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Network Topology in Decentralized Finance

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Abstract

The composability and anonymity of participants in Decentralized Finance pose significant challenges in understanding their interactions and the buildup of risk within the network. We map the interconnections among decentralized finance protocols using transactions among contracts and addresses, explore single-layer and multiplex network properties and quantify the financial exposure of the most critical nodes. We observe scale-free properties similar to traditional financial networks, but the inclusion of user interactions and the influence of externally owned accounts yield distinct network characteristics. Furthermore, centrality measures and high-frequency metrics provide insights into systemically important participants and at-risk protocols, necessitating further research to develop robust risk measures. By identifying potential vulnerabilities and developing appropriate risk management strategies, the stakeholders can help ensure the stability and safety of decentralized finance as a viable alternative to traditional financial systems.

Keywords: blockchain; composability; networks;
JEL Classification: G20; D85; D53; L14.

1. Introduction

The emergence of blockchain technology has revolutionized the way we think about financial systems. Decentralized finance (DeFi), in particular, has emerged as an alternative to traditional financial systems, providing potentially greater access to financial services and fostering innovation (Harvey, Ramachandran, & Santoro, 2021) (Schär, 2021) (Werner, et al., 2021). The blockchain network provides a public infrastructure where smart contracts automate different services. In addition, the shared database provides a unique registry of transactions across the network. This open-access network is an essential advantage in terms of interoperability concerning the technological stack of traditional financial services (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023) (Rossi, 2023). From an economic point of view, this implies that there is free entry for service providers. Furthermore, there are no minimum capital restrictions and licenses to offer financial services. An additional benefit of transparency is that all transactions on the network are public information; anyone can download the dataset and determine the transactions between counterparties and estimate their underlying balances in terms of the tradable digital assets.

One of the most innovative features of this new financial infrastructure has been called *DeFi compositions* or *DeFi Lego*. In other words, the possibility of using different independent protocols and tokens to offer new financial services or existing services at a lower cost. For example, 1inch protocol compares executions prices and volume over different decentralized exchanges to execute a swap between two tokens at the best price for the final user. Such composition is feasible because smart contracts can interact without explicit coordination between independent entities (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023). There are many types of compositions: yield aggregators, staking, bridges, and derivatives. Another feature of the blockchain network is that counterparties are not identified; one or many digital addresses can refer to any person or institution anywhere in the world.

The high composability of DeFi protocols and the anonymity of participants pose significant challenges to understanding the interactions among different protocols, making it difficult to identify potential risks

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and vulnerabilities in the network. In order to address these challenges, a possible course of action is to map the interconnection among protocols using transactions among contracts and addresses. Mapping interconnections is feasible with network analysis techniques, which enable the exploration of the evolution of network properties and the identification of the most critical nodes in the network. Network analysis in finance has a long history, and it is now part of the standard set of tools of central banks in macroprudential policy and financial stability (Caccioli, Barucca, & Kobayashi, 2018) (Neveu, 2018).

In this article, we map the interconnection among DeFi protocols using the information on token transfers among addresses and contracts. We measure the transaction flows in USD and estimate outstanding balances for different protocols and relevant addresses. Estimating the consolidated transaction flows and balances for the nodes in the network is performed by identifying the addresses related to each of the relevant DeFi entities and aggregating across addresses. We explore the evolution of the network topology using monthly data, starting with DeFi summer of 2020 until the end of 2022. Once the interconnection among DeFi protocols is mapped, researchers, practitioners, and regulators can use the information to identify potential vulnerabilities and develop appropriate risk management strategies. For example, they can identify the protocols that are most susceptible to attacks or that may significantly impact the overall stability of the network if they fail.

This research study contributes significantly to the existing literature by examining the financial transactions (flows) and exposures (balances) within prominent DeFi protocols. While prior studies have primarily focused on transactions occurring among financial institutions, such as interbank and central clearing networks, there is limited knowledge regarding interactions beyond these institutions. DeFi, offering an inclusive infrastructure accessible to investors of all types, presents an ideal ecosystem for comprehending such interactions. By utilizing monthly data, this research provides a comprehensive overview of the dynamics within the financial network, which has experienced various significant phases, namely initial consolidation, expansion, and contraction. Furthermore, this analysis enables us to zoom in at higher frequencies, allowing for an exploration of the network's dynamics surrounding specific events, such as the exploits and failures of certain protocols or tokens (e.g., Titan, Terra, FTX), as well as their consequential ripple effects across the network.

We utilize transaction data to construct various single-layer and multiplex networks and compute metrics that allow for a comparison between the DeFi network and traditional financial networks. The findings reveal that the DeFi network exhibits similar topological characteristics to traditional financial networks. These regularities include sparsity, heavy-tailed degree distributions, high clustering, and short average path length. However, what sets the DeFi network apart is its inclusion of information beyond financial service providers, enabling direct observations of user interactions. Furthermore, this user interaction significantly influences the network metrics. When externally owned accounts (EOAs) are included, we observe a disassortative pattern of interactions among participants, indicating that high-degree nodes tend to interact with low-degree nodes.

Furthermore, our analysis demonstrates that centrality measures, commonly used in the financial network literature to identify systemically important institutions, are sensitive to excluding EOAs. We also find that high-frequency centrality measures like PageRank are valuable tools for identifying at-risk protocols. However, a more thorough analysis is necessary to propose a suitable risk measure that can anticipate protocols at risk. Recent empirical literature in computer science and finance uses information on the blockchain to determine the extent to which some of the promises of the technology are being realized. Some papers explore ownership concentration among Bitcoin holders (Makarov & Schoar, 2022) and Ether holders (Nadler & Schar, 2020) (Cong, Tang, Wang, & Zhao, 2022). In the Ethereum network, they find a significantly concentrated ecosystem, predominant among DeFi protocol contracts and crypto exchanges, representing 90% of Ether in circulation. For the Bitcoin (Ethereum) network, 0.014% (0.1%) of addresses hold 26% (50%) of the wealth. Ownership concentration among smart contract-generated tokens (COMP, MKR, BAL, CREAM, CRV, NXM, UMA) is similar: the top 100 addresses control more than 75% of outstanding tokens.

Another line of research explores the interconnections among the protocols, particularly DeFi compositions. (Kitzler, Friedhelm, Saggese, & Haslhofer, 2022) propose algorithms based on execution trees of contract functions to identify the building blocks of DeFi compositions. This algorithm identifies which protocols use other protocols to provide their services, and examples of such protocols are Instadapp, 1inch, and 0x. The authors use transaction data to build a network graph of the DeFi network using data from January to August 2021. Their results indicate that the network has scale-free properties and is dominated by a few nodes related to Uniswap, 0x, and Maker. Later, (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023) and (Rossi, 2023) introduce the DeFi Stack Reference (DSR) model and defines the essential technical primitives, what crypto assets are, and the classifications of prominent DeFi protocol families. They also describe how these protocols can be combined into DeFi compositions and propose future research directions. The work of (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023) underscores the need to systematically evaluate DeFi's risks, interpretation, and regulation by financial institutions and regulators. As token flows between addresses and contracts can occur for many reasons, (Darlin, Palaiokrassas, & Tassiulas, 2022) propose an algorithm to identify the flows into and out of collateralized lending protocols (Aave, Compound, and Maker). Their result indicates that on-chain stablecoins (DAI) or depository receipts (c- or a-tokens) facilitate highly levered investment positions and opaque interconnection, possibly due to collateral re-use and debt recycling.

Finally, there are a group of papers that analyze the characteristics of networks based on one protocol: DAI (Saengchote, Where do DeFi stablecoins go? A closer look at what DeFi composability really means., 2021), Aave (Ao, Horvath, & Zhang, 2023) or some events involving a particular protocol/token: the bank run on Iron Finance (Saengchote, A DeFi Bank Run: Iron Finance, IRON Stablecoin, and the Fall of TITAN, 2021) or a counterfactual run on USDT (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023).

Our research is closely related to (Kitzler, Friedhelm, Saggese, & Haslhofer, 2022) as we study protocols on the entire Ethereum network rather than focus on specific protocols, and also (Darlin, Palaiokrassas, & Tassiulas, 2022) as our primary focus is on five tokens (USDT, USDC, DAI, WETH, and stETH) that are often involved in inter-protocol asset-liability relationships, which can lead to systemic risk buildups.

2. The dataset

The Ethereum blockchain data used in this article is obtained from Google BigQuery, hosted and listed by Google Cloud[2]. In particular, we use the information on the token transfer table containing time-stamped events denoting bilateral transfers between addresses, which can be Externally Owned Accounts (EOAs) or smart contracts. We retrieve all historical transactions for DAI, USDC, USDT, WETH, and stETH and build balances from June 2020 to December 2022. The information retrieved considers more than 30.5 million consolidated monthly balances between 15.3 million unique addresses. In order to associate addresses to a particular protocol, we obtain data from three sources: First, we scraped public address labels on Etherscan. Second, we use a user-published list of DAI holdings from Dune Analytics. Third, we use the list derived from the identification of DeFi compositions in (Kitzler, Friedhelm, Saggese, & Haslhofer, 2022)[3] Finally, we manually inspect the obtained labels and classify the named entities into ten categories: centralized exchanges (CEX), decentralized exchanges (DEX), derivatives funds, lending, staking, bridge, crypto bank, MEVbot, and others. We label 239 such entities, and each entity often involves more than one Ethereum address. In Table A1 in the Appendix, we indicate the number of addresses successfully identified to belong to a selected group of protocols. We also include the top 100 addresses that cannot be explicitly labeled in the sample to estimate balances and track the transaction flows over time. The financial transactions (flows) and exposures (balances) are expressed in USD taking token prices from Yahoo Finance or CoinMarketCap.

Because in the blockchain network, an address can represent any level of organization (for example, a trader, a division, or a business unit), address-level network analysis can be confusing. Therefore, to make the analysis more comparable to traditional finance, where reporting is done at an entity level, we aggregate the activities for all addresses belonging to the same named entity. We are aware that aggregating over identified protocols and limiting the scope to these labeled protocols and the top 100 addresses may significantly impact the network graph compared to using individual addresses. However, our main interest is understanding the network dynamics across the different financial services and the most significant non-institutional that are part of the ecosystem. Thus, we believe that results from the aggregated network would be more appropriate. In addition, and as a robustness check, we provide evidence indicating that the main

[2] This blog contains detail information on the construction of the dataset.
[3] The list is provided in the GitHub repo referred by the authors.

features of the network are maintained in the sample of representative nodes that provide the main results (Table A2 in the Appendix).

First, we show the degree of concentration in token balances. Previous studies show that balances are intensely concentrated in the top addresses (Makarov & Schoar, 2022) (Cong, Tang, Wang, & Zhao, 2022) (Nadler & Schar, 2020). Figure 1 shows the percentage of the total outstanding balances held by the 100 top addresses for the five tokens. The DAI, WETH, and stETH percentages are stable over time and above 70% over the whole sample. However, for USDC, the concentration decreased from 82% in June 2020 to 53% in December; for USDT, the concentration is between 32% and 66%.

The network can be more easily visualized and understood by analyzing a subset of all addresses. The concentration of the DeFi network allows us to investigate the top addresses while still accounting for a meaningful proportion of activities on the network. We can increase the coverage significantly by expanding the sample from the top 100 addresses to the named entities (collectively referred to as protocols) *plus* additional top 100 addresses denoted as externally owned accounts (EOAs). In this case, the coverage increases from 70% to 90% for DAI, WETH, and stETH, up to 95% in some months. For USDC and USDT, the coverage increases to about 70%. Thus, even though aggregating over addresses to obtain unique nodes related to known protocols and including additional 100 EOAs reduces the participants and relationships across them, the economic activities intermediated by the different financial services in this subset still constitute an adequate representation of the DeFi ecosystem.

The network in our sample contains 5,168 unique nodes (95.7% EOA, 1.6% MEVbot, 0.8% CEX, 0.4% fund, and 0.4% bridge) and 61,016 edges between them. Figure 2 plots a selected portion of the network graph for the entire sample period. The node sizes represent the degree centrality of each node.

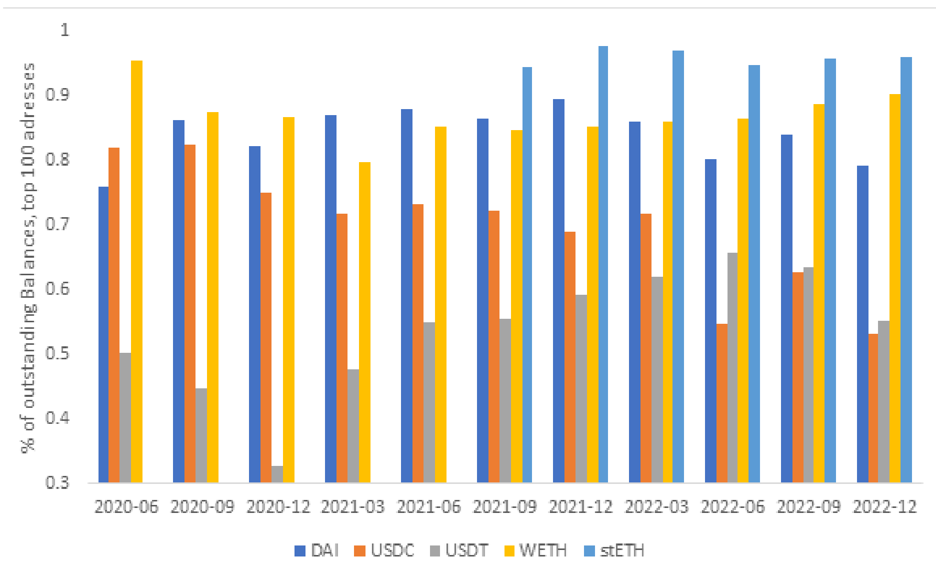

Figure 1: Percentage of outstanding balances held in the top 100 addresses for each token.

3. DeFi and financial networks

Network science has found fertile ground in finance to showcase significant developments in analyzing complex systems (Bardoscia, y otros, 2021). In this section, we use topological measurements to characterize networks from a macroscopic perspective. We will not provide a detailed account of the different metrics used. Instead, we will use them directly and refer interested readers to relevant articles (Berndsen, León, & Renneboog, 2018) and books (Kolaczyk, 2009). Our analyses are inspired by the insights from the rich empirical literature on interbank and multinational credit networks, highlighting some common statistical features of such single-layer networks. For example, these financial networks tend to have the following characteristics: (1) predominantly sparse, with heavy-tailed degree distributions, and (2) high clustering, with short average path length (Bardoscia, y otros, 2021).

Because of financial networks' inhomogeneous and scale-free nature, *preferential attachment* is the most appropriate mechanism behind the generating process. Under this mechanism, new nodes in a network tend to be linked to highly connected nodes (hence, preferential). In addition, older nodes with high degrees are more likely to continue receiving new connections. Consequently, some researchers call this mechanism the *rich-get-richer* phenomenon (León & Berndsen, 2014). In financial networks, preferential attachment is mainly related to two phenomