

Is decentralized finance actually decentralized? A social network analysis of the Aave protocol on the Ethereum blockchain

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Decentralized finance (DeFi) has the potential to disrupt centralized finance by validating peer-to-peer transactions through tamper-proof smart contracts and thus significantly lowering the transaction cost charged by financial intermediaries. However, the actual realization of peer-to-peer transactions and the levels and effects of decentralization are largely unknown. Our research pioneers a blockchain network study that applies social network analysis to measure the level, dynamics, and impacts of decentralization in DeFi token transactions on the Ethereum blockchain. First, we find a significant core-periphery structure in the AAVE token transaction network where the cores include the two largest centralized crypto exchanges. Second, we provide evidence that multiple network features consistently characterize decentralization dynamics. Finally, we document that a more decentralized network significantly predicts a higher return and lower volatility of the DeFi tokens. We point out that our approach is seminal for inspiring future extensions related to the facets of application scenarios, research questions, and methodologies on the mechanics of blockchain decentralization.

Keywords: Decentralized finance, social network analysis, AAVE, Ethereum, core-periphery, modularity, giant component ratio

ACM CCS: E.0, G.1, G.3, I.6, J.4, J.6

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1 INTRODUCTION

DeFi, short for decentralized finance, is a blockchain-powered peer-to-peer financial system [Werner et al. 2021]. Harvey et al. [2021] predict that DeFi could disrupt centralized finance by validating peer-to-peer transactions by tamper-proof smart contracts and thus significantly lower the transaction cost charged by financial intermediaries. However, the actual realization of peer-to-peer transactions and the levels of decentralization are largely unknown [Cong et al. 2022; Zhang et al. 2022]. Moreover, how the levels of decentralization would affect the economic performance of the blockchain platform is broadly unexplored. How can decentralization be measured? The comparative study of decentralized and centralized financial markets is not new [Canales and Nanda 2012; Miao 2006]. However, before blockchain technology existed, decentralized markets tended to have worse performance. For example, decentralized over-the-counter markets and the lack of a central market-maker induce high trading costs and give rise to intermediations between trading partners [Battiston et al. 2012; Bosma et al. 2017; Yun et al. 2019]. Moreover, Bovet et al. [2019]; Motamed and Baharak [2019]; Vallarano et al. [2020] find that network features, a proxy for the market structure in decentralized markets affect important market outcomes (e.g., liquidity and volatility) that individual traders, at the hub of the network, make more profit in general [Di Maggio et al. 2017; Hollifield et al. 2017; Li et al. 2019]. Does blockchain live up to its promise of empowering peer-to-peer transactions in decentralized financial markets? Our research applies social network analysis [Jackson 2008; Otte and Rousseau 2002; Scott 1988] to blockchain transaction data and aims to answer the following research questions:

- **Realization of decentralization:** Are the transactions in decentralized banks on blockchain indeed decentralized?
- **Blockchain network dynamics:** How do different network features of blockchain transactions correlate and change over time?
- **Counterfactual impact evaluation:** How do network features predict and interact with the economic performance of the blockchain applications under time series momentum at different horizons?

We pioneer a blockchain network study that applies social network analysis to measure the level, dynamics, and impacts of decentralization in DeFi token transactions on the Ethereum blockchain. We analyze our research questions with an application to the transaction network of AAVE, the native utility token of a top-ranked decentralization finance application on Ethereum. We have three main findings.

- (1) There exists a significant core-periphery structure in the AAVE token transaction network where the cores include the two largest centralized exchanges and central smart contracts with specific functions.
- (2) Multiple network features including the number of components, the relative size of giant components, modularity, and standard deviation of degree centrality consistently characterize decentralization dynamics.
- (3) A more decentralized network as represented by the network measures significantly predicts a higher return and lower volatilities of the DeFi tokens.

1.1 Literature Review

Our research contributes to the literature on the interplay of the financial market, social network studies, and crypto-economics.

1.1.1 Social network analysis in the financial market and core-periphery structures. The application of social network analysis (SNA) to financial markets has gained momentum after the 2008-2009

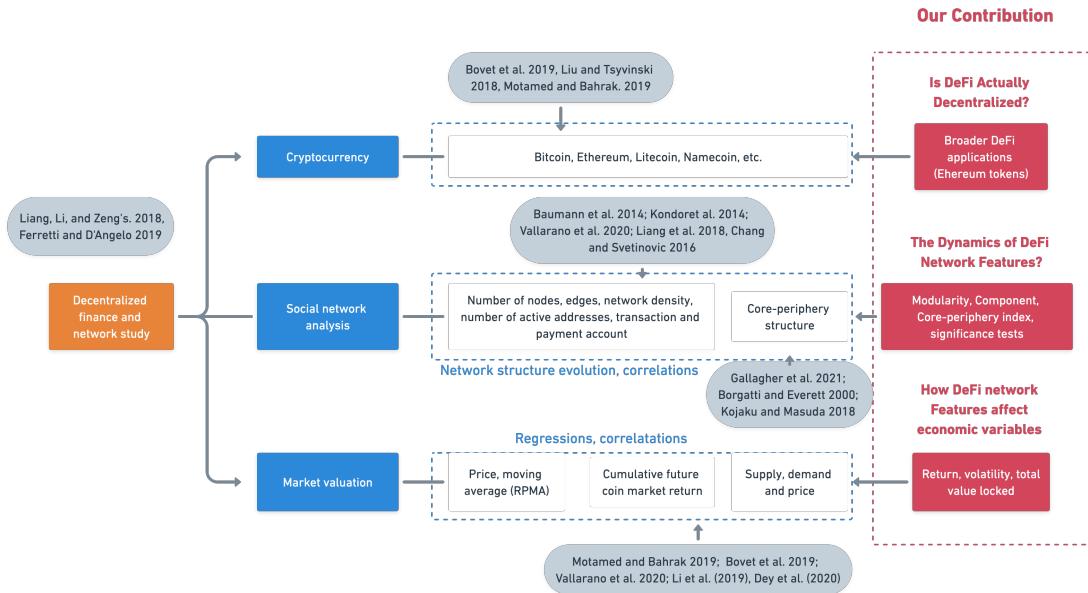


Fig. 1. Contribution Map of this Study

Note: This figure displays the contribution map of our study on the existing literature.

financial crisis. Lending relationships among banks and other financial institutions proved to be conduits of contagion of liquidity shortages and financial distress [Anand et al. 2013; Blasques et al. 2018,?; Gai et al. 2011; Langfield et al. 2014]. Regulators came to realize that studying the structure of financial networks is key to identifying sources of systemic risk, for example, in the form of financial institutions that are ‘too central to fail’, meaning that their failure may generate a cascade that ruins the whole financial system [Bardoscia et al. 2017; Battiston et al. 2012; Bosma et al. 2017; Yun et al. 2019]. The decentralized financial market on blockchain in our research thus serves as a potential solution to the “too central to fail” problem. However, one of the most important conclusions of this literature was that in many financial markets, transactions are not carried out in an anonymous market but through stable trading relationships that reduce transaction costs [Babus and Kondor 2018; Duffie et al. 2005]. The peer-to-peer transactions on the blockchain are instead anonymous by default and might not benefit from stable exchange relationships like those observed in the traditional financial market.

A commonly adopted notion in social network analysis is the core-periphery structure, which presents two qualitatively distinct components: “core” nodes that are densely connected, and “periphery” nodes that are loosely connected to the core members but not necessarily to each other [Gallagher et al. 2021]. The core-periphery structure enables us to compare and analyze the properties of the two types of nodes more accurately and efficiently under different contexts structurally and functionally [Csermely et al. 2013]. SNA has already been widely applied to study financial networks. For example, Sui et al. [2019] compares the resilience between core-peripheral networks and complete networks by analyzing the financial contagion of interbank networks. Barucca and Lillo [2016] proposes methods to identify different network architectures including bipartite and the core-periphery structure in the case of the interbank network. In the cryptocurrency market, the core-periphery structure of stable assets based on liquidity and

capital inferred by a network feature has been examined to study the market impact and evolution [Polovnikov et al. 2020].

