model 6: $TR_{i,t} = \alpha_i + \beta_1 Liq_{i,t} + \beta_2 Liq_{i,t} Lay_i + \beta_3 Liq_{i,t} Ver_i + \beta_4 Liq_{i,t} Platf_i + \gamma_1 DRM_{i,t} + \gamma_2 VolETH_t + \gamma_3 VolGasPri_{i,t} + \gamma_4 VolUSDCbor_{i,t} + \gamma_5 Wd_{i,t} + \gamma_6 FGI_t + \gamma_7 VIX_t + \varepsilon_{i,t}$

Asterisks indicate statistical significance of estimates; with $*$ indicating p < 0.10, $**$ indicating p < 0.05, and $***$ indicating p < 0.01.

APPENDIX C

Table C.1: Results of Granger Causality Tests (Dumitrescu–Hurlin)

Direction	Lags	W-Bar	Z-bar	p-value
Panel A: TVL and Liquidations				
Liquidations → TVL	1	0.1558	-0.597	0.551
	2	0.9922	-0.504	0.614
TVL → Liquidations	1	15.1706	10.020	< 0.001***
	2	49.7701	23.885	< 0.001***
Panel B: TR and Liquidations				
Liquidations → TR	1	17.2367	11.481	< 0.001***
	2	19.0356	8.518	< 0.001***
TR → Liquidations	1	5.8992	3.464	< 0.001***
	2	15.5294	4.265	< 0.001***

Note: Asterisks indicate statistical significance of estimates; with * indicating $p < 0.10$, ** indicating $p < 0.05$, and *** indicating $p < 0.01$.Results are consistent across both lag orders, confirming a unidirectional causal relationship: TVL → liquidations.

Chapter 5

From cash to Code: Assessment of Risks and Opportunities in Blockchain-Based Complementary Currencies for Universal Basic Income

(Erum Iftikhar)

(Under Review in International Journal of Complementary Currency Research)

Abstract

This paper investigates the socio-technical evolution of Complementary Currencies for Basic Income using a data-driven approach to three different case studies i.e. GiveDirectly, Circles, and GoodDollar. While blockchain-based solutions have several advantages in terms of efficiency, scalability, and transparency, their adoption remains limited compared to traditional cash and community-led systems. In existing studies, much emphasis is given to their technical potential, while less attention is paid to the socio-economic barriers that impede widespread adoption. Therefore, this paper identifies this gap and analyses territorially cash-based UBI, represented by GiveDirectly, with two blockchain-based models, GoodDollar and Circles, using the Impact Assessment Matrix (AIM) to present the associated impediments and opportunities with each case, respectively. Finally, based on the trade-offs of each system, we propose a hybrid model for UBI for financial inclusion and poverty elimination.

1. Introduction

UBI has re-emerged as one of the most debated social and economic innovations of the 21st century. Originally conceived as a policy instrument to provide every individual with an unconditional basic income, UBI has gained renewed traction in both developed and developing countries. Amid the rise of inequality, labor market transformations, artificial intelligence, robotics, and digital platforms, in developed countries (Dibo et al., 2025) and the shortcomings of welfare systems that already exist to alleviate poverty and income inequality (Coletta, 2025) in developing countries, UBI has been proposed as an ideal social policy to address these problems (Afscharian et al., 2022). In this context, the same technology formerly considered a risk for traditional labour markets become a source of redistribution through social welfare programs such as decentralized UBI projects based on blockchain and AI.

Traditional UBI programs mostly funded by the governments have struggled with the structural, administrative and political issues. One of the main challenge is the flow of continuous funding (Manole et al., 2024) which requires excessive money, political support and consensus that is usually lacking is developing countries. Moreover, bureaucratic inefficiencies, eligibility verification processes, and centralized control tend to undermine the universality and inclusiveness that UBI promises. Another challenge is the logistic control and flow to ensure the payment reaches the targeted population without fraud particularly in areas with weak governance and underdeveloped financial structure. The lack of trust and transparency can also reduce the public support for the UBI initiatives (Coletta, 2025). On the other hand, blockchain-based UBI initiatives emerged as both a technological and social response to such constraints. Embedding redistribution into decentralized infrastructures, these models seek to eliminate bureaucratic intermediaries and enhance transparency while providing the ability to distribute income among peers across borders. The immutability of blockchain records and the automation provided by smart contracts reduce administrative costs and corruption risks, while decentralized governance offers a novel model of collective participation across borders.

In the past decade, many blockchain based UBI programs have been launched indicating a technological shift in UBI structure, mechanism and governance. These projects presents a fusion of technology and economic theory in the form of blockchain, DeFi, cryptocurrencies, and tokenomics implemented through smart contracts without centralized authorities e.g. Circles and GoodDollar, ImpactMarket. But these advanced features also introduce real concerns about governance, accountability, and the social and technical risks (crypto volatility, technology accessibility, governance mechanism, smart contract exploitation, privacy, and data security). Moreover, leveraging decentralized technology for unprecedented scale, transparency, and programmability, the classic challenges regarding adoption, trust, and sustainability still persist. Despite growing interest in theory and pilot projects of UBIs around the world, there is a lack of systematic market data-driven empirical research on blockchain-based UBI projects assessing their operational models and social impact. This leaves a crucial gap in our understanding of whether blockchain-based technological mediation really makes UBI more open, fair, and long-lasting, or if it just reproduces the problems of traditional UBI programs in a digital form. Therefore, our main research question is "how the transition from fiat based traditional systems to digital decentralized systems has influenced the efficiency, affordability, scalability, user empowerment, and the nature of impact of different UBI models." To address this question, we perform a comparative analysis of three UBI models, including both traditional frameworks (GiveDirectly as a benchmark) and blockchain-based systems (Circles and GoodDollar) by using a data-driven mixed-method approach. We combined the onchain transaction and user data of blockchain based UBI projects with the previous empirical studies and impact evaluation reports and presented our findings through an IAM. The IAM was proposed by (Place et al., 2015; Palace, 2018) designed specifically to assess performance of complementary currencies across different dimensions by employing multiple criteria. This approach provides a multidimensional view of how technology changes the way UBI is designed and delivered in comparison with traditional UBI model.

Our findings reveal that, GiveDirectly project has many shown positive outcomes for key development indicators such as health, education, and financial stability. The offline payment delivery system via mobile money (M-Pesa) made accessibility and local acceptance easy and convenient. However, its long-term viability is still limited by high operating costs, reliance on centralised middlemen, and the need for continuous funding. Circles, on the other hand, has shown positive outcomes for building and fostering social trust, reciprocity, and financial independence in local networks. However, in Circles version 1, the participation rate declined after reaching its initial peak due to structural fragilities. Even though Circles 2.0 added better features, recent data shows that user engagement has been slowly going down over time. This shows how the difficulties in the engagement of people involved in decentralised spaces. GoodDollar transaction and user activity data show that the platform after reaching its initial peak, is facing a decline in the number of new claimers and active participants on both the Celo and Fuse blockchains. But positive outcomes are observed in various social trust and cohesion criteria. Blockchain based solution though address the issues of traditional UBI model but also introduce new set of risks that hinder their scalability and wide adoption. Based on the trade-offs of both systems , we suggest a hybrid blockchain-based UBI framework, that addresses the existing issues and can lead to a more sustainable, apolitical and fair UBI ecosystem.

2. Background

UBI has been defined in multiple ways by different economists and policy makers, however, a comprehensive definition is given by (Van Parijs, 2004), "An [unconditional] income paid by a government, at a uniform level and at regular intervals, to each adult member of society. The grant is paid, and its level is fixed, irrespective of whether the person is rich or poor, lives alone or with others, is willing to work or not." This payment should be enough to avoid poverty, meet basic needs, and to have basic financial and psychological security (Perkins et al., 2022). It is evident from hundreds of UBI-like projects around the world that these initiatives can have far-reaching beneficial consequences. The positive outcomes are well recorded for main development indicators such as poverty, health, nutrition, well-being, educational outcomes, social cohesiveness, political engagement, economic inequality (Banerjee et al., 2020) and entrepreneurial initiatives (Hamilton et al., 2023). Conversely, UBI programs are often criticized due the concerns regarding their cost, financial burden for the government, and the dissuasion for the labour participation (Ashford et al., 2020). Therefore, to explore the socio-economic and technical transition of UBI models and their real-world outcomes, we employed a comparative case approach by examining three distinct UBI projects:

- GiveDirectly, a fiat based prominent cash-transfer program primarily functioning in low-income areas
- Circles, a blockchain-based community currency fostering local trust and reciprocity
- GoodDollar, a global blockchain-enabled digital UBI initiative propelled by impact investment.

The cases were chosen owing to their differences in conceptual and operational frameworks and data availability.

2.1 GiveDirectly

GiveDirectly is the most expensive, sustained and longest UBI pilot project running in Kenya (Dibo et al., 2025). The initial trials were run in 2011 and 2012 with random sampling by directly transferring cash (around $45 US a month) to the recipients through mobile transfer

(M-Pesa) system. This trial led to the development of a long-running cash transfer scheme that is expected to last for twelve years. In 2016, the pilot project was launched and since 2017, over 23,000 individuals from Bomet and Siaya counties across more than 195 rural villages and an additional 100 villages as a control group were enrolled in a twelve years long UBI project with a budget of $30M and has three different groups including, long-term monthly recipients ($22.50 per month for twelve years), short-term recipients ($22.50 per month for two years), and one-time lump-sum ($500) recipients. The project aims to assess the impact of different UBI cash transfer plans on poverty reduction, social welfare, psychological and behavioural improvement and economic activity (Ali, 2025; Skeyi, 2024; Wooldridge et al., 2024). The initiative was established by the students from Harvard and MIT, who subsequently commenced fundraising in 2011, and carried out detailed analysis of the UBI project in Kenya e.g. (Banerjee et al., 2023; Haushofer & Shapiro, 2013, 2016). The main idea behind this experiment was that the immediate transfer of cash to people in poor regions is a far more effective method of assisting poor families than the complex assistance programs.

2.2 Circles

Globally, there has been a significant attempts in UBI projects built on the blockchain that aim to provide a "basic income" to all citizens (Torry, 2019). The Circles UBI, known as Circles Berlin project started in October 2020, is one of the few projects that uses blockchain-based tokenisation. The system issues, distributes, govern, and transfer personal tokens (CRC) via smart contracts deployed on the Gnosis blockchain (Avanzo, et al., 2023). Users register on the Circles DApp to join the Circles network. After registering on the Circles DApp, users become a part of the Circles network. All users receive personal currencies periodically that can be used to claim goods and services provided by other users. The Web of Trust (WoT) feature of the DApp allows all users to trust one another's accounts and guarantees security by preventing untrusted users from interacting in the network. Furthermore, a negative interest rate of 7% per annum, commonly known as demurrage, is applied to all issued Circles. The purpose of demurrage is to narrow the gap between early and late adopters by increasing the rate of spending and bringing closer all individuals with more or less number of CRC tokens, over time (Papadimitropoulos & Perperidis, 2024). Circles was launched as a test phase in February 2020 in Berlin, and was adopted by a loosely organised local network of approximately 500 individuals. This small network engaged in diverse market activities of providing goods and services grew into a community of more than 100,000 individuals after the official launch of Circles in October 2020. This Berlin test over time, however, encountered significant operational and financial difficulties such as scalability challenges of the protocol design, insufficient funding for the subsidy program, high cash-out rates into fiat (which hindered circulation of the CRC token), and structural weaknesses in the economic model that caused its operations to cease around January 2024. To address these limitations, Circles v2 was launched on 21 May 2025 along with enhanced new features. The aim behind the redesign was to build a fairer form of money whose value is derived from social trust networks rather than capital accumulation.

2.3 GoodDollar

GoodDollar is a non-profit initiative to reduce global wealth inequality by leveraging blockchain technology and decentralised finance (DeFi). Launched in 2020 by eToro, a large multi-asset public investment company that has attracted over 750,000 users from 181 countries, making it one of the largest blockchain applications for active users. The GoodDollar project seeks to mitigate persistent financial instability and foster economic empowerment by reallocating capital and liquidity via a daily digital universal basic income (Bhattacharya, 2024; Martín, 2024).

The technical and organizational structure of GoodDollar implements algorithmic governance to provide transparent and apolitical alternative to traditional UBI models. It operates through a decentralized mechanism that converts yield from staked assets into the issuance of its native currency, called GoodDollar token (G$). "Supporters", in this system are the investors who stake their assets into a stablecoin i.e. DAI and the interest earned on these assets is then deposited into GoodReserve, which serve as a collateral backing for the issuance of G$ which are minted (daily) in a decreasing reserve ratio. The newly minted token are distributed between investors, as a financial return and UBI claimers as a daily basic income in their wallets (Ghezzi et al., 2024). An automated market-maker controls and manage the system's liquidity by changing the price of G$ in relation to the reserve assets. Consequently, the supply of G$ fluctuates in direct response to investor activity tokens are minted when assets are staked and burned when withdrawn. Participants can earn additional tokens by promoting the project, educating others about financial literacy, or engaging in community-building activities (Farry, 2024). The main goal of GoodDollar UBI is to create a digital economy where everyone, regardless of where they live or their socioeconomic standing, has access to opportunities and support by democratising wealth distribution through the use of blockchain, thus removing existing obstacles to financial access (Banda, 2024). The features comparison of all three case studies has been provided in Table 1.

Table 1 Features Comparison of Traditional and Blockchain based UBI Models

Features	GiveDirectly	Circles UBI	GoodDollar
Launch Date	Pilot launched in 2016 Full Scale project in 2017	Circles Berlin Project launched on 16 Oct 2021 Circles v2 launched on May 21 2025	Launched on Fuse chain August 2020 Launched on Celo chain March 2023
Association	GiveDirectly Inc. (non-profit organization)	Circles Cooperative (Germany) and Gnosis-based developer community	GoodDollar Foundation (non-profit) supported by e-Toro and governed through GoodDAO
Value Proposition	Empowering individuals in poverty by providing unconditional cash transfers directly to their mobile wallets, providing them with choice, dignity, and measurable impact	Distribution of decentralized, apolitical UBI based on mutual trust to facilitate communities and foster cooperation and social cohesion	Distribution of decentralized, self-sustainable, apolitical UBI to facilitate communities and foster cooperation and social cohesion
Ethic Charter	Human dignity, evidence-based poverty alleviation, autonomy, and transparency	Global financial inclusion, equality of opportunity, digital transparency, and redistribution through DeFi	Mutual trust, cooperation, community self-organization, and social sustainability
System	Direct Fiat Transfer System (donor-funded)	Mutual Credit System (personal token issuance via WoT	Crypto-based Issued Currency (staking yield-backed UBI)
Conversion	cash transfers in national currencies	Not directly convertible to fiat (USD, EUR, etc.) The Value is *derived from underlying crypto yields*	Not directly convertible to fiat
Scale/Community	Local	Global	Local/National
Blockchain	None (uses M-Pesa mobile money)	xDai / Gnosis Chain	Ethereum (and later sidechains like Celo and Fuse)
Funding Mechanism	Donations from NGOs and philanthropies	Trust-based issuance: each user mints Circles tokens that are backed by social trust	Yield from DeFi staking (Aave, Compound etc.) funds the UBI pool
Token	Kenyan Shilling (KES) via mobile transfers	CRC (Circles token, one per person)	G$ (GoodDollar token)
Distribution Logic	Periodic unconditional cash to selected rural households	Each person receives a personal token daily, usable only if others trust them	Daily claim for all verified users worldwide (free G$ drops)
Adoption Scale	Thousands of households in Kenya	More than ten thousand users	More than 500,000 users globally
Economic Impact	Proven measurable impact on well-being and consumption	Local circular economies, not scalable globally yet	Very low per-user income (fractions of USD/day)
Barriers to Adoption	Depends on continuous donor funding	Complex onboarding, reliance on trust networks	Limited value, no real-world spendability, tech barriers
Governance	NGO-managed (GiveDirectly)	Decentralized trust network DAO	GoodDAO (community + founders)

Previous studies has primarily examined existing UBI initiatives as isolated case studies, without undertaking a comparative analysis across traditional and blockchain-based models. There is also a lack of systematic, data-driven research examining the nature and extent of impact specifically for blockchain based initiatives. Our research adds to the growing literature that focuses on the impact assessment of UBI models by using most recent blockchain data and impact evaluation studies and presents the findings with IAM.

3 Data Collection

The frequency and nature of data is different for all three UBI cases selected for our study. For GiveDirectl**y** we used evaluation data from field studies, randomized controlled trial (RCT) findings, impact reports and secondary performance indicators published in peer-reviewed evaluations. For Circles v2 UBI network, the data is collected from peer reviewed impact reports, questionnaire and interview based surveys. The blockchain data i.e. daily user engagement, daily active/inactive users, and daily new registered users is collected from open API available at https://dune.com/product/datashare for the period of October 2024 to October 2025. For the Good dollar project deployed on Celo and Fuse sidechain, the data for daily active users, daily unique and total claimers is available on https://thegraph.com/ . On Fuse sidechain the daily frequency data is available from 10 August 2020 to 21 October 2025 and on the Celo sidechain the data is available from 02 March 2023 to 21 October 2025.

Transaction-level data for GoodDollar and Circles was obtained from their respective publicly available subgraphs indexed through The Graph protocol. Subgraphs provide structured access to smart contract event data via GraphQL queries at the transaction level. These raw event logs were downloaded and cleaned to remove incomplete records. All transactions were aggregated to daily frequency to construct network level indicators. Key variables include total transaction volume, number of active unique users, and (or Circles the formation of new user profiles. These measures serve as proxies for user participation, liquidity circulation, and network growth dynamics. By mapping smart contract events to economically interpretable indicators, the aggregation procedure ensures that on-chain technical records are translated into meaningful measures of system activity and engagement.

4 Methodology

In our research we have used mixed-method (qualitative and quantitative) approach. For qualitative assessment we have used insights from previous studies and impact evaluation reports based on interviews, questionnaire and surveys, and from the whitepapers of blockchain based UBI projects. To show temporal trends of user engagement and transactions dynamics, the most recent on-chain data for Circles and GoodDollar is plotted against time. Lastly, by integrating both results the findings are presented through an impact assessment matrix (IAM) proposed by (Place et al., 2015; Place, 2018), designed to assess each project's performance across different dimensions by employing multiple criteria.

The IAM was originally designed after a wide synthesis of the best leading international assessment standards to evaluate the performance of complementary currencies and their sustainability impact. Varying from existing evaluation tools that usually focuses on single aspect, this framework uses an integral approach that combines four interconnected quadrants including subjective (existential reflection), objective (neuro-behavioral science), inter-subjective (cultural and ethical reflection), and inter-objective (systemic and economic complexity). This allows for multidimensional analysis of both tangible and intangible effects measured through 71 indicators (qualitative and quantitative) divided across different dimensions i.e. culture, governance, economy, society, and environment. Each dimension is assessed through the logic model hierarchy, namely activities, outputs, and outcomes, at different levels (meta, macro, meso, and micro). We tailored certain metrics of IAM for each UBI case to ensure their relevance and suitability. Impact of each indicator is represented by a score starting from 1 (very low), 2 (low), 3 (high), and 4 (very high). The justification and recommendations for each indicator are presented in the subsequent columns. To facilitate a multidimensional comparison across variables, we employ a radar chart (also known as a spider chart), which allows simultaneous visualization of multiple indicators. Each axis represents a specific dimension, enabling an intuitive comparison of its relative performance. The values plotted in the radar chart are based on a qualitative scoring system ranging from 1 (very low), 2 (low), 3 (high), to 4 (very high). This scoring reflects the relative standing of criterion across the considered dimensions, following established approaches in the literature (e.g., Place (2018) impact assessment method).

4.1 Operationalization of the Impact Assessment Matrix

The criteria included in the Impact Assessment Matrix were derived from existing literature. To enhance transparency and replicability, each criterion in the Impact Assessment Matrix was operationalized using clearly defined functional indicators. Rather than evaluating technological form directly, the criteria were constructed at the outcome level (e.g., transparency, cost efficiency, governance robustness, financial inclusion), allowing comparison between fiat-based and blockchain-based UBI systems on equivalent conceptual grounds. For each dimension, observable indicators were identified from policy documentation, academic studies, and protocol design specifications. Scoring was based on documented evidence and publicly available data to reduce discretionary bias. This framework enables a structured evaluation of systemic strengths and limitations across heterogeneous institutional designs. Where quantitative indicators were unavailable, qualitative assessments were anchored in documented institutional characteristics and cross-referenced with secondary literature.

5 Results and Findings

5.1 GiveDirectly

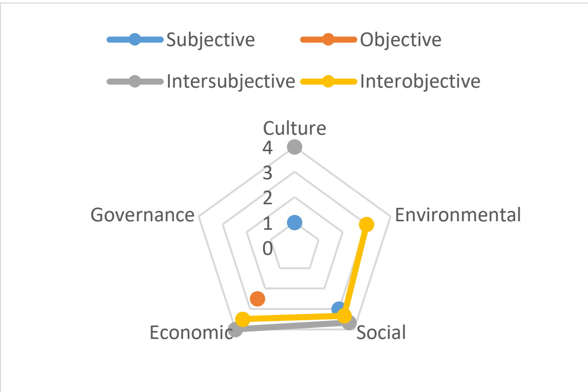
The studies as shown in Table 2, indicate that the GiveDirectly UBI program generated significant positive results across all dimensions. Although the nature and strength of impact varies for each type of cash transfer, but overall the project deliverables were aligned to the objective of providing basic income for individuals.

Fig 1 shows that social, culture, and economic dimensions exhibit the high scores, suggesting that GiveDirectly provides substantial social and cultural empowerment with economic stability among recipients. Furthermore, the inter-subjective component of the social and economic dimension highlights a strong positive influence on community level relations and overall well-being. Similarly, the inter-objective dimension of the economic category and social cohesion points to significant improvements in income security and local consumption capacity. Finally, the governance dimension registers no measurable effect, which aligns with GiveDirectly's operational model as an external non-governmental actor delivering direct transfers, rather than a system seeking to reform institutional structures.

Table 2 Studies on the Impact Evaluation of GiveDirectly

Study	Sample	Results	Details
Salifu, H. A. H. (2025). Reconstructing the Social Contract Theory: Inculcating Ubi as the Antidote to Socio-Economic Inequality.	Qualitative data of Surveys and Interviews, and quantitative data	The findings reflects Rawls's vision of justice and Rousseau's ideal of the common good, emphasizing equality and social cohesion	The GiveDirectly project embodies the social contract theory'ideals of justice, fairness, and welfare, particularly relevant in low-income economies.
Walker, M. W., Shankar, N., Miguel, E., Egger, D., & Killeen, G. (2025). *Can cash transfers save lives? Evidence from a large-scale experiment in Kenya* (No. w34152). National Bureau of Economic Research.	Questionnaires based	A substantial decrease in child death rate	Results are aligned with the objectives of the project

Ali, M. (2025). Universal Basic Income: A Social Experiment In Reducing Poverty And Promoting Economic Justice In The Context Of Technological Advancements. *Journal of Social Impact Studies*, *3*(1), 63-79.	Public Opinion Based	22.5 % Poverty Reduction, +3.0 %Employment Change, High Social Trust and Positive welfare impact	Results are aligned with the objectives of the project
Banerjee, A., Faye, M., Krueger, A., Niehaus, P., & Suri, T. (2023). Universal basic income: Short-term results from a long-term experiment in Kenya. *Accessed April*, *5*, 2024.	Three sets of data were compiled via interviews, phone and household surveys to determine the impact of long-term, short-term, and lump sum cash transfers	Improved economic activity, well-being, and mental health, fostered local enterprise growth and structural shifts in communities	Long term transfer resulted in strong local explosion, enterprises, non-agriculture retails sector, better well-being and mental health, and structural growth. Lump sum amount results were similar to long term transfer, also shift towards self-employment, economic gains but weaker mental health outcomes were observed. Short term transfers resulted in moderate growth and limited strauctural changes with a slight rise in work and consumption.
Banerjee, A., Faye, M., Krueger, A., Niehaus, P., & Suri, T. (2020). Effects of a Universal Basic Income during the pandemic. *Innovations for Poverty Action Working Paper*.	Households surveys during COVID-19	Enhanced food security, physical and emotional well-being, and less disease and hospital visits during the COVID-19 pandemic.	GiveDirectly project results show that it is beneficial for maintaining welfare and resilience, but insufficient as a standalone response to large-scale crises



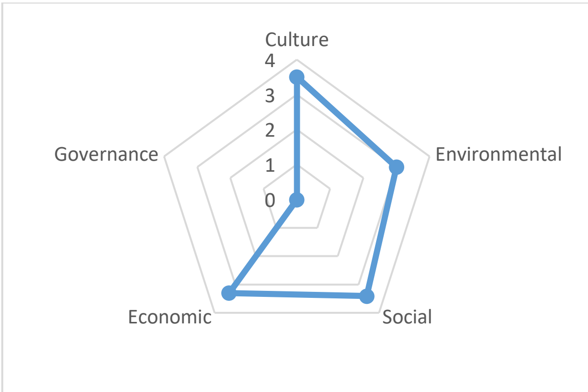


Fig 1. Radar Chart for the Impact Assessment Matrix of GiveDirectly. The values are based on a qualitative scale from 1 (very low) to 4 (very high), representing the relative performance across dimensions.

5.2 Circles

The onchain data shows the temporal trends in the user engagement, total registered users, and claimers on circles UBI network as shown in Fig 2 and Fig 3.

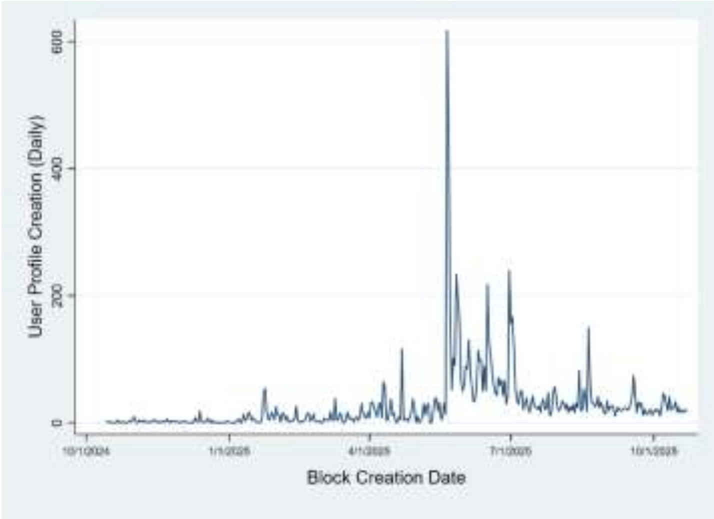


Fig 2. User Profile Creation on Circles UBI Network

Fig 2 reveals that on the Circles v2, the number of new profile creations by users indicate a decreasing trend after reaching its peak on 21-05-2025, the last recorded data shows number of new profile creations was 17 on 20-10-2025.

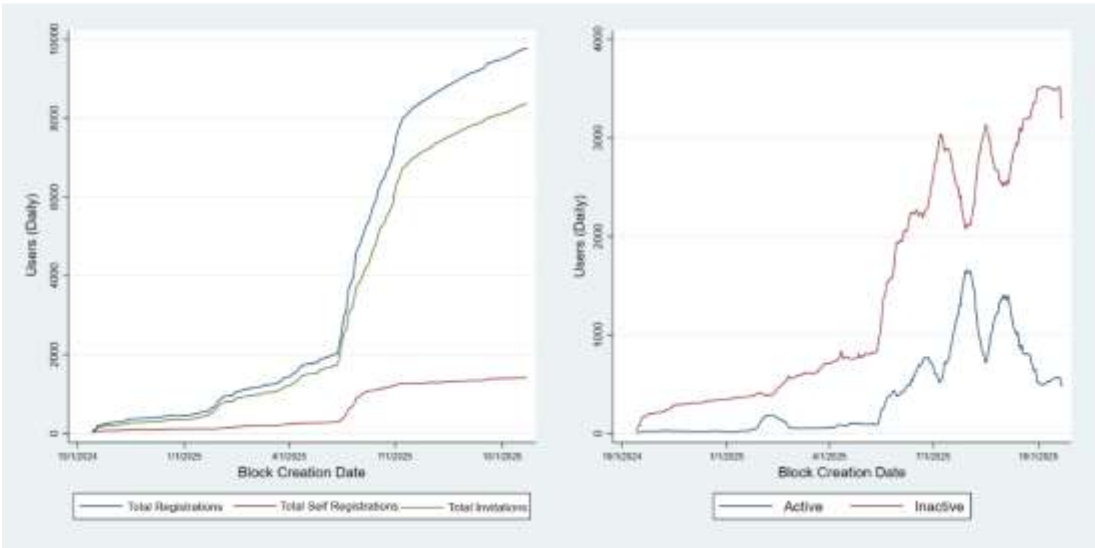


Fig 3. User data statistics on Circles UBI Network

According to Fig 3 during the second quarter of 2025, there was a sharp increase in the number of total registrations on Circles v2 network out of which mostly belonged to the invitations. The last recorded number of total registrations was 9768 on 22-10-2025. The number of self-registration also observed a small increase which became steady till our last recorded data of 1410 users on 22-10-2025. Furthermore, the number of active users remained below than 200 during entire period with a decreasing trend after 14-09-2025, and last recorded number of active users was 491 on 22-10-2025. The impact distribution drawn from the studies indicated in Table 3 of the Circles UBI project reflects a multidimensional profile with marked strengths in the social and economic dimensions as shown in Fig 4.

Table 3 Studies on the Impact Evaluation of Circles

Study	Sample	Results	Details
Longo, A., Criscione, T., Linares, J., & Avanzo, S. (2025). Impact of a Blockchain-based Universal Basic Income Pilot: The case of Circles UBI currency. *arXiv preprint arXiv:2504.02714*.	25 individuals from Circle's community, questionnaire and interviews	Participants shared different levels of involvement and participation within Circles, such as strong influence on social relations, mutual support, and shared values	Results showed that Circles' experience is intimately tied to its community.
Papadimitropoulos, V., & Perperidis, G. (2024). Universal basic income on blockchain: the case of circles UBI. *Frontiers in Blockchain*, *7*, 1362939.	Interviews, LR, Filed work, and observatory	Ethical and sustainable system alternative to capitalism, promotes local communities and money of commons but have certain limitations	Circles aligns with the principles of open cooperativism, rooted in fairness, sustainability, and shared value creation to foster a post-capitalist economy. However, the project is limited by scalability issues, economic inefficiencies, limited trust network, governance and systemic integration.
Avanzo, S., Criscione, T., Linares, J., & Schifanella, C. (2023, September). Universal basic income in a blockchain-based community currency. In *Proceedings of the 2023 ACM conference on information technology for social good* (pp. 223-232).	Blockchain data	Supported active trade within local network. Subsidy program increased trust, participation, and network consolidation with increased user activity and transactions	can foster community-level trade and inclusivity, but concerns raised for long-term sustainability and user engagement in the absence of monitory subsidies
Cabaña, G., & Linares, J. (2022). Decolonising money: learning from collective struggles for self-determination. *Sustainability Science*, *17*(4), 1159-1170.	Interview based	A decentralised and democratic monetary creation approach generates value by forming economic relationships grounded in mutual trust and profit.	Apolitical decentralized community currency system enhancing social cohesion and inclusivity but limited by local trust networks, infrastructure, and limited usability.

The subjective and inter-subjective section of the social dimension reveals that Circles promotes collective engagement, trust, and community reciprocity. This aligns with the idea behind the Circles' design of making a social currency based on personal connections instead of money. The economic dimension in objective and inter-objective dimension also indicates strong effects on local economic exchange. Inter-objective quadrant for social and economic dimensions show low value. Overall, Circles' impact matrix shows that its biggest strength is in boosting social capital, democratic governance and decentralised community economies.

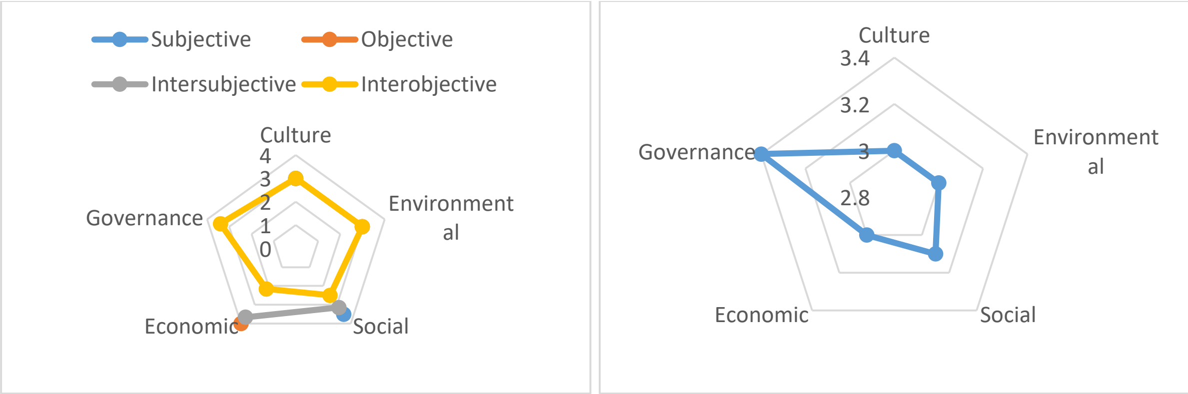


Fig 4. Radar Chart for Impact Assessment Matrix of Circles. The values are based on a qualitative scale from 1 (very low) to 4 (very high), representing the relative performance across dimensions.

5.3 GoodDollar

The on-chain data shows how user engagement, total claimants, and unique claimants have changed over time on the Celo and Fuse sidechains of the GoodDollar network as shown in Fig 5 and 6.

Fig 5 shows that the most active users on the Fuse chain were 134451 on 11-05-2022, and on the Celo chain, 68140 on 13-12-2023. The number of active users has been going down after reaching its peak. The last recorded number of active users on the Fuse chain was 36326, and on the Celo chain, 13508, as of 22-10-2025.

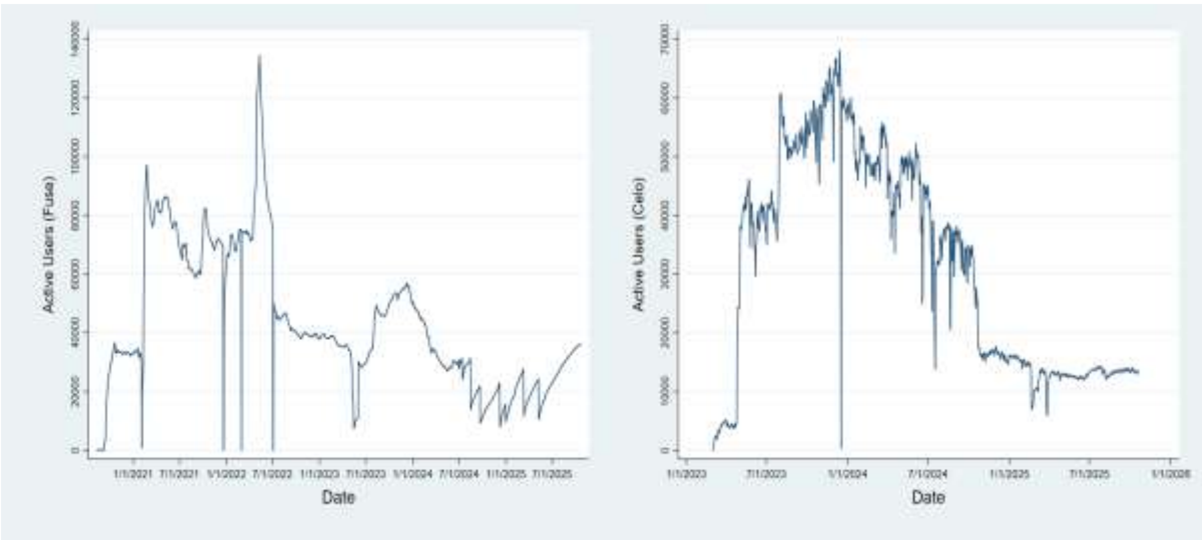


Fig 5. Active Users on Fuse and Celo sidechains of GoodDollar UBI Network

Figure 6 shows the trends of total and new claimers on Fuse and Celo sidechains. On Fuse chain the total number of claimers reached at maximum of 60363 on 28-04-2022, and a continuous decreasing trend is observed in the last quarter on 2023 till recently, where it stands on 6113 on 20-10-2025. The maximum number of new claimers on Fuse chain was recorded to be 15243 on 09-02-2021. Another peak was observed on 29-07-2023, where the number of recorded new claimers was 13985, since then it is showing a downward trend and currently it was 142 on 21-10-2025.

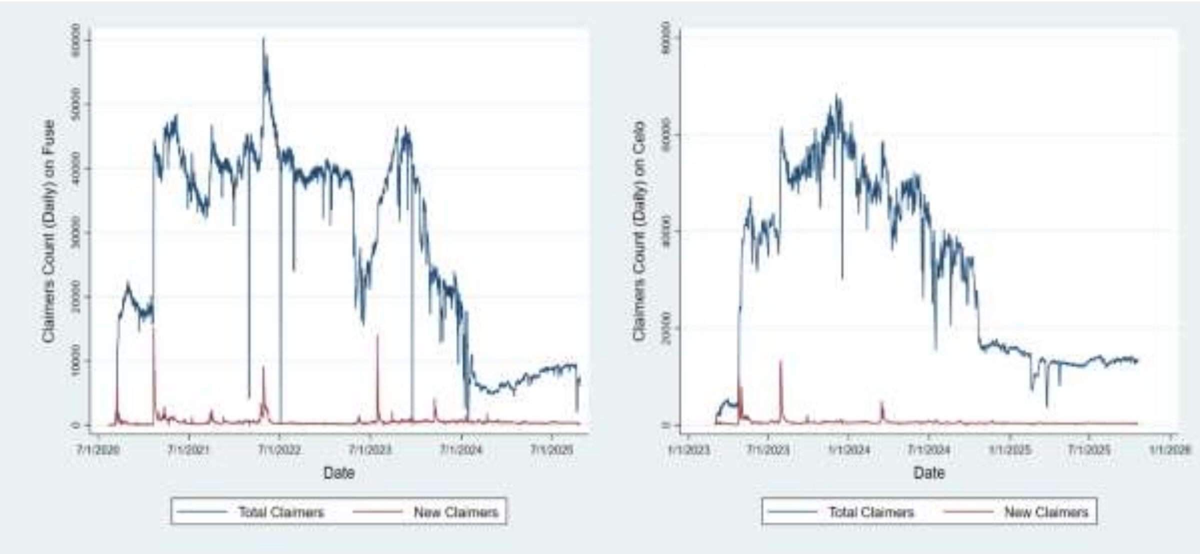


Fig 6. Claimers Count on Fuse and Celo sidechains of GoodDollar UBI Network

On Celo chain the total number of claimers reached at maximum of 68286 on 03-12-2023, and after that a continuous decreasing trend is observed, and the last recorded data shows it was 13579 on 20-10-2025. The maximum number of new claimers on Celo chain was recorded to be 13245 on 30-07-2023. Since then it is showing a downward trend and currently it was 279 on 21-10-2025.

Table 4 Studies on the Impact Evaluation of GoodDollar

Study	**Sample**	**Results**	**Details**
Martín, E. B. (2024). Freeing Monies: Remaking Money for Inclusive Economies. In *Remaking Money for a Sustainable Future* (pp. 139-158). Bristol University Press.	Blockchain transaction data, White papers, and Blogs	Global reach and accessibility, innovative funding mechanism which turns financial returns into social payments blending ethical finance and technological efficiency. Certain limitations are detected in this project such as the structure was meant to be a political but the governance mechanism, creation and distribution of money is political in nature with low integration into real economy, and also provides negligible UBI value. Low user engagement is also observed.	The GoodDollar project mechanism and governance structure doesn't align with its objectives of democratic, apolitical community currency.

The impact distribution drawn from Table 4, for GoodDollar is dominated by economic and governance dimensions with the highest score value as shown in Fig 7. The economic inter-objective component also shows that it has a big impact on promoting digital financial inclusion and yield-backed redistribution mechanisms. The objective sub dimension makes this impact measurable in material terms: wallet creation, token circulation, and staking yield. On the other hand, social and cultural effects are still low, which means that GoodDollar has been successful in financial innovation and governance transparency, but it hasn't yet brought about changes at the community or cultural level. Overall, the results show that GoodDollar is a techno-economic and institutional innovation that focusses on systemic transparency and redistribution.

In all three systems, the environmental and cultural dimensions remain marginal, which is also a general feature as UBI and complementary currency initiatives put more emphasis on socio-economic inclusion than ecological transformation.

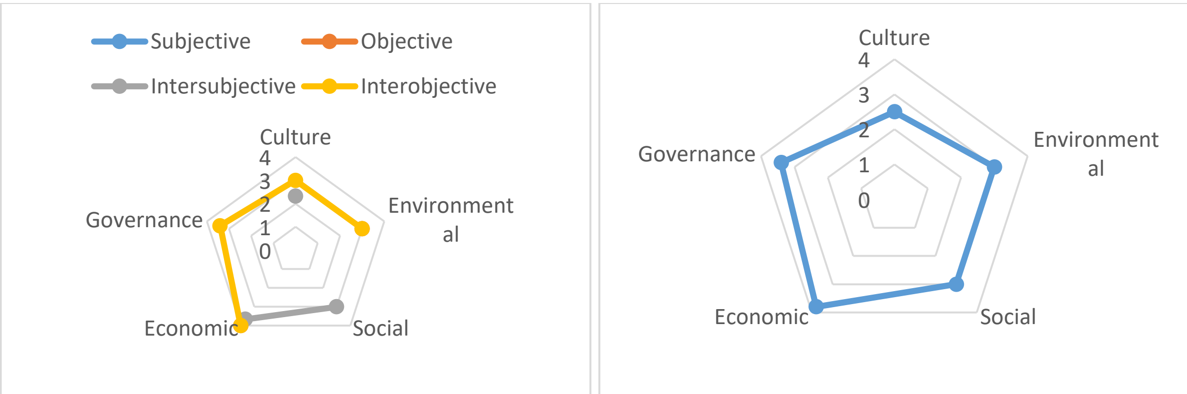


Fig 7. Radar Chart for Impact Assessment Matrix of GoodDollar. The values are based on a qualitative scale from 1 (very low) to 4 (very high), representing the relative performance across dimensions.

5.4 Discussion

A cross-case comparison shows that GiveDirectly, Circles UBI, and GoodDollar all share common objective of economic inclusion, but they differ in their structure, mechanism and impact. GiveDirectly shows the strong outcome in both social and economic areas at the household level due to its focus on unconditional direct cash transfer. Also because fiat money is widely trusted and already embedded in the existing economic infrastructure, recipients face no barriers in using it. This broad acceptability enables immediate spending according to individual preferences, and facilitates seamless integration into local markets. As a result, fiat-based UBI tends to benefit from faster adoption, smoother economic participation, and higher levels of user confidence compared to alternative currency systems. Conversely, fiat currency is also more prone to broader macroeconomic conditions, lack of transparency, involvement of intermediaries (personnel and institutions), and need for continuous donor funding, affecting the long term stability and sustainability of the project.

Circles UBI, on the other hand, has its biggest effect on the social inter-subjective level, where trust, cooperation, and reciprocity support a network-based complementary economy. GoodDollar has best impact outcomes in both the economic and governance areas due to its through unconditional decentralised token transfer system and on-chain governance. GiveDirectly and Circles focus on empowering people and communities, while GoodDollar puts into action a system-wide, protocol-level redistribution mechanism. The user and transaction data for both Circles and GoodDollar reveal that initially there is an upward trend in new users and registered profiles on the network followed by a decreasing trend in the user activity (daily), new registrations, and number of total claimers. Moreover, the crypto volatility and recession during 2023, also influenced the GoodDollar performance indicating a systemic dependence on volatile crypto market. Users also face a demand and supply imbalance in CRS tokens and G$ creation and distribution. The lack of diversity for goods and services also blocks the circulation of these tokens in Circles and GoodDollar trust network, necessary for the smooth functioning and growth. These problems highlight the core issues in the blockchain based systems including consistent user engagement, sustainability of basic income creation, and lack of market diversity for goods and services. After deriving insights from the market data and impact evaluation matrix for all models, we propose a decentralized multi-layered hybrid UBI model that effectively tackles these challenges and provide a more robust and inclusive solution by integrating core strengths of traditional and blockchain based solutions.

5.5 A decentralized hybrid UBI model

The proposed architecture, illustrated in Figure 8, is a multi-layered system in which each design component directly addresses a specific weakness identified in the comparative case analysis. The top layer is a real-time monitoring dashboard that tracks fund inflows, outflows, and price mechanisms with full on-chain transparency. By placing a transparent monitoring layer at the top of the architecture, the hybrid model ensures that accountability is structurally embedded rather than dependent on external audits as observed in GiveDirectly model.

The second layer is a global reserve pool in which funds whether from donations or DeFi staking yield are held in a global stablecoin (such as USDC) rather than a volatile native token. This directly addresses the most significant structural vulnerability of GoodDollar where platform’s issuance volume declined sharply during the 2022–2023 crypto market contraction because G$ minting is directly coupled to the yield generated by staked volatile assets. Denominating the reserve in a fiat-pegged stablecoin decouples the UBI distribution mechanism from crypto market volatility, preserving the DeFi-based self-sustainability of GoodDollar's funding model. The third layer is a crosschain bridge, whose function is to lock the global stablecoin on the source chain and mint an equivalent pegged local token on the destination chain. This responds to the scalability constraints observed in both blockchain cases. Circles' operations are confined to the Gnosis chain and its trust network remains geographically bounded; GoodDollar required separate deployments on Fuse and Celo to reach different user populations, but these chains operate independently without seamless interoperability. A crosschain bridge enables a single global reserve to serve multiple local deployments without fragmentation, directly addressing the network scale limitation recorded in Circles' IAM.

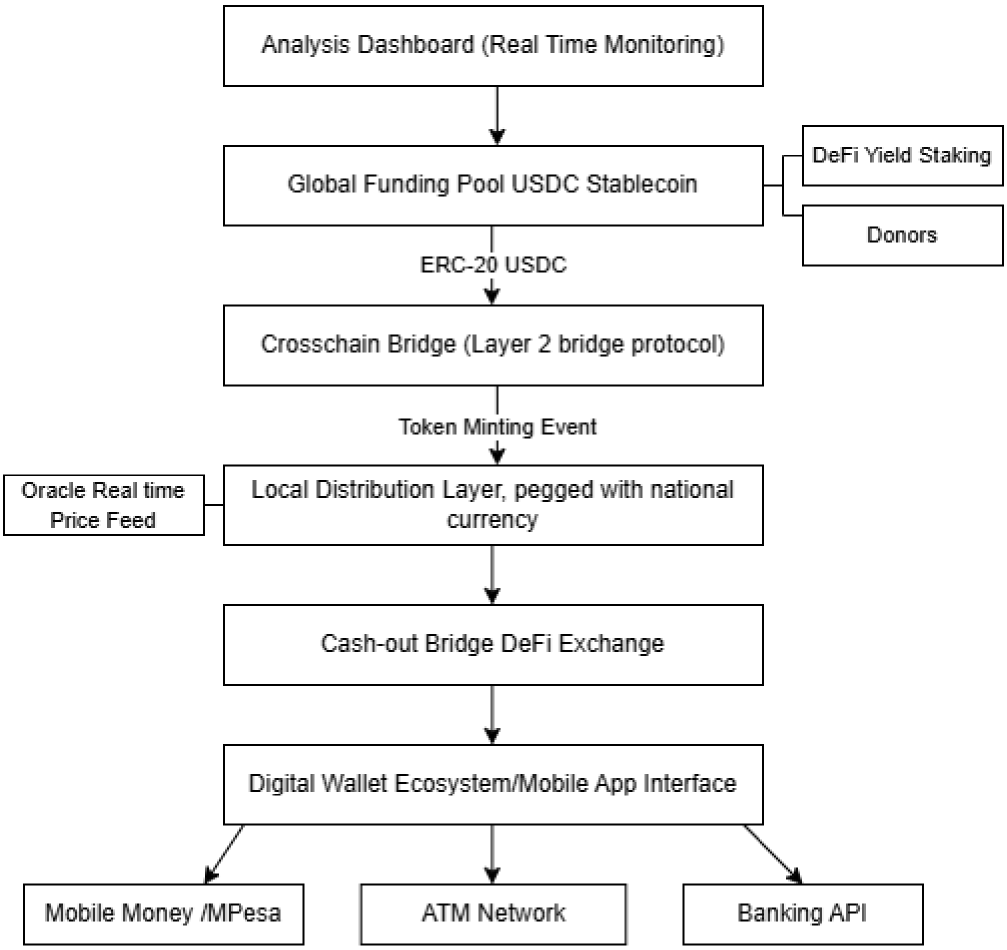


Fig 8. A multi-layered decentralized hybrid UBI model

The fourth and fifth layers together form the local distribution and cash out mechanism. Local stablecoins are minted and distributed to recipients' wallets, and a cash-out bridge then enables conversion into mobile money or physical cash through partner agents or local banks including integration with systems such as M-Pesa. This responds directly to the most persistent barrier observed in both Circles and GoodDollar: the limited real-world spendability of their native tokens. By enabling conversion to mobile money, the hybrid model ensures that recipients can participate in the broader economy. This multi-layered design therefore synthesises the best features of all three cases including GiveDirectly's real-world accessibility and measurable impact, Circles' decentralised trust-based governance, and GoodDollar's self-sustaining DeFi funding mechanism to provide a more robust and inclusive UBI model.

5.6 Limitations

Several limitations of this study should be acknowledged when interpreting its findings. First, the study does not involve primary data collection as no interviews, surveys, or direct fieldwork were conducted with participants or administrators of any of the three programmes. The qualitative evidence underpinning the IAM scoring is drawn entirely from published secondary sources peer-reviewed studies, impact evaluation reports, and project documentation which vary in methodological rigour and depth across the three cases. Second, the cross-case comparison is constrained by the substantially different contexts in which the three programmes operate. These contextual differences mean that differences in IAM scores across the three cases cannot be attributed solely to differences in programme design but they also reflect differences in recipient populations, implementation environments, and the baseline conditions against which impact is measured. The comparative analysis is therefore best understood as a structured exploration of design trade-offs rather than a controlled evaluation of relative effectiveness. Third, the hybrid UBI model proposed in Section 5.5 is conceptual in nature. While each design layer is grounded in the specific weaknesses identified through the comparative analysis, the model has not been implemented, simulated, or validated against empirical data. Its technical feasibility, governance dynamics, and real-world impact remain to be tested. It is proposed as a research informed design framework intended to guide future pilot development for UBI program.

6 Conclusions

Conventional UBI initiatives designed to mitigate income inequality and poverty have always faced obstacles related to sustainable financing, political reliance, affordability, and administrative complexity. Recently many blockchain based UBI models were introduced as a prospective solution to these challenges. These models offer transparent, autonomous, scalable and self-sustainable systems e.g. Circles UBI and GoodDollar. Despite being in their nascent phases, initial feedback from network users suggests favourable experiences regarding mutual trust, shared values, and community empowerment. However, the pace of adoption has been slow and, in certain instances, is on the decline due to various technical and social constraints. Drawing from the insights identified in our study regarding traditional and blockchain based UBI models, we have proposed a hybrid decentralised UBI model aimed at addressing these limitations. By combining best features of both traditional and blockchain based models, it provide a basis for a fairer and more robust economic future.

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Appendix A

Impact Assessment Matrix (Prototype)

Integral approach	Dimension	Level	Vision Goal	Guideline Principle	Evaluation Objective	T/C	LM	Progress Measurement Indicators	M & E Methodology	C	F	L
Subjective (Existential reflection)	Culture	Macro	Inner–Outer Sense Harmony	Altruism	Other-Oriented Cooperation & Self-Oriented Competition Equilibrium	A	C	% other-oriented vs. self-oriented	System Database	2	M	A
	Social	Meso	Needs Satisfaction	Well-being	Mental health	BMI	C	% agree & strongly agree	Interview	1	Y	B
					Depression	BMI	C	% agree & strongly agree	Interview	2	Y	B
					Improve quality of life	BMI	C	% agree & strongly agree	Interview	1	D	2
					Mindfulness and Spirituality	A	P	% agree & strongly agree	Interview	2	D	1
Objective (Neuro-behavioral science)	Economic	Micro	Financial Autonomy Development	Risk	Disaster mitigation	UCI	P	Backup system Frequency	System Database	1	Y	D
					Currency Security features	A	P	N° security features	Best Practices	3	W	D
					Transaction and Data Safety	A	A	N° failure accident	System Database	2	W	D
					Record keeping and statistics	A	A	Backup system Frequency	System Database	1	W	D
	Environment	Meta	Transition and Autonomy	Relocation	GHG emission	CI	C	%CO2 & CH4 decrease	Regional Database	3	M	12B
		Meso	Ecological Footprint Reduction	Biodiversity	Reforestation	CI	C	N° tree plantation	Regional Database	3	Y	12B
				Eco-Friendly	Behaviour change	CI	C	% agree & strongly agree	Interview	3	W	13AB
					Waste management	CI	C	%recycling increase	Regional Database	3	D	12B
					Water management	CI	C	%water consumption decrease	Regional Database	2	W	12B
		Micro	Responsible Consumption Motivation		Green economy	CI	C	%organic & fair product increase	Regional Database	2	D	12B
Inter-subjective (Critical reflection)	Culture	Meta	Societal Acceptance	Societal	Recognition Credibility Legitimacy from (Inter-) Governmental Institution	A	C	N° institutional support	Management Database	3	M	C
					Transverse Cross-Disciplinary Integral Holistic collective intelligence	A	C	N° scholar expert specialist involved	Management Database	2	M	C
		Meso	Pluralism Inclusivity Diversity	Creativity	Alternative Flexible Libertarian Measure of Value	A	C	Yes / No	Best Practice	1	D	C
					Soft Skills and Hard Skills Design Thinking	A	C	% soft skills vs. hard skills	Management Database	3	Y	D
	Economic	Macro	Make Exchange Possible	Resilience	Training	A	P	% trained	Interview	3	M	ID
						A	P	N° training hours per year	Management Database	2	M	1D
		Meso	Inclusive Community-Building	Viability	Participation	A	C	N° training hours per year	Management Database	1	Y	3D
					Friendly user	UCI	C	% agree & strongly agree	Interview	2	Y	3D
					Intelligibility	A	P	% agree & strongly agree	Interview	1	D	3D
					Team Capacity	A	A	N° management team	Management Database	3	Y	3D
	Social	Meta	Link Share Reciprocity Solidarity	Cooperation	Exchangeability	A	C	N° compensation systems	System Database	2	M	3
					Co-creation	A	P	N° involved in design	Management Database	3	M	3
					New skills	A	A	% agree & strongly agree	Interview	3	Y	3
		Macro	Equity and Justice	Engagement	Involvement	A	C	% agree & strongly agree	Interview	1	D	13
					Inclusion	BMI	C	N° solidarity inclusion	Management Database	1	W	13
					Social service dependence	BMI	C	N° social service dependant	Management Database	2	Y	13
					Cohesion	BMI	C	N° new relationship	Interview	2	D	13
		Meso	Needs Satisfaction	Diversity	Education level repartition	A	A	%High & Graduate school	Interview	3	W	3
		Micro	Cohesion Cooperation Sharing Vector	Mission	Ethic Charter	A	A	Yes / No	Best Practice	1	D	3
					Conducts Code	A	A	Yes / No	Best Practice	2	W	3
				Education	Enrolment	A	C	N° children enrolled in school	Interview	3	D	23
Inter-objective (Complexity economics)	Culture	Micro	Innovation Confidence Humility	Innovation	Open Questioning Capacity	A	C	N° yearly improvement	Management Database	2	Y	23D
	Governance	Meta	Participatory Democracy	Democracy	Collaborative Election Process Consent Sociocracy Holacracy	A	P	N° stakeholder involved	Interview	2	Y	123D
						A	A	N° administrative person	Management Database	1	Y	123D
		Macro	Citizenship Engagement Recognition	Democracy	Effective Stakeholder Involvement stimulation	A	P	% participation among users	Management Database	1	Y	123D
		Meso	Independent Control	Legal	Independent Quality Control Process	A	P	Certification	External auditing	2	Y	12D
		Micro	Monetary Creation as a Common Good		National Legislation	A	P	N° legal text	System Database	2	W	1C
				Transparency	Taxation	A	C	%rate (fixed & variable)	External auditing	1	W	1C
					Open source system	A	C	Certification	External auditing	1	M	1C
					Open banking	A	C	Certification	External auditing	2	M	2D
					Free Code and Legality	A	C	% free code	External auditing	3	W	2D

	Economic	Meta	Crisis Resiliency	Resiliency	Market diversity	A	C	N° goods & services category	Certification Standards	3	M	12D
						A	P	N° & % users & producers	System Database	3	D	IC
		Macro	Make Exchange Possible		Tipping Point Network Scale	UCI	C	N° users & N° business	Min best Practices: 500 & 100	2	Y	IC
					Interoperability	CI	A	N° systems users	System Database	3	M	IC
		Micro	Financial Autonomy Development	Finance	Investment standards	UCI	P	Certification	External auditing	2	D	2D
					Loan Standards	UCI	P	Certification	External auditing	3	D	2D
				Financial Autonomy	Agricultural Products/Tools	UCI	P	N° Agricultural Products &Tools	Interview			
					Household Consumption	UCI	P	Increased consumption	Interview			
				Accountancy	Accountancy standards	UCI	P	Certification	External auditing	1	D	12D
					Socio-Environmental Accountancy	UCI	P	Certification	External auditing	2	M	12D
				Management	Monitoring and Evaluation	A	P	N° standards & tools used	Best Practice	3	M	2D
				Exchange	Demurrage / Interest	A	C	%rate	Best Practice	3	W	23D
					Debt levels	A	C	Minimum and maximum	Best Practice	2	D	23D
					Discount rate	A	P	%discount	Best Practice	2	W	23D
					Salary bonus	UCI	P	%bonus	Best Practice	1	D	23D
					Exchange rates	A	A	%rate	Best Practice	2	M	23D
					Backed system	A	A	%backing	Best Practice	2	D	23D
	Social	Micro	Cohesion Cooperation Sharing Vector	Poverty	Income increase	BMI	C	%income increase	Interview	2	W	123C
						A	C	N° risen out of acute poverty	Interview	1	W	123BC
					Employment	BMI	C	%employment increase	Interview	2	D	123BC
						A	C	N° Self employment	Interview	3	D	123BC
		Macro	Health/Human Development	Public Health	Child Mortality		C	%Mortality rate	Regional Database			
	Environment	Meta	Transition and Autonomy	Relocation	Local growth	UCI	C	%GDP local increase per year	Regional Database	2	M	13AB
						UCI	C	N° profitable enterprise support	Interview	1	Y	13AB
						UCI	C	N° new profit & wage generated	Interview	2	Y	13AB
		Macro	Eco-Localization		Local consumption	UCI	C	%products locally produced	System Database	2	M	13AB
					Currency exchange	A	P	%salary exchanged in SCC	Interview	1	M	13CB
						A	P	N° of SCC spent & earned	System Database	2	Y	13CB

Impact Assessment Matrix (GiveDirectly)

Salifu, H. A. H. (2025). Ali, M. (2025).	
Banergee, 2020	
Ali, M. (2025).	
https://www.givedirectly.org/research/	
Walker, M. W., Shankar, N., Miguel, E., Egger, D., & Killeen, G. (2025).	
Banerjee, 2023	

Impact of each indicator is represented by a score starting from 1 (very low), 2 (low), 3 (high), and 4 (very high).

Integral approach	Dimension	Level	Vision Goal	Guideline Principle	Evaluation Objective	Progress Measurement Indicators	Score	Study	Justification	Recommendation
Subjective (Existential reflection)	Culture	Macro	Inner–Outer Sense Harmony	Altruism	Other-Oriented Cooperation & Self-Oriented Competition Equilibrium	% other-oriented vs. self-oriented	2		Issued Currency	Integrate community based cooperatives
	Social	Meso	Needs Satisfaction	Well-being	Mental health	% agree & strongly agree	3		Sense of financial security	Integration of community engagement features
					Depression	% agree & strongly agree	2		Sense of financial security	Integration of community engagement features
					Improve quality of life	% agree & strongly agree	4		Money appropriation for services	Include services diversity
					Mindfulness and Spirituality	% agree & strongly agree	N/A			
Objective (Neuro-	Economic	Micro	Financial Autonomy Development	Risk	Disaster mitigation	Backup system Frequency	1		Not a strong backup during crises	Should create a backup fund specific for crises

behavioral science)					Currency Security features	N° security features	3		Transfer via mobile money	Maintain audits and communicate safety measures to users
					Transaction and Data Safety	N° failure accident	3		Few failures; reliable encrypted transactions.	Add transparent reporting and monitoring of data protection.
					Record keeping and statistics	Backup system Frequency	3		Detailed digital records ensure traceability.	Share anonymized data for evaluation
	Environment	Meta	Transition and Autonomy	Relocation	GHG emission	%CO2 & CH4 decrease	N/A			
		Meso	Ecological Footprint Reduction	Biodiversity	Reforestation	N° tree plantation	N/A			
				Eco-Friendly	Behaviour change	% agree & strongly agree	N/A			
					Waste management	%recycling increase	N/A			
					Water management	%water consumption decrease	N/A			
		Micro	Responsible Consumption Motivation		Green economy	%organic & fair product increase	N/A			
Inter-subjective (Critical reflection)	Culture	Meta	Societal Acceptance	Societal	Recognition Credibility Legitimacy from (Inter-) Governmental Institution	N° institutional support	4		Strong collaboration with government and local partners	Maintain partnerships and formalize continued policy alignment.
					Transverse Cross-Disciplinary Integral Holistic collective intelligence	N° scholar expert specialist involved	4		Supported by academic and practitioner networks contributing to evaluation.	Continue research partnerships and invite policy researchers for cross-learning.
		Meso	Pluralism Inclusivity Diversity	Creativity	Alternative Flexible Libertarian Measure of Value	Yes / No	4		Inclusive framework adaptable to different community contexts.	Preserve flexibility while ensuring transparency
					Soft Skills and Hard Skills Design Thinking	% soft skills vs. hard skills	N/A			
	Economic	Macro	Make Exchange Possible	Resilience	Training	% trained	N/A			
						N° training hours per year	N/A			
		Meso	Inclusive Community-Building	Viability	Participation	N° active members per year	4		56,875 people reached in total	Increase user diversity
					Friendly user	% agree & strongly agree	4		Fiat /mobile money easy to use	Increase logistics security
					Intelligibility	% agree & strongly agree	4		Users show good comprehension of system principles and purpose.	Maintain user ease for rules and methods
					Team Capacity	N° management team	N/A			
	Social	Meta	Link Share Reciprocity Solidarity	Cooperation	Exchangeability	N° compensation systems	4		System efficiently enables peer-to-peer and local transfers with multiple partners.	Strengthen interoperability and cross-platform integration.
					Co-creation	N° involved in design	N/A			
					New skills	% agree & strongly agree	N/A			
		Macro	Equity and Justice	Engagement	Involvement	% agree & strongly agree	2		Moderate community participation; engagement mostly top-down.	Encourage bottom-up participation through feedback and co-design.
					Inclusion	N° solidarity inclusion	2		Reaches marginalized groups but limited diversity in participation.	Broaden outreach through local NGOs and inclusive campaigns.
					Social service dependence	N° social service dependant	N/A			
					Cohesion	N° new relationship	3		Transfers foster local trust and cooperation networks.	Reinforce social bonds through group-based projects or forums.
		Meso	Needs Satisfaction	Diversity	Education level repartition	%High & Graduate school				
		Micro	Cohesion Cooperation Sharing Vector	Mission	Ethic Charter	Yes / No	4		Clear ethical guidelines ensure accountability and transparency.	Regularly update and publicize code of ethics.
					Conducts Code	Yes / No	4		Governance and operational standards are well established.	Maintain compliance monitoring and stakeholder training.
				Education	Enrolment	N° children enrolled in school	3		Transfers indirectly support schooling through improved income.	Introduce educational incentives or community learning initiatives.
	Culture	Micro	Innovation Confidence Humility	Innovation	Open Questioning Capacity	N° yearly improvement	N/A			
	Governance	Meta	Participatory Democracy	Democracy		N° stakeholder involved	N/A			

					Collaborative Election Process Consent Sociocracy Holacracy	N° administrative person	N/A			
		Macro	Citizenship Engagement Recognition	Democracy	Effective Stakeholder Involvement stimulation	% participation among users	N/A			
		Meso	Independent Control	Legal	Independent Quality Control Process	Certification	N/A			
		Micro	Monetary Creation as a Common Good		National Legislation	N° legal text	N/A			
				Transparency	Taxation	%rate (fixed & variable)	N/A			
					Open source system	Certification	N/A			
					Open banking	Certification	N/A			
					Free Code and Legality	% free code	N/A			
	Economic	Meta	Crisis Resiliency	Resiliency	Market diversity	N° goods & services category	3		Cash transfers stimulate varied local spending but limited supply diversification.	Support small producers and local market expansion.
						N° & % users & producers	3		Active user base but few productive linkages beyond consumption.	Foster local entrepreneurship and producer networks.
		Macro	Make Exchange Possible		Tipping Point Network Scale	N° users & N° business	N/A			
					Interoperability	N° systems users	4		System operates efficiently across major mobile payment platforms.	Continue improving integration and ensure cross-operator compatibility.
		Micro	Financial Autonomy Development	Finance	Investment standards	Certification	N/A			
					Loan Standards	Certification	N/A			
				Financial Autonomy	Agricultural Products/Tools	N° Agricultural Products &Tools	4		Transfers enable asset purchases and farming investments.	Reinforce training and long-term asset management support.
					Household Consumption	Increased consumption	4		Noticeable rise in household spending and welfare indicators.	Encourage savings and productive reinvestment.
Inter-objective (Complexity economics)				Accountancy	Accountancy standards	Certification	N/A			
					Socio-Environmental Accountancy	Certification	N/A			
				Management	Monitoring and Evaluation	N° standards & tools used	3		Regular monitoring, but limited community-level feedback.	Introduce participatory evaluation tools for continuous learning.
				Exchange	Demurrage / Interest	%rate	N/A			
					Debt levels	Minimum and maximum	N/A			
					Discount rate	%discount	N/A			
					Salary bonus	%bonus	N/A			
					Exchange rates	%rate	N/A			
					Backed system	%backing	N/A			
	Social	Micro	Cohesion Cooperation Sharing Vector	Poverty	Income increase	%income increase	3		Evident income growth among recipients, though uneven across regions.	Strengthen financial literacy and local investment options.
						N° risen out of acute poverty	N/A			
					Employment	%employment increase	N/A			
						N° Self employment	3		Transfers encourage small-scale entrepreneurship.	Provide mentorship and business support programs
		Macro	Health/Human Development	Public Health	Child Mortality	%Mortality rate	4		Improved nutrition and healthcare spending reduce child mortality.	Maintain focus on maternal and child health initiatives.
	Environment	Meta	Transition and Autonomy	Relocation	Local growth	%GDP local increase per year	N/A			
						N° profitable enterprise support	N/A			
						N° new profit & wage generated	N/A			
		Macro	Eco-Localization		Local consumption	%products locally produced	3		Transfers boost local demand but sourcing remains partly external.	Promote local production chains and community enterprises.
					Currency exchange	%salary exchanged in SCC	N/A			
						N° of SCC spent & earned	N/A			

Impact Assessment Matrix (Circles)

Longo, A., Criscione, T., Linares, J., & Avanzo, S. (2025).	
Avanzo, S., Criscione, T., Linares, J., & Schifanella, C. (2023, September).	
Papadimitropoulos, V., & Perperidis, G. (2024).	
https://handbook.joincircles.net/docs/developers/whitepaper/	
Cabaña, G., & Linares, J. (2022).	
www.DuneAnalytics.com	
https://circles.garden/welcome/onboarding	
https://github.com/CirclesUBI/circles-api?tab=readme-ov-file	

Integral approach	Dimension	Level	Vision Goal	Guideline Principle	Evaluation Objective	Progress Measurement Indicators	Score	Study	Justification	Recommendation
Subjective (Existential reflection)	Culture	Macro	Inner–Outer Sense Harmony	Altruism	Other-Oriented Cooperation & Self-Oriented Competition Equilibrium	% other-oriented vs self-oriented	3		Trust-based mutual credit network	Increase local pools and user diversity
	Social	Meso	Needs Satisfaction	Well-being	Increased self confidence	% agree & strongly agree	3		Regular UBI boosts perceived security and self-worth among participants.	Maintain continuity of transfers
					Friendship and Trust	% agree & strongly agree	4		Strong community interaction and mutual trust observed among users.	Increase local meet-ups and co-learning spaces.
					Improve quality of life	% agree & strongly agree	N/A			
					Mindfulness and Spirituality	% agree & strongly agree	N/A			
Objective (Neuro-behavioral science)	Economic	Micro	Financial Autonomy Development	Risk	Disaster mitigation	Backup system Frequency	N/A			
					Currency Security features	N° security features	4		Strong blockchain-based security with transparent transaction verification.	Continue periodic audits of smart-contracts
					Transaction and Data Safety	N° failure accident	4		Reliable and traceable transactions through decentralized ledger.	Maintain high security standards
					Record keeping and statistics	Backup system Frequency	4		Full transaction history immutably stored on-chain, ensuring transparency.	Enhance analytics dashboards to support performance tracking and research.
	Environment	Meta	Transition and Autonomy	Relocation	GHG emission	%CO2 & CH4 decrease	N/A			
		Meso	Ecological Footprint Reduction	Biodiversity	Reforestation	N° tree plantation	N/A			
				Eco-Friendly	Behaviour change	% agree & strongly agree	N/A			
					Waste management	%recycling increase	N/A			
					Water management	%water consumption decrease	N/A			
		Micro	Responsible Consumption Motivation		Green economy	%organic & fair product increase	N/A			
						Proof of stake consensus cause negligible carbon footprint	4		Operates on energy-efficient blockchain with minimal emissions.	Maintain PoS framework
Inter-subjective (Critical reflection)	Culture	Meta	Societal Acceptance	Societal	Recognition Credibility Legitimacy from (Inter-) Governmental Institution	N° institutional support	3		Moderate legitimacy through local initiatives and NGO networks.	Strengthen dialogue with EU-level bodies
					Transverse Cross-Disciplinary Integral Holistic collective intelligence	N° scholar expert specialist involved	3		Involvement of academics and blockchain practitioners ensures technical soundness.	Collaborate with social scientists and policymakers.
		Meso	Pluralism Inclusivity Diversity	Creativity	Alternative Flexible Libertarian Measure of Value	Yes / No	3		Inclusive approach allows diverse participation	Improve coordination between user groups.
					Soft Skills and Hard Skills Design Thinking	% soft skills vs. hard skills	N/A			
	Economic	Macro	Make Exchange Possible	Resilience	Training	% trained	N/A			
						N° training hours per year	N/A			
		Meso	Inclusive Community-Building	Viability	Participation	N° users hours per year	3		Strong community engagement in onboarding and mutual support.	Continue developing peer-support and training initiatives.

					Friendly user	% agree & strongly agree	4		Interface and onboarding process are user-friendly and accessible.	Regularly update UX based on user feedback.
					Intelligibility	% agree & strongly agree	4		Users show good comprehension of system principles and purpose.	Maintain user ease for rules and methods
					Team Capacity	N° management team	N/A			
	Social	Meta	Link Share Reciprocity Solidarity	Cooperation	Exchangeability	N° compensation systems	3		Effective mutual credit exchanges among active users.	Strengthen liquidity mechanisms and expand user network.
					Co-creation	N° involved in design	4		Co-design process involves users and developers collaboratively.	Maintain participatory design
					New skills	% agree & strongly agree	N/A			
		Macro	Equity and Justice	Engagement	Involvement	% agree & strongly agree	3		Moderate involvement across user demographics.	Enhance outreach and participation from diverse groups.
					Inclusion	N° solidarity inclusion	3		Inclusive by design, yet still small-scale in reach.	Foster diversity through targeted communication campaigns.
					Social service dependence	N° social service dependant	N/A			
					Cohesion	N° new relationship	3		Community interactions foster local trust and cooperation.	Encourage offline meet-ups and shared projects.
		Meso	Needs Satisfaction	Diversity	Education level repartition	%High & Graduate school	N/A			
		Micro	Cohesion Cooperation Sharing Vector	Mission	Ethic Charter	Yes / No	3		Shared values and ethical norms are recognized informally.	Maintain open charter and guidelines
					Conducts Code	Yes / No	3			
				Education	Enrolment	N° children enrolled in school	N/A			
Inter-objective (Complexity economics)	Culture	Micro	Innovation Confidence Humility	Innovation	Open Questioning Capacity	N° yearly improvement	3		Continuous experimentation with design and governance.	Share open improvement reports.
	Governance	Meta	Participatory Democracy	Democracy	Collaborative Election Process Consent Sociocracy Holacracy	N° stakeholder involved	3		Users take part in governance through voting and proposals.	Enhance transparency and diversify participation channels.
						N° administrative person	3		Decentralization	Maintain decentralized power
		Macro	Citizenship Engagement Recognition	Democracy	Effective Stakeholder Involvement stimulation	% participation among users	3		Users actively engage in governance discussions and updates.	Incentives for user engagement
		Meso	Independent Control	Legal	Independent Quality Control Process	Certification	N/A			
		Micro	Monetary Creation as a Common Good		National Legislation	N° legal text	N/A			
				Transparency	Taxation	%rate (fixed & variable)	N/A			
					Open source system	Certification	4		Fully open-source platform fosters transparency and trust.	Maintain open access and promote community-driven development.
					Open banking	Certification	N/A			
					Free Code and Legality	% free code	4		Codebase publicly accessible and verifiable.	Continue open development
	Economic	Meta	Crisis Resiliency	Resiliency	Market diversity	N° goods & services category	1		Very limited number of goods and services available inside the Circles network.	Incentivize producers and merchants to join.
						N° & % users & producers	1		User base still small relative to potential local market; few active producers.	Develop community outreach campaigns
		Macro	Make Exchange Possible		Tipping Point Network Scale	N° users & N° business	1		Network below critical mass for self-sustaining exchange volume.	Improve growth strategies
					Interoperability	N° systems users	2		Partial interoperability with selected wallets and platforms.	Improve compatibility and open APIs to broaden usability.
		Micro	Financial Autonomy Development	Finance	Investment standards	Certification	N/A			
					Loan Standards	Certification	N/A			
				Accountancy	Accountancy standards	Certification	N/A			
					Socio-Environmental Accountancy	Certification	N/A			
				Management	Monitoring and Evaluation	N° standards & tools used	4		Strong system for on-chain tracking and transparent performance monitoring.	Maintain regular evaluations and publish aggregated insights.

				Exchange	Demurrage / Interest	%rate	4		Demurrage mechanism effectively encourages active circulation.	Continue monitoring impact and reasonable adjustments
					Debt levels	Minimum and maximum	N/A			
					Discount rate	%discount	N/A			
					Salary bonus	%bonus	N/A			
					Exchange rates	%rate	N/A			
					Backed system	%backing	N/A			
	Social	Micro	Cohesion Cooperation Sharing Vector	Poverty	Income increase	%income increase	N/A			
						N° risen out of acute poverty	N/A			
					Employment	%employment increase	3		Participation supports small informal jobs and self-initiated work.	Introduce micro-enterprise support or skill-building incentives.
						N° new job created/Self employment	2			
	Environment	Meta	Transition and Autonomy	Relocation	Local growth	%GDP local increase per year	N/A			
						N° profitable enterprise support	N/A			
						N° new profit & wage generated	N/A			
		Macro	Eco-Localization		Local consumption	%products locally produced	N/A			
					Currency exchange	%salary exchanged in SCC	N/A			
						N° of SCC spent & earned	3		Active circulation within the network but still limited to early adopters.	Incentives for local trading and merchant

Impact Assessment Matrix (GoodDollar)

https://whitepaper.gooddollar.org/	
https://www.gooddollar.org/	
Martín, E. B. (2024).	
https://thegraph.com/	

Integral approach	Dimension	Level	Vision Goal	Guideline Principle	Evaluation Objective	Progress Measurement Indicators	Score	Study	Justification	Recommendation
Subjective (Existential reflection)	Culture	Macro	Inner–Outer Sense Harmony	Altruism	Other-Oriented Cooperation & Self-Oriented Competition Equilibrium	% other-oriented vs self-oriented	N/A		DeFi-based universal basic income backed by crypto yield	Implement impact-weighted distribution and sustainability-linked staking pools
	Social	Meso	Needs Satisfaction	Well-being	Increased self confidence	% agree & strongly agree	N/A			
					Friendship and Trust	% agree & strongly agree	N/A			
					Improve quality of life	% agree & strongly agree	N/A			
					Mindfulness and Spirituality	% agree & strongly agree	N/A			
Objective (Neuro-behavioral science)	Economic	Micro	Financial Autonomy Development	Risk	Disaster mitigation	Backup system Frequency	N/A			
					Currency Security features	N° security features	4		Strong blockchain-based security with transparent transaction verification.	Continue periodic audits of smart-contracts
					Transaction and Data Safety	N° failure accident	4		Reliable and traceable transactions through decentralized ledger.	Maintain high security standards
					Record keeping and statistics	Backup system Frequency	4		Full transaction history immutably stored on-chain, ensuring transparency.	Enhance analytics dashboards to support performance tracking and research.
	Environment	Meta	Transition and Autonomy	Relocation	GHG emission	%CO2 & CH4 decrease	N/A			

		Meso	Ecological Footprint Reduction	Biodiversity	Reforestation	N° tree plantation	N/A			
				Eco-Friendly	Behaviour change	% agree & strongly agree	N/A			
					Waste management	%recycling increase	N/A			
					Water management	%water consumption decrease	N/A			
		Micro	Responsible Consumption Motivation		Green economy	%organic & fair product increase	N/A			
					Carbon Footprint	Proof of stake consensus cause negligible carbon footprint	3		Operates on energy-efficient blockchain with minimal emissions.	Maintain PoS framework and promote Good Collective initiative
						GoodCollectives for climate positive action	3			
Inter-subjective (Critical reflection)	Culture	Meta	Societal Acceptance	Societal	Recognition Credibility Legitimacy from (Inter-) Governmental Institution	N° institutional support	2		strong private-sector and NGO support	Collaboration with governmental or intergovernmental institutions.
					Transverse Cross-Disciplinary Integral Holistic collective intelligence	N° scholar expert specialist involved	2		Involves developers and practitioners but limited academic engagement.	Collaboration with researchers and policy experts.
		Meso	Pluralism Inclusivity Diversity	Creativity	Alternative Flexible Libertarian Measure of Value	Yes / No	3		Fully decentralized, non-pegged token enables alternative valuation.	Maintain openness
					Soft Skills and Hard Skills Design Thinking	% soft skills vs. hard skills	N/A			
	Economic	Macro	Make Exchange Possible	Resilience	Training	% trained	N/A			
						N° training hours per year	N/A			
		Meso	Inclusive Community-Building	Viability	Participation	N° users hours per year	3		Participation levels are steady but still limited to a core active group.	Expand outreach and create incentives for it
					Friendly user	% agree & strongly agree	4		Interface and onboarding process are user-friendly and accessible.	Regularly update UX based on user feedback.
					Intelligibility	% agree & strongly agree	4		Users show good comprehension of system principles and purpose.	Maintain user ease for rules and methods
					Team Capacity	N° management team	N/A			
	Social	Meta	Link Share Reciprocity Solidarity	Cooperation	Exchangeability	N° compensation systems	N/A			
					Co-creation	N° involved in design	N/A			
					New skills	% agree & strongly agree	N/A			
		Macro	Equity and Justice	Engagement	Involvement	% agree & strongly agree	N/A			
					Inclusion	N° solidarity inclusion	N/A			
					Social service dependence	N° social service dependant	N/A			
					Cohesion	N° new relationship	N/A			
		Meso	Needs Satisfaction	Diversity	Education level repartition	%High & Graduate school	N/A			
		Micro	Cohesion Cooperation Sharing Vector	Mission	Ethic Charter	Yes / No	3		Shared values and ethical norms are recognized informally.	Maintain open charter and guidelines
					Conducts Code	Yes / No	3			
				Education	Enrolment	N° children enrolled in school	N/A			
Inter-objective (Complexity economics)	Culture	Micro	Innovation Confidence Humility	Innovation	Open Questioning Capacity	N° yearly improvement	3		Continuous experimentation with design and governance.	Share open improvement reports.
	Governance	Meta	Participatory Democracy	Democracy	Collaborative Election Process Consent Sociocracy Holacracy	N° stakeholder involved	3		Users take part in governance through voting and proposals.	Enhance transparency and diversify participation channels.
						N° administrative person	3		Decentralization	Maintain decentralized power
		Macro	Citizenship Engagement Recognition	Democracy	Effective Stakeholder Involvement stimulation	% participation among users	3		Users actively engage in governance discussions and updates.	Incentives for user engagement
		Meso	Independent Control	Legal	Independent Quality Control Process	Certification	N'A			
		Micro	Monetary Creation as a Common Good		National Legislation	N° legal text	N/A			
				Transparency	Taxation	%rate (fixed & variable)	N/A			
					Open source system	Certification	4		Fully open-source platform fosters transparency and trust.	Maintain open access and promote

									community-driven development.
					Open banking	Certification	N/A		
					Free Code and Legality	% free code	4	Codebase publicly accessible and verifiable.	Continue open development
	Economic	Meta	Crisis Resiliency	Resiliency	Market diversity	N° goods & services category	N/A		
						N° & % users & producers	N/A		
		Macro	Make Exchange Possible		Tipping Point Network Scale	N° users & N° business	N/A		
					Interoperability	N° systems users	4	Interoperability with wallets and platforms.	Broaden usability.
		Micro	Financial Autonomy Development	Finance	Investment standards	Certification	N/A		
					Loan Standards	Certification	N/A		
				Accountancy	Accountancy standards	Certification	N/A		
					Socio-Environmental Accountancy	Certification	N/A		
				Management	Monitoring and Evaluation	N° standards & tools used	4	Strong system for on-chain tracking and transparent performance monitoring.	Maintain regular evaluations and publish aggregated insights.
				Exchange	Demurrage / Interest	%rate	N/A		
					Debt levels	Minimum and maximum	N/A		
					Discount rate	%discount	N/A		
					Salary bonus	%bonus	N/A		
					Exchange rates	%rate	N/A		
					Backed system	%backing	N/A		
	Social	Micro	Cohesion Cooperation Sharing Vector	Poverty	Income increase	%income increase	N/A		
						N° risen out of acute poverty	N/A		
					Employment	%employment increase	N/A		
						N° new job created	N/A		
	Environment	Meta	Transition and Autonomy	Relocation	Local growth	%GDP local increase per year	N/A		
						N° profitable enterprise support	N/A		
						N° new profit & wage generated	N/A		
		Macro	Eco-Localization		Local consumption	%products locally produced	N/A		
					Currency exchange	%salary exchanged in SCC	N/A		
						N° of SCC spent & earned	3	Active circulation within the network but still limited to early adopters.	Incentives for local trading and merchant

La borsa di dottorato cofinanziata con risorse dell'Unione europea-*NextGeneration EU*
Piano Nazionale di Ripresa e Resilienza Missione 4 – Componente 1 – Riforma 4.1 Riforma dei Dottorati - Inv. 4.1 Borse Generici Ricerca PNRR – CUP J11J22002130006