A variety of algorithms have been developed by scholars for extracting the core-periphery structure [Malliaros et al. 2019], which differ typologically based on their definitions of the nature of the network and the way in which core and peripheral nodes are connected. The most popular is the Borgatti-Everett (BE) algorithm, which partitions the network into a central hub with interlacing nodes and a periphery radiating outward from the hub [Borgatti and Everett 2000]. Cucuringu et al. [2016] detected the core-periphery structure through spectral methods and geodesic paths based on the transportation networks. In addition to the classical two-block methods, there exist algorithms that build a continuous spectrum between a core and a periphery which have been applied in examples related to collaboration, voting, transportation, etc. [Boyd et al. 2010; Rombach et al. 2017; Rossa et al. 2013]. The continuous structure enables the exploration of network components and features that are not apparently categorized as core or periphery [Rombach et al. 2017]. Considering that there may be more than one core-periphery pair in the network, Kojaku and Masuda [2017, 2018a,b] propose scalable algorithms to detect multiple core-periphery groups in a network and demonstrate their application in networks of political blogs and airports.

Given the diverse core-periphery structures defined by algorithms, we apply the Borgatti-Everett (BE) algorithm [Borgatti and Everett 2000] to our AAVE transfer network while examining algorithms of multiple pairs [Kojaku and Masuda 2018a] along with SNA to test the level of decentralization comprehensively. Details of algorithms and packages utilized will be given in the data section to provide reliable network inference and methodology for further studies.

1.1.2 Crypto tokens and decentralized banking. Crypto tokens are digital assets that utilize blockchain and cryptography technology to ensure security [Halaburda et al. 2022]. As of Jan. 20, 2022, the market value of crypto tokens was beyond 1.9 trillion U.S. dollars. Cong and Xiao [2021] categorize cryptocurrencies into general security, utility (general payment and platform), and product tokens based on their functions. Bitcoin, the first cryptocurrency, was designed as a transaction mechanism and classified as utility (general payments) tokens. Although Bitcoin dominated the market between 2009 and 2016, other alternatives emerged later on [Härdle et al. 2020]. Ethereum blockchain proved revolutionary in its support for smart contracts that allow automatic transactions and the issuance of Ethereum Request for Comments (ERC) tokens [Lehar and Parlour 2021; Liang et al. 2018]. Our research studies the transaction network of AAVE, an ERC-20 token that is the native utility (platform) token of Aave, a top-ranked decentralized finance application on Ethereum. The market value of AAVE was beyond 2.9 billion U.S. dollars as of Jan. 20, 2022 [coinmarketcap 2022]. Aave is a decentralized bank that allows users to lend and borrow crypto assets and earn interest on assets supplied to the protocol [Whitepaper.io 2020]. In general, decentralized banks differ from centralized banks in two aspects: 1) they replace centralized credit assessments with coded collateral evaluation [Gudgeon et al. 2020], and 2) they employ smart contracts to execute asset management automatically [Bartoletti 2020]. The open-source codes of the decentralized bank, Aave, and the transparent trading data of the AAVE token enable us to reproduce the historical network dynamics.

1.1.3 Network studies in cryptoeconomics. An extensive body of literature explores the key features of trading networks and the way in which they relate to the price dynamics of cryptocurrencies. Liang et al. [2018] show that both Bitcoin and Ethereum trading networks display fluctuations in growth rates. For example, the clustering coefficient¹ of Bitcoin was initially 0.15, qualifying it as a small-world network, and decreased to approximately 0.05 later [Baumann et al. 2014; Kondor

¹The clustering coefficient describes the extent to which a network is aggregated [Baumann et al. 2014].

et al. 2014]; in contrast, the clustering coefficient of Ethereum has fluctuated between 0.15 and 0.2 over time and has never been identified as a small world² [Ferretti and D'Angelo 2019]. Motamed and Bahrak [2019] built both monthly and accumulative networks of Ethereum. They found that the number of components³ is approximately ten and increases over time; however, similar to that of the Bitcoin trading network, the network density⁴ of Ethereum decreases over time [Vallarano et al. 2020]. Liang et al. [2018] also found that the largest components of Bitcoin and Ethereum have large sizes in terms of both their diameters (approximately 100 for Bitcoin and gradually increasing for Ethereum) and percentages (40-60%). The network structures differ significantly across blockchains. For instance, Chang and Svetinovic [2016] found that the Bitcoin network has grown denser over time, with more nodes tending to be connected with each other, leading to a strong community while Namecoin has shown a decrease in density, resulting in an unclear community structure. [De Collibus et al. 2021] hints that the growth and concentration indexes can be measured by network calculations via analyzing the aggregated transaction networks of Ethereum-based crypto assets, and conclude that wealth is much more concentrated than in-degree and out-degree. Polovnikov et al. [2020] demonstrate a core-periphery structure [Gallagher et al. 2021] in cryptocurrency exchange networks.

The literature has also found an effect of network features on economic variables such as price and volatilities. Motamed and Bahrak [2019] found that the price of Bitcoin, Ethereum and Litecoin is positively correlated with the size of the graph and the number of nodes and edges. Vallarano et al. [2020] showed that the price of Bitcoin is negatively correlated with the average outdegree. Cong et al. [2022] discovered that the current Ethereum is more and more centralized in block rewards, ownership, and transactions. Bovet et al. [2019], using a Granger causality test, found that the past degree distributions, especially the outdegree⁵ of the Bitcoin trading network can predict future price increases [Bovet et al. 2019]. Several studies have also used network features. Li et al. [2019] built an ARIMA time-series model to forecast price anomalies using network features.

Our research extends network studies on Bitcoin and Ethereum to DeFi tokens. Moreover, we aim to conduct a comprehensive analysis of the blockchain network and the core-periphery structure by comparing a variety of network features including the numbers of nodes and edges, the mean and standard deviation of degree., top 10 degrees mean ratio, relative degree, modularity, the count of components, the count of core, and giant component ratio, etc. Furthermore, we conduct counterfactual analysis to simulate the effect of removing cores on AAVE network dynamics. Finally, to evaluate economic performance, in addition to price and volatility, we include total value locked (TVL) [George 2022], a feature unique to the DeFi market.

2 CONCEPTUAL FRAMEWORK

The computer science literature has defined three types of communication networks since [Baran 1964], these are depicted in Figure 2, borrowed from [Barabási 2016]. In a centralized network, one central node connects all other nodes, and the degree distribution is unequal since one node has N-1 links while all other nodes have only 1 link. In a decentralized network, there are several hubs that connect to peripheral nodes and to each other. In this network, the degree distribution is equal to that in the centralized network but there are hubs that have considerably more links than the peripheral nodes. The third type of network is the distributed network in which there are no

²A small-world network refers to a network in which most nodes are not neighbors of each other, but most nodes can be reached from other nodes by a small number of steps [Baumann et al. 2014].

³Components are parts of the network that are disconnected from each other [Vallarano et al. 2020].

⁴Network density describes the portion of the potential connections in the network that are actual connections [Vallarano et al. 2020].

⁵Outdegree is the number of edges that are directed out of a node in the directed network graph [Vallarano et al. 2020].

hubs and all nodes have approximately the same number of neighbors. We regard the network on the left as the most centralized and the network on the right as the most decentralized network structure. Ideally, DeFi aims to be completely decentralized, facilitating peer-to-peer transactions, which corresponds to the distributed network in the computer science literature.

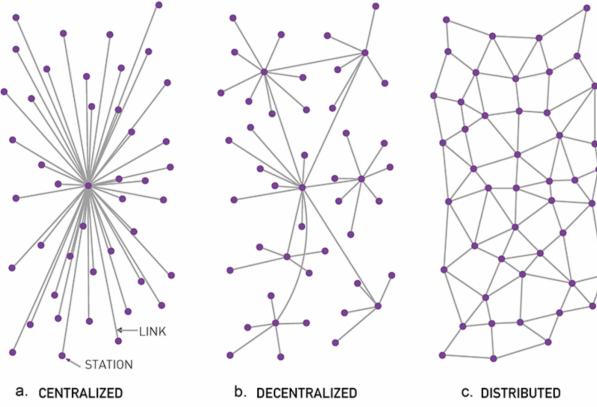


Fig. 2. Different types of network structures

Note: This figure illustrates three types of communication networks (borrowed from [Barabási 2016]).

[Campajola et al. 2022] in their paper presents a wide array of indexes to display the different levels of decentralization of Bitcoin, including clustering index, degree distribution, core-periphery structure, etc. In our study, we introduce various network measures to capture the differences between these network features in the token networks of Aave. The first thing to note is that in Figure 2, the network consists of only one component, that is, all nodes are connected by direct or indirect paths. In our transaction data, however, the network consists of many disconnected components. In an ideally centralized market, all nodes should be connected to a single hub; thus the number of components should be one. In a very fragmented market, in contrast, we may observe many components. This argument leads to our first measure of centralization: **the number of components** (disconnected parts in the network) shows how centralized or fragmented the network is. We compute this measure for every day observed in the data.

The second related measure is **the relative size of the largest (giant) component**. If the network is more centralized, we expect the largest component to cover a high fraction of nodes, in a fragmented network we observe many small components. We calculate the size of the giant component divided by the total number of nodes in the daily transaction network; the larger this value is, the more centralized the network.

A related measure is the **modularity score** (formally defined in Table 1) which measures the strength of division of a network into small groups (Newman 2006). A market structure with lower modularity is more centralized, which means that there are no separate communities in the transaction network. This measure can be applied to both connected and disconnected graphs.

Fourth, we capture the characteristics of the structures in Figure 2 by computing the **standard deviation of the number of neighbors (degree)** in the network. In a centralized network, we have the largest disparity in degree, while in the distributed case, the degree distribution is equal.

Last but not least, we use the concept of **core-periphery networks** to measure the degree of centralization. In a core-periphery network, a limited number of core members constitute a densely connected hub that are connected to each other and to the peripheral nodes. The peripheral nodes

Table 1. Major Network Features

Name	Definition
num_nodes	Number of unique addresses in the daily transaction network.
num_edges	Number of transactions in the daily transaction network.
Components_cnt	The various disconnected parts of the network, where there is no path that can connect from a node in one component to a node in another component. Components_cnt here refers to the number of components in the daily transaction network
giant_com_ratio	Size of the giant component divided by the total number of nodes in the daily transaction network.
DCstd	Standard deviation of degree centrality. Degree centrality measures the number of neighbors one node has: the higher the number, the more central the node is.
Modularity	Measure of the strength of a network divided into modules. A network with a high degree of modularity has dense connections between nodes within a module but sparse connections between nodes in different modules.
cp_test_pvalue	P value of the significance test of the core-periphery structure.
cp_significance	1 if cp_test_pvalue is less than 0.05 and, else 0 otherwise.
core_cnt	Number of nodes in the core based on the BE core-periphery structure algorithm in the daily transaction network.
avg_core_neighbor	the Average number of neighbors (degree) of the core nodes detected by the core-periphery structure algorithm in the daily transaction network.

Note: This table gives the general definitions of the network features included in our study with an explanation and equation.

are not connected to each other, only the core members. Note that the centralized structure in the left panel of Figure 2 corresponds to a core-periphery structure with one core member, and the decentralized structure to a core-periphery network with multiple core members. The distributed network in the right panel is not a core-periphery network.

Based on these arguments, we run statistical tests to detect the core-periphery structure in the data, comparing it to a random network with the same degree distribution [KOJAKU 2022]. Our first measure of decentralization is the **significance level** of this test, which we convert to a binary measure. This measure is equal to 1 when the p value of the test is less than 0.05, which indicates the presence of core-periphery structure. In the other case, when the p-value is larger than 0.05, the measure takes the value 0, which indicates that the presence of a core-periphery structure can be rejected.

In addition, for the days when a core-periphery structure describes the data well, we measure the number and degree of core members in the network. In a more centralized network, the number of core members is lower and each core member has a larger degree.

Table 1 summarizes the network measures that we use to capture market centralization in the data.

Turning to the economic variables of the market, we focus on two common outcomes of interest: price and 30 day volatility ⁶. We expect market centralization to affect these outcome variables. Table 2 summarizes the economic variables and our predictions.

⁶We also present the definition and regression results on the total value locked (TVL) in USD in Appendix B and C

Table 2. Major Economic Variables

Name	Definition
PriceUSD	Fixed closing price of the asset in USD.
VtyDayRet30d	Volatility over 30 days, measured as the standard deviation of the natural log of daily returns over the past 30 days.

Note: This table gives the general definitions of the economic variables used as dependent variables in regressions.

3 DATA

3.1 Data source

Our data are from three open sources: general economic variables of the AAVE token from Coinmetrics [Coinmetrics 2022], TVL in Aave from DeFi Pulse [Pulse 2022], and blockchain transaction records of AAVE token from Bigquery public datasets on the Ethereum blockchain [Bigquery 2022], ranging from Oct. 10, 2020, to Oct. 9, 2021. Our processed datasets for analysis are at a daily level. We include a detailed datasets overview and dictionary for each dataset in Appendix A.

3.2 Data processing

3.2.1 *Calculate network features.* Using the Python NetworkX package [Hagberg et al. 2008], we build daily transaction network graphs using `from_address`, `to_address` as nodes and the values as weights. We consider an undirected network between the addresses with weights equal to the total value of transactions between the accounts. This means that we add the transaction values between two duplicate accounts without considering the direction before network building. Based on the daily network, we calculate 24 network features using the NetworkX algorithms [Hagberg et al. 2008], given in Appendix A. We keep only the network features listed in Table 1 to answer the research questions of this paper but open source the rest for future research.

3.2.2 *Extract the core-periphery structure.* To extract the core-periphery structure, we utilize the Python cpnet package [KOJAKU 2022], which contains algorithms implemented in Python for detecting core-periphery structures in networks. `cpnet.BE` [KOJAKU 2022] is the algorithm used for the Borgatti-Everett (BE) algorithm, which, identifies nodes either as either core or periphery in a single group [Borgatti and Everett 2000]. `cpnet.KM_config` [KOJAKU 2022] is used for examining multiple pairs of core-periphery nodes, which can return the coreness and pair of each node. This package also allows us to conduct significance testing via the q-s test on the core-periphery structure of the daily network to assess the fitness of this algorithm for our data, where we use 0.05 as the significance level. The core-periphery structure detected for the input network is considered significant if it is stronger than those detected in randomized networks [Kojaku and Masuda 2018b]. We calculate the number of cores and the average number of neighbors of the core nodes to further investigate the levels of decentralization given the core-periphery structure. Additionally, based on the daily networks constructed using the core-periphery algorithm, we record all core addresses that appear during the period and the number of days that they become core. The type (contract or address) and information links of those cores are extracted from Etherscan.io [etherscan.io 2019] and recorded for further comparison.

3.2.3 *Analyze interactions with economic variables.* Among the economic metrics queried as shown in Appendix B, the price in USD `PriceUSD`, 30-day volatility `VtyDayRet30d` and total value locked (TVL) in USD `tvUSD` are chosen as the dependent variables in our regression models since they are significant and commonly used economic metrics in market valuation. Specifically, the price

intuitively reflects the market value of the AAVE token, which is perfectly correlated with the market capitalization for the Aave protocol⁷ during the time range of our data. The 30-day volatility can reflect the degree of volatility in the token market over the past month and the potential existence of risks or tendencies [Coinmetrics 2022]. The total value locked, which is the overall value of crypto assets deposited in the Aave protocol in USD [George 2022], is a unique economic metric in the context of the cryptocurrency market. Furthermore, before regression, we need to ensure stationarity of time-series data—that is, that the mean, variance, and autocorrelation structure remain constant over time [Brownlee 2017], and the values give an approximately normal distribution. We transform the variables using methods including differencing the data and taking the logarithm difference, or percentage change based on the Dickey-Fuller test results to ensure that they become stationary. After that, we scale all the stationary variables between 0 and 1 for scale comparison and test the correlation for all the independent variables (after transformation) to avoid high correlation in the regressions.

4 METHODS AND RESULTS

4.1 The realization of decentralization (the core-periphery structure)

4.1.1 *Construct core-periphery structures.* As introduced and discussed in the previous sections, we apply the Borgatti-Everett (BE) algorithm [Borgatti and Everett 2000] and the multiple-pairs core-periphery structure algorithm [Kojaku and Masuda 2018b] to the AAVE transaction network to investigate whether the daily graphs can be separated into dense transactions between some active addresses (defined as the core) and some other loose transactions between some small addresses (defined as the periphery) in either a single pair or multiple pairs. In this section, we connect the properties of the core-periphery structure in the AAVE transaction network with the real functions and types of the specific addresses (some typical addresses) to further explore the question of centralization vs. decentralization.

We test the significance of all 365 observations. The results indicate that the AAVE daily transaction network is insignificant in the multiple-pair core-periphery structure, but partially significant in the one-pair structure with 232 significant (64%) and 133 insignificant (36%) days. Comparing the distribution (displayed in Figure 3) of the number of nodes in the core and the average number of degrees of the core nodes (described in Table 1) in the significant and nonsignificant daily graphs that we tested, we find that the number of nodes in the core in the significant graph is much smaller. The average number of average neighbors of the core nodes is more prominent in those significant graphs and vice versa. By interpretation, when the transaction network significantly fits the core-periphery structure, it can be divided into small groups of denser and looser connections. The transaction difference between nodes is larger; thus, the degree of centralization is greater. In this case, a few addresses are likely to dominate most transactions.

To depict the structure and comparison in a more intuitive and explainable way, we pick two representative days of the significant and nonsignificant graph to visualize the network, as displayed in Figure 4. It shows the core-periphery network graphs of transactions among the identified core accounts based on the cpnet.BE algorithms in a spiral layout on 2020-10-12 (left panel) and 2021-02-22 (right panel), where the dark dots represent the core nodes and the light dots are the periphery nodes. The two panels clearly illustrate that on a significant core-periphery graph (left panel), all core nodes are closely linked, and each core node forms an aggregation group with periphery nodes (each with a high degree) so that any two nodes can connect in a few steps. The overall network structure of the transactions among the identified core accounts is very compact and

⁷Rather than matching a lender to a borrower, lenders deposit funds into the Aave liquidity pools, ensuring a continuous supply of funds, which leads to market capitalization perfectly correlated with price [Whitepaper.io 2020].

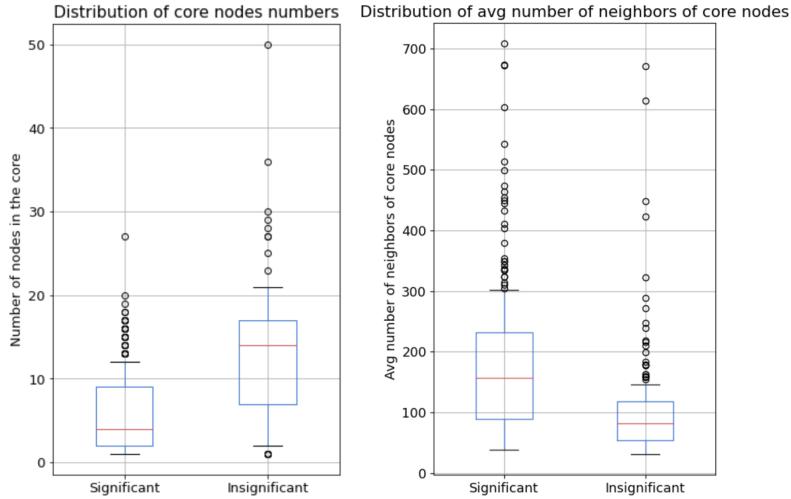


Fig. 3. Core-periphery structure features distribution box plots

Note: This figure plots the distribution of the number of core nodes (left panel) and the average number of neighbors of core nodes (right panel) on days with significant (p value smaller than 0.05) and insignificant core-periphery test results.

cohesive, resulting in a significant core-periphery structure, which is also more centralized in the transaction since the core nodes are dominant. In contrast, the right panel shows a looser overall connection. Each identified core node has a smaller degree, with many scattered periphery nodes; some nodes require a long step size to connect to other nodes, which prevents the structure from being significantly certified as core-periphery and adds to the level of decentralization in the transaction network.

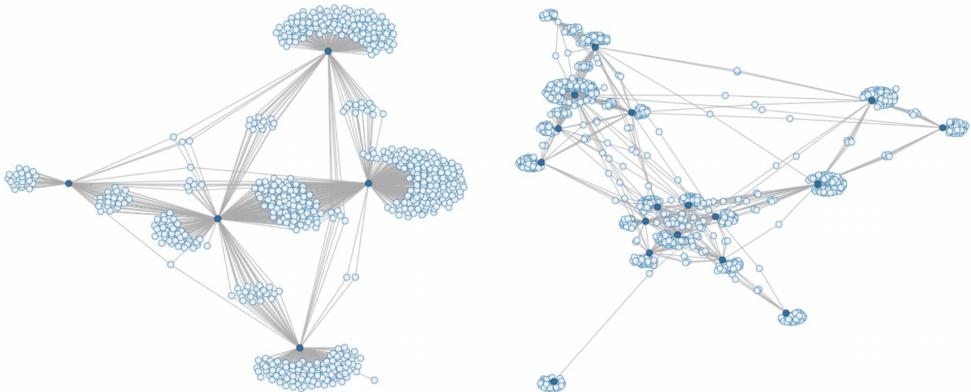


Fig. 4. Network graphs on 2020-10-12 (left panel) and 2021-02-22 (right panel)

Note: This figure shows the core-periphery network graphs of transactions among the identified core accounts based on the cpnet.BE algorithms in a spiral layout on 2020-10-12 (left panel) and 2021-02-22 (right panel), where the dark dots represent the core nodes and the light dots are the periphery nodes. The left panel returns a. significant p-value in the significance test, while the right panel is nonsignificant.

4.1.2 Compare the core-periphery structure for externally owned and contract account. Furthermore, we investigate addresses/accounts that were once identified as core members in the graphs. There are two types of accounts defined on Ethereum: externally owned accounts (EOAs) and contract accounts (CAs, also called smart contracts) [Hu et al. 2021]. EOAs are created and owned by users with a private key set and can be utilized to deposit and transfer assets and call smart contracts [Hu et al. 2021]. The CAs are execution programs composed of smart contract code, which also possesses asset balance and will be automatically executed if the trigger condition in met [Szabo 1997]. We record the accounts that appear to be identified as core nodes during the period and the number of days that they become core, based on the daily networks constructed by the Borgatti-Everett (BE) algorithm [Borgatti and Everett 2000]. We extract the type of account (EOA or CA) according to Etherscan.io [etherscan.io 2019].

Figure 5 plots the distribution of the number of core days for EOAs and CAs. From the graph, the range of day counts is generally larger for the contract accounts, where the extreme value is much larger than its counterpart for externally owned accounts. The four outliers identified (two for CA and two for EOA) appear to be in the core for many of the days, resulting in a centralized transaction that could significantly affect the level of decentralization. We investigate the detailed account information of these four accounts by Etherscan.io [etherscan.io 2019] for further explanation.

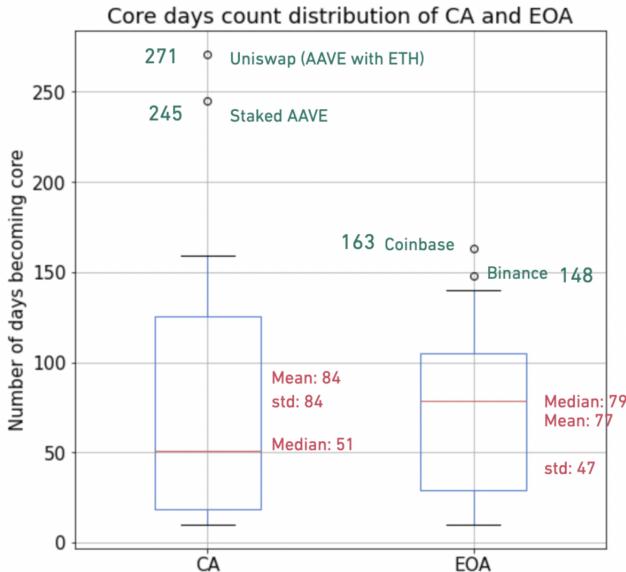


Fig. 5. Core day count distribution box plots

Note: This figure plots the distribution of the number of core days for EOAs and CAs, where the y axis is the number of days in which the node is in the core.

The two outliers among EOAs are *Binance* and *Coinbase*, which are the two top centralized exchanges in the cryptocurrency market. A centralized exchange is a significant online platform for users to buy and sell cryptocurrencies, offering security and monitoring for the individual to complete the transaction in a trustworthy environment [Reiff 2019]. Due to the popularity of these two centralized exchanges, a tremendously large number of transfers occur through these two accounts daily between the same and different types of cryptocurrencies by many EOAs. Given the

results of the core-periphery structure, the centralized exchange exerts a significant influence on the AAVE daily transaction network and brings a high level of “centralization” to it.

The two outliers among CAs are decentralized exchanges, we find that one of them is an automated market maker on Uniswap, a decentralized exchange for transactions between AAVE and Ether. Automated market makers (AMMs), first introduced by Hanson’s logarithmic market scoring rule (LMSR) [Hanson 2003], are contracts that allow liquidity to be automatically provided to the crypto market automatically [Fritsch and Zürich 2021]. Based on the AMM, this contract is built on Uniswap, which allows agents to trade between AAVE and Ether at the price and rates specified by the pricing function, and the price is kept enormous centered transaction network around this account, which greatly influences the core-periphery structure and increases the centralization of the AAVE transaction graph. Another is the smart contract of Stated AAVE, which performs the functions in the Aave decentralized bank of staking (moving assets to long-term saving account), redeeming (getting collateral back), getting rewards (claiming interest rates), etc. [Whitepaper.io 2020].

On the one hand, the two outliers of centralized exchanges put the promise of blockchain decentralization in doubt; on the other hand, the two outliers of decentralized exchanges evidence that blockchain can mitigate the dependence on trusted centralized entities.

4.2 Blockchain network dynamics and correlations

In addition to the core-periphery structure, we use other network properties to capture market centralization. We find that all the intertemporal network features indicate consistent dynamics whereby the AAVE token transaction network first becomes more decentralized and then reverts to being more centralized.

4.2.1 Numbers of components. When the market is more centralized, we expect to have fewer components in the network since most transactions go through a central node that connects most nodes indirectly, forming a network component. The left upper panel of Figure 6 plots the number of components over time. The graph suggests that the AAVE market first became increasingly decentralized, as indicated by the increase in the number of components up to February 2021, and then showed a tendency to centralize as the number of components increased. The network structure of the market converged to approximately 100 components after July 2021.

4.2.2 Giant component size ratio. A related network property is the relative size of the giant component. In a centralized market, the giant component covers a large fraction of the nodes, while in a decentralized market, the giant component is relatively small. The lower right panel of Figure 6 shows that the relative size of the giant component first decreased and then increased. This again suggests that the market was initially decentralized and then became more centralized.

4.2.3 Modularity score. The modularity score is small when the market is centralized, meaning that there are no separate communities in the network. In contrast, in a decentralized market, many communities are not or are only weakly connected to each other, implying a high modularity score. The right upper panel of Figure 6 shows the evolution of modularity. The modularity score increased first, indicating a tendency to decentralize, and then it started to decrease, suggesting centralization.

4.2.4 The standard deviation of degree centrality. The standard deviation of degree centrality is large (small) when the market is centralized (decentralized) since, in a centralized market, a few hubs have a high degree while the other nodes have only a few connections. In the right middle panel of Figure 6, we see that the standard deviation of degree centrality first decreased and then

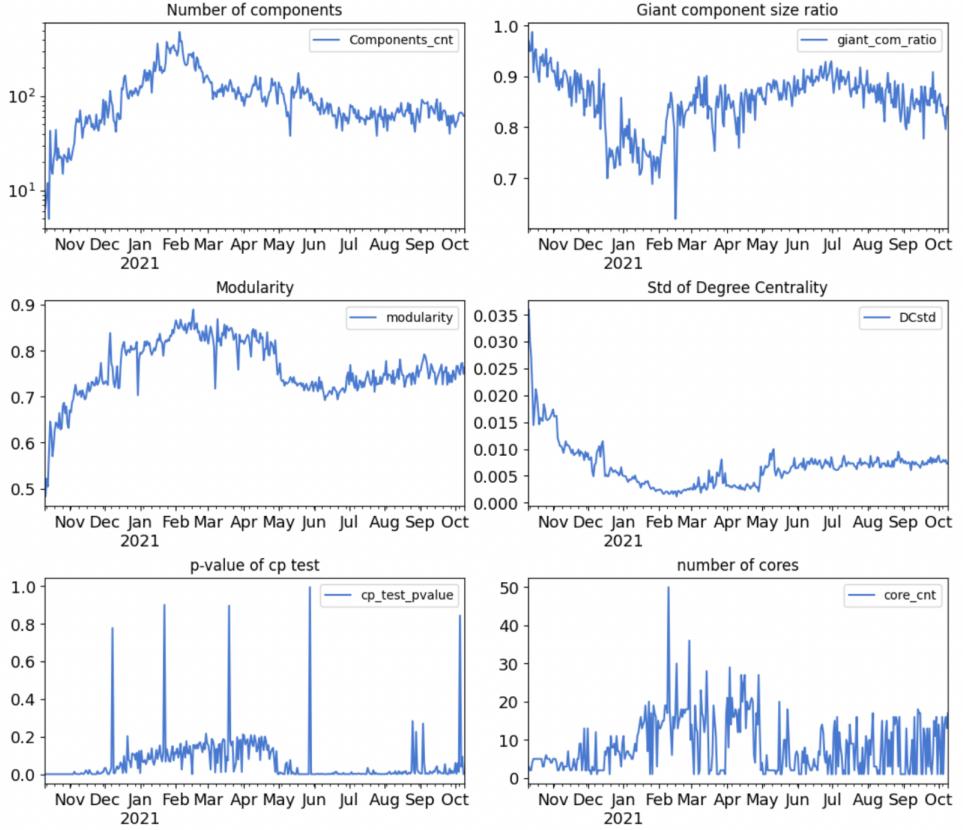


Fig. 6. Time-series plots of network features

Note: This figure gives time-series plots of network features included in our study, with the feature name in the title of each panel.

increased, suggesting that the market first showed a tendency toward decentralization and then toward centralization.

4.2.5 *P value of core-periphery structure test.* We plot the significance level of the core-periphery model test and the number of cores returned by the BE algorithm. The transaction network is more centralized if the core-periphery test gives a significant result ($p < 0.05$) or the number of cores is lower. We observe in the two lowest panels of Figure 6 that, according to these measures, the AAVE transaction network first decentralized around the middle of the sample period and then centralized toward the end of the sample period.

4.2.6 *More on the core-periphery structure.* Finally, we compute the correlations between the different network features that we use as measures of centralization to confirm that they move together as expected by our explanation. Centralization implies the significance of the core-periphery structure statistical tests (low p-value), a low number of components, a low modularity score, the large size of the giant component, and a high standard deviation of degree centrality. This implies that the sign of the correlations between these network features should be as indicated in Figure 7,

where we also show the empirical values of these correlations. We can observe that the signs of the correlations are as expected based on our network-based measures of centralization.

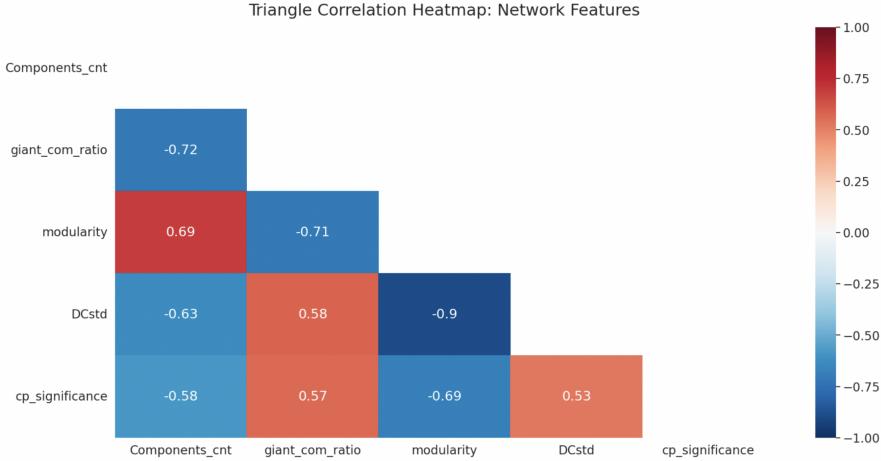


Fig. 7. Correlation heatmap of network features

Note: This figure plots the correlation between network features, red represents a positive correlation while blue represents a negative correlation. The depth of the color is proportional to the correlation coefficient value.

4.3 Counterfactual impact evaluation

4.3.1 Background and Methods. Liu and Tsyvinski [2018]’s study demonstrated that there is strong evidence of time-series momentum at various time horizons of the cryptocurrency network features; this evidence could potentially indicate a momentum effect of the network on DeFi economic metrics. In addition, considering that the economic metrics of DeFi tokens are volatile at a daily level, the technique indicators may not have predictive power for them. To assess this, we conduct OLS regression to predict the effect of the cumulative future economic variables’ change at different time horizons on the network structure variation. We utilize Python smf.ols for the OLS regressions with return (ROI), total value locked, and volatility as the dependent variables. Each dependent variable is regressed on each of the seven measures of changes in the token transfer network and each of the two measures of changes in economic metrics⁸. To avoid the issues of heterogeneity and autocorrelation, we generalize the regressions with Newey-West estimators [Liu and Tsyvinski 2018]. We predict the cumulative future economic variables’ growth at one-day, one-week to eight-week and ninety-day horizons using the 7-day moving average of network features [Liu and Tsyvinski 2018] to compare the effect of momentum on the regressions.

4.3.2 Results on market returns. Figure 8 presents the results of the token market returns (USD) using the 7-day moving average of network variables (The regression table is given in Table 5 in Appendix). Considering token market returns, we find evidence that the level of market centralization predicts token returns in the long run; namely, in a more decentralized market, the token returns

⁸7-days moving average is not applied to cp_significance considering the meaning and explainability of the binary variable.

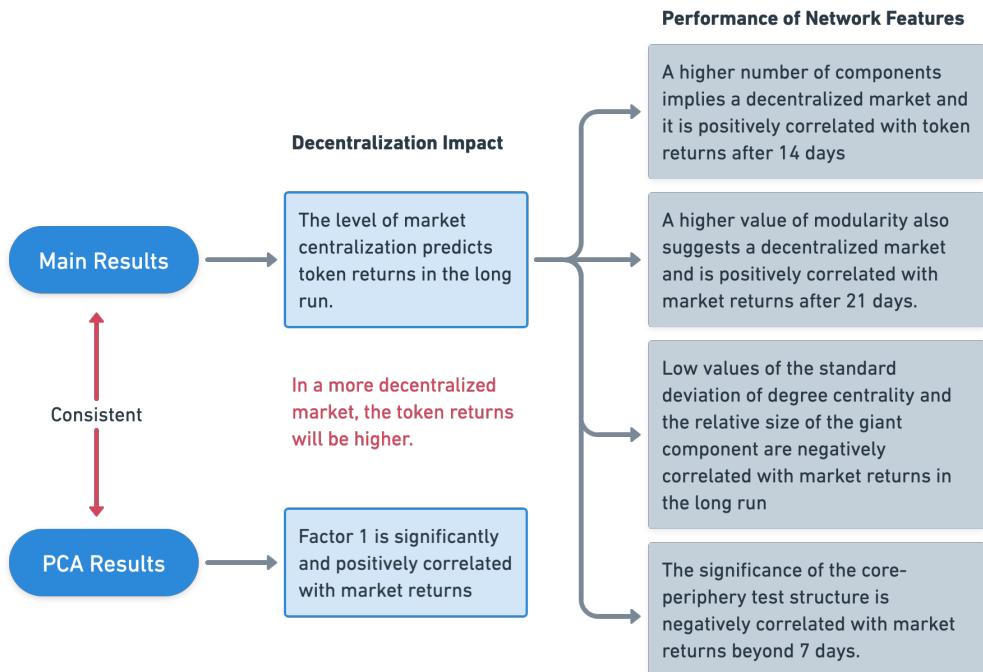


Fig. 8. Results of the token market returns (USD)

Note: This figure reports the results of predicting the token market returns (USD) using the 7-day moving average of network variables (except cp significance).

will be higher.⁹ All our regressions based on network features point in this direction. A higher number of components implies a decentralized market and it is significantly and positively correlated with token returns after 14 days. A higher value of modularity also suggests a decentralized market and is significantly and positively correlated with market returns after 21 days. Conversely, low values of the standard deviation of degree centrality and the relative size of the giant component imply decentralization. Both of these measures are significantly and negatively correlated with market returns in the long run. In addition, the significance of the core-periphery test structure, which indicates the property of a centralized core-periphery network, is negatively correlated with market returns for most time horizons beyond 7 days. We note that considering the short run, the market returns are very volatile and, hence, our network measures are not significantly correlated with it. This is also reflected in the R-squared value in our regressions: it is very close to zero for the short-run regressions and increases with the time horizon.¹⁰

4.3.3 Results of the principal-component analysis of market returns. We further confirm our results by principal-component analysis. We determine the optimal number of factors by maximizing the explained variance of the five network features that we use as measures of centralization. This

⁹The prediction results are consistent with stakeholders' expectations of blockchain to be decentralized, i.e., if the transaction network of DeFi tokens is more decentralized, stakeholders would be more optimistic about the future returns, which leads to a self-confirming equilibrium of higher returns.

¹⁰The result that short-term returns of crypto tokens is less likely to be predictable by other features is consistent with [Liu and Zhang 2022]

gives us three factors that together explain 97% of the variance. The factor loadings are depicted in Figure 9. Factor 1 explains most of the variance at 84% and can be interpreted as a measurement of decentralization since it is positively correlated with the number of components and the modularity score, and negatively correlated with the size of the giant component, the standard deviation of degree centrality and the significance of the core-periphery test. Factors 2-3 are also highly correlated with the network features but capture much less of the variance. We use these factors in the regressions of market returns at different horizons; the results are shown in Table 5. Focusing on Factor 1, which measures decentralization, we find that it is significantly and positively correlated with market returns. This means that a higher degree of decentralization is associated with higher market returns, which is consistent with our findings considering the individual network measures discussed above.

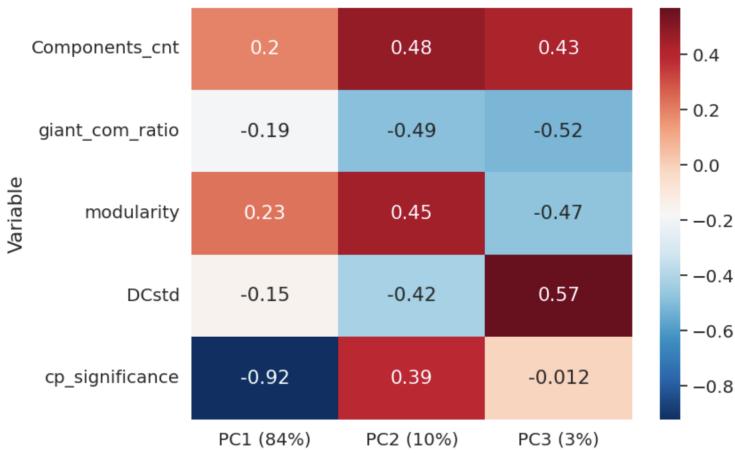


Fig. 9. Interpretation of PCA

Note: This figure depicts the correlation coefficient between the original variables and the components. Positive and negative values in the graph reflect the positive and negative correlation of the variables with the PCs. Red represents a positive correlation, blue represents a negative correlation, and the depth of the color is proportional to the correlation coefficient value.

4.3.4 Results on market volatility. Turning to our measure of market volatility, shown in Figure 10 we perform a similar analysis (the regression table is given in Table 6 in Appendix). We find mixed results regarding the impact of our centrality measures on market volatility. Considering the number of components, we find that a higher number of components is significantly and positively correlated with future market volatility in the short run (7-28 days) and is not significant in the long run. This suggests that a more decentralized market leads to higher volatility. In contrast, the modularity score is significantly and negatively correlated with market volatility in the medium run (24-42 days) and is not significant otherwise. This suggests that in a decentralized market with a higher modularity score, volatility is lower. We also find that the significance of the core-periphery network structural test is negatively correlated with market volatility. This means that for centralized core-periphery networks, the volatility is lower. In addition, the relative size of the giant component and the standard deviation of the degree centrality is not significantly correlated with market volatility at any time horizon. Our mixed results on the impact of centralization on market volatility can be rationalized on the grounds of the complex relationship between centralization

and volatility. On the one hand, a more decentralized market should have lower volatility since the impact of shocks is more distributed in a decentralized market. In contrast, in a centralized market, shocks in central hubs are easily transmitted to all participants. On the other hand, higher volatility is correlated with higher returns and we have seen that decentralization leads to higher returns which may also be correlated with higher volatility. Our different network measures may capture different parts of these effects.

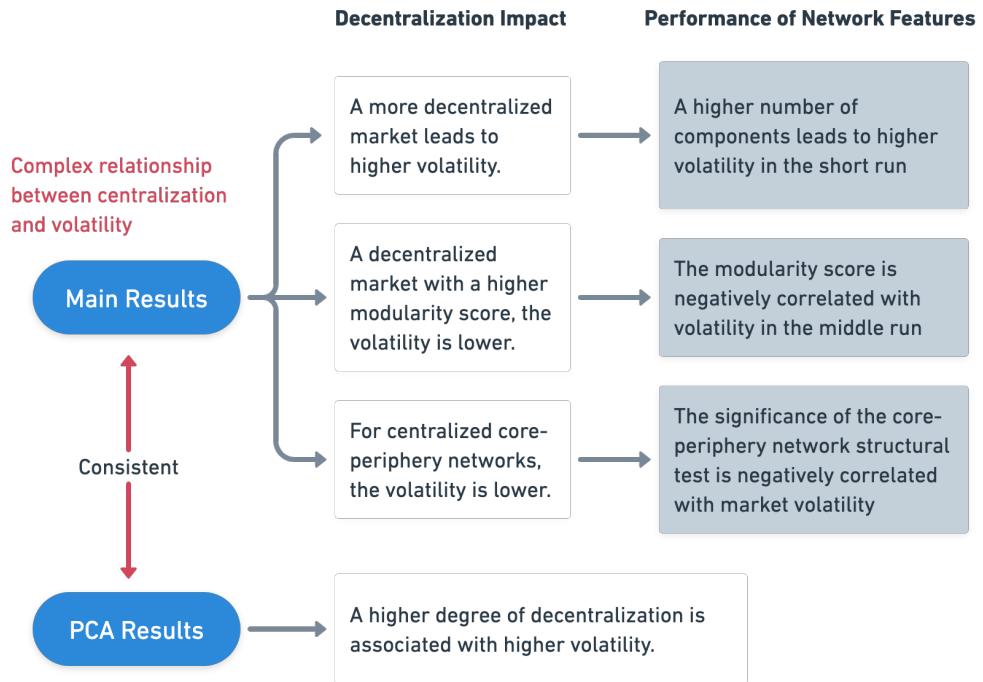


Fig. 10. Results of the 30-day volatility growth rate

Note: This figure reports the results of predicting the 30-day volatility growth rate using the 7-day moving average of network variables (except cp significance).

4.3.5 Results of the principal component analysis of volatility. We also use the factors from the principal component analysis in the regression of volatility, and the results are shown in Table 6. Considering Factor 1, which measures the degree of decentralization, we find that a higher degree of decentralization is associated with higher volatility. Our combined measure of decentralization thus supports the view that in a decentralized transaction network, market volatility is higher.

For the total value locked, we do not obtain too many significant results in this study; more variables representing network decentralization could be added as independent variables in the future to refine the model. The regression result table is in Appendix B.

5 CONCLUSIONS AND DISCUSSION

5.1 Extensions in three facets

Our study shows that social network analysis is instrumental in characterizing the level, dynamics, and impacts of decentralization in DeFi token transactions. Our research is also seminal in terms

of inspiring future research on the three facets of application scenarios, research questions, and methodology.

- (1) **Application Scenarios.** Our methods can be generally applied to transaction tokens issued by other DeFi protocols, such as decentralized payment, exchange, assets, derivatives and even non-financial applications on blockchains.¹¹
- (2) **Research Questions.** We can extend our analysis to study the interplay of other network features and economic variables. For example, one straightforward follow-up research is to extend the analysis to include other network features for which we have provided open-source data as defined in Appendix A.
- (3) **Methodology.** We can further explore the interplay of network dynamics and token economics by causal inference through advanced econometrics and prediction algorithms in machine learning [Athey 2015].

5.2 On the mechanics of blockchain decentralization

Is decentralized finance actually decentralized? The answer from our pioneering blockchain network study is intriguing. We found that the current research on decentralization tends to neglect two important aspects of the mechanics of blockchain decentralization:

- (1) How do incentives affect agents' behavior in transaction network formations?
- (2) How do incentives affect the final realizations of network decentralization?

These two gaps neglections in the literature leave a door for future research to improve the mechanism to support a truly decentralized economy. Why? The blockchain infrastructure only provides the possibility for peer-to-peer transactions. However, the actually realized decentralization of blockchain transaction networks depends on the behavior of stakeholders, who are affected by incentives. If we can better understand the incentives that govern the stakeholders' behavior and the formation of transaction networks, we can design incentives schemes to support desired levels of decentralization.¹² Future research can experiment with other scientific methods of theoretical modeling and simulations. For example, we can further apply network game theory [Azouvi and Hicks 2020] to distributed systems to study how incentives affect agents' strategic behaviors and the transaction network formations on the blockchain. We can also apply agent-based modeling [Iori and Porter 2012] to simulate the transaction networks on blockchain to systematically evaluate the effect of incentive design changes.

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¹¹Refer to [Zhang et al. 2022] and the references therein.

¹²Our results resonate with those of Zhang et al. [2022], but with a unique perspective from social network analysis.

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A NETWORK FEATURES

Table 3 contains 24 daily network features calculated from the AAVE transaction data we calculated using the NetworkX package, which can be used as a reference for further network studies.

B ECONOMIC VARIABLES

Table 4 contains 3 economic variables for the AAVE transaction data, which can be used for further studying the interaction between network features and economic variables.

C SUPPLEMENTARY REGRESSION TABLE

Table 5 gives the regression result table of the token market returns (USD).

Table 6 gives the regression result table of the 30-day volatility growth rate.

Table 7 gives the regression result table of total value locked.

Table 3. Network Features

Name	Definition
num_nodes	Number of unique addresses in daily transaction network.
num_edges	Number of transactions in daily transaction network.
Degree mean	The number of edges a node has, an average of nodes.
Degree std	The number of edges a node has the standard deviation of nodes.
Top10Degree mean	Average degree of the addresses with top 10 highest degree values during the whole period.
Top10Degree std	Standard deviation of the degree of the addresses with the top 10 highest degree values during the whole period.
Top10 Degree mean ratio	Top 10 addresses' degree mean divided by the general degree mean.
Relative degree	Network density. The portion of the potential connections in a network is actual connections.
DCmean	The average value of degree centrality.
DCstd	The standard deviation of degree centrality.
Cluster_mean	Mean of clustering coefficient. The degree to which nodes in a graph tend to cluster together.
Cluster_std	Standard deviation of clustering coefficient. The degree to which nodes in a graph tend to cluster together.
Modularity	Modularity is a way to measure the strength of a network divided into modules. A network with a high degree of modularity has dense connections between nodes within a module, but sparse connections between nodes in different modules.
Transitivity	Transitivity is the overall probability for the network to have adjacent nodes interconnected, thus revealing the existence of tightly connected communities.
eig_mean	Mean of eigenvector centrality. Measures the degree to which the division of a network into communities.
eig_std	Standard deviation of eigenvector centrality. Measures the degree to which the division of a network into communities.
closeness_mean	Mean of closeness centrality. The reciprocal of the farness.
closeness_std	Standard deviation of closeness centrality. The reciprocal of the farness.
giant_com_ratio	Size of the giant component divided by the total number of nodes in the daily transaction network.
Components_cnt	The components of the network are the various disconnected parts, where there is no path that can connect from a node in one component to a node in another component. Components_cnt here refers to the number of components in the daily transaction network
cp_test_pvalue	P-value of the significant test of the core-periphery structure.
cp_significance	1 if cp_test_pvalue is less than 0.05, else 0.
core_cnt	Number of nodes in the core based on the BE core-periphery structure algorithm in the daily transaction network.
avg_core_neighbor	the Average number of neighbors (degree) of the core nodes detected by the core-periphery structure algorithm in daily transaction network.

Note: This table gives the general definitions of all network features calculated in our study with the explanation.

Table 4. Major Economic Variables

Name	Definition
PriceUSD	The fixed closing price of the asset in USD.
VtyDayRet30d	The volatility over 30 days, measured as the standard deviation of the natural log of daily returns over the past 30 days.
tvIUSD	The total amount locked in that particular token in USD.

Note: This table gives the general definitions of the economic variables used as dependent variables in regressions.

Table 5. Results of the token market returns (USD)

Time horizon	t, t+1 (1)	t, t+7 (2)	t, t+14 (3)	t, t+21 (4)	t, t+28 (5)	t, t+35 (6)	t, t+42 (7)	t, t+49 (8)	t, t+56 (9)	t, t+90 (10)
Δ component cnt	-0.015	0.113	0.281**	0.423***	0.342***	0.318***	0.261**	0.293**	0.320**	0.258**
R ²	0	0.007	0.029	0.047	0.037	0.033	0.021	0.025	0.025	0.017
Residual Std. Error	(0.129)	(0.132)	(0.163)	(0.192)	(0.178)	(0.177)	(0.185)	(0.192)	(0.213)	(0.221)
Δ giant com ratio	0.024	-0.028	-0.086	-0.188*	-0.212*	-0.144	-0.176	-0.377**	-0.442***	-0.332***
R ²	0	0.001	0.003	0.012	0.017	0.008	0.011	0.049	0.056	0.032
Residual Std. Error	(0.129)	(0.132)	(0.165)	(0.195)	(0.180)	(0.179)	(0.186)	(0.190)	(0.209)	(0.219)
Δ log(modularity)	0.011	0.059	0.089	0.278***	0.288***	0.212**	0.239**	0.351***	0.368**	0.592***
R ²	0	0.003	0.004	0.027	0.034	0.019	0.023	0.046	0.041	0.108
Residual Std. Error	(0.129)	(0.132)	(0.165)	(0.194)	(0.179)	(0.178)	(0.185)	(0.190)	(0.211)	(0.211)
Δ log(DCstd)	0.018	0.005	-0.082	-0.217***	-0.268***	-0.220***	-0.220***	-0.267**	-0.257*	-0.337***
R ²	0	0	0.004	0.021	0.037	0.026	0.025	0.034	0.026	0.046
Residual Std. Error	(0.129)	(0.132)	(0.165)	(0.195)	(0.178)	(0.178)	(0.185)	(0.191)	(0.212)	(0.218)
cp significance	-0.014	-0.090**	-0.163***	-0.278***	-0.322***	-0.324**	-0.314*	-0.188	0.056	1.834***
R2	0.007	0.031	0.039	0.061	0.046	0.028	0.018	0.005	0	0.124
Residual Std. Error	(0.080)	(0.242)	(0.391)	(0.528)	(0.718)	(0.931)	(1.138)	(1.269)	(1.351)	(2.432)
PCA component1	0.024	0.047*	0.063*	0.092***	0.076**	0.059*	0.045	0.018	-0.033	-0.236***
PCA component2	-0.015	-0.117	-0.196	-0.401***	-0.332***	-0.279***	-0.266***	-0.249**	-0.256**	-0.651***
PCA component3	0.056	0.228***	0.400***	0.575***	0.487***	0.438***	0.435***	0.459***	0.469***	0.561***
R ²	0.011	0.107	0.194	0.3	0.252	0.202	0.177	0.172	0.146	0.42
Residual Std. Error	(0.129)	(0.126)	(0.149)	(0.165)	(0.158)	(0.161)	(0.170)	(0.178)	(0.200)	(0.170)

Note: This table reports the results of predicting the future market return (USD) using the 7-day moving average of network variables (except cp significance). Columns (1)-(10) represent one day, one week to eight weeks, and 90 days respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels. The data frequency is daily. The residual standard errors are reported in parentheses.

Table 6. Results of the 30-day volatility growth rate

Time horizon	t, t+1 (1)	t, t+7 (2)	t, t+14 (3)	t, t+21 (4)	t, t+28 (5)	t, t+35 (6)	t, t+42 (7)	t, t+49 (8)	t, t+56 (9)	t, t+90 (10)
Δ component cnt	0.062	0.300***	0.294**	0.349**	0.348**	0.223	0.164	0.155	0.045	-0.279**
R ²	0.005	0.04	0.026	0.025	0.021	0.008	0.005	0.005	0	0.022
Residual Std. Error	(0.085)	(0.151)	(0.185)	(0.226)	(0.253)	(0.264)	(0.237)	(0.237)	(0.246)	(0.219)
Δ giant com ratio	-0.022	-0.041	-0.017	0.01	-0.043	-0.034	-0.061	-0.106	-0.079	0.049
R ²	0.001	0.001	0	0	0	0	0.001	0.003	0.001	0.001
Residual Std. Error	(0.085)	(0.154)	(0.187)	(0.229)	(0.255)	(0.265)	(0.238)	(0.237)	(0.246)	(0.221)
Δ log(modularity)	-0.013	-0.036	-0.128	-0.277**	-0.280*	-0.338**	-0.249**	-0.137	-0.131	-0.082
R ²	0	0.001	0.008	0.024	0.02	0.027	0.018	0.006	0.005	0.003
Residual Std. Error	(0.085)	(0.151)	(0.187)	(0.226)	(0.253)	(0.262)	(0.238)	(0.237)	(0.245)	(0.221)
Δ log(DCstd)	-0.041	-0.162*	0.016	0.128	0.16	0.232	0.153	-0.036	-0.022	0.2
R ²	0.004	0.018	0	0.005	0.007	0.013	0.007	0	0	0.017
Residual Std. Error	(0.085)	(0.152)	(0.187)	(0.228)	(0.254)	(0.263)	(0.237)	(0.237)	(0.246)	(0.219)
cp significance	-0.002	-0.028	-0.068**	-0.122***	-0.210***	-0.294***	-0.364***	-0.412***	-0.425***	-0.431***
R2	0.001	0.01	0.02	0.035	0.068	0.103	0.131	0.152	0.152	0.191
Residual Std. Error	(0.043)	(0.137)	(0.233)	(0.315)	(0.384)	(0.432)	(0.467)	(0.485)	(0.500)	(0.444)
PCA component1	0.007	0.03	0.036	0.072*	0.136***	0.191***	0.217***	0.252***	0.267***	0.307***
PCA component2	0.035	-0.004	-0.196	-0.271	-0.286	-0.280*	-0.141	-0.019	0.009	0.441***
PCA component3	0.025	0.132*	0.220**	0.201*	0.066	-0.109	-0.291**	-0.468***	-0.573***	-0.831***
R ²	0.008	0.031	0.044	0.05	0.076	0.124	0.184	0.257	0.299	0.508
Residual Std. Error	(0.085)	(0.152)	(0.184)	(0.224)	(0.246)	(0.249)	(0.215)	(0.205)	(0.207)	(0.156)

Note: This table reports the results of predicting the 30-day volatility growth rate using the 7-days moving average of network variables (except cp significance). Columns(1)-(10) represent one day, one week to eight weeks, and 90 days respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels. The data frequency is daily. The residual standard errors are reported in parentheses.

Table 7. Results of the total value locked change (USD) using the 7-days moving average of network variables

Time horizon	t, t+1 (1)	t, t+7 (2)	t, t+14 (3)	t, t+21 (4)	t, t+28 (5)	t, t+35 (6)	t, t+42 (7)	t, t+49 (8)	t, t+56 (9)	t, t+90 (10)
Δ component cnt	0.038	-0.032	0.128	0.192**	0.149	0.123	0.083	0.095	0.021	-0.349**
R ²	0.001	0.001	0.008	0.015	0.007	0.005	0.002	0.002	0	0.037
Residual Std. Error	(0.101)	(0.132)	(0.144)	(0.158)	(0.187)	(0.180)	(0.185)	(0.202)	(0.200)	(0.198)
Δ giant com ratio	0.029	0.081	0.036	-0.018	-0.038	0.003	-0.017	-0.097	-0.126	0.177
R ²	0.001	0.005	0.001	0	0.001	0	0	0.003	0.005	0.011
Residual Std. Error	(0.101)	(0.132)	(0.144)	(0.159)	(0.187)	(0.181)	(0.203)	(0.214)	(0.199)	(0.201)
Δ log(modularity)	-0.02	-0.091*	-0.098*	-0.039	-0.141**	-0.049	-0.1	0.008	-0.032	-0.107
R ²	0	0.006	0.006	0.001	0.008	0.001	0.003	0	0	0.004
Residual Std. Error	(0.101)	(0.132)	(0.144)	(0.159)	(0.187)	(0.181)	(0.202)	(0.215)	(0.200)	(0.202)
Δ log(DCstd)	0.039	0.193***	0.061	-0.026	-0.043	-0.027	0.019	-0.005	0.013	0.073
R ²	0.002	0.035	0.003	0	0.001	0	0	0	0	0.003
Residual Std. Error	(0.101)	(0.130)	(0.144)	(0.159)	(0.187)	(0.181)	(0.203)	(0.215)	(0.200)	(0.202)
cp significance	-0.052	-0.290*	-0.700***	-1.161***	-1.283***	-1.412***	-1.656***	-1.740***	-1.599***	-1.528***
R2	0.002	0.012	0.042	0.078	0.082	0.078	0.09	0.093	0.084	0.175
Residual Std. Error	(0.558)	(1.254)	(1.618)	(1.938)	(2.090)	(2.367)	(2.570)	(2.664)	(2.605)	(1.657)
PCA component1	0.001	0.076*	0.092**	0.048	0.108	0.132*	0.231***	0.273***	0.311***	0.126*
PCA component2	0.011	-0.007	0.025	0.087**	0.073	0.051	0.015	0.001	-0.042	0.158***
PCA component3	-0.005	-0.055	-0.054	-0.128*	-0.200**	-0.199***	-0.285***	-0.297***	-0.289***	0.205**
R ²	0.002	0.022	0.054	0.082	0.097	0.101	0.143	0.155	0.173	0.227
Residual Std. Error	(0.101)	(0.131)	(0.141)	(0.153)	(0.179)	(0.172)	(0.188)	(0.198)	(0.182)	(0.178)

Note: This table reports the results of predicting the total value locked change using the 7-days moving average of network variables (except the cp significant). (1) - (10) represents one day, one week to eight weeks, and 90 days respectively. *, **, and *** denote significance levels at the 10%, 5%, and 1% levels. The data frequency is daily. The residual standard errors are reported in parentheses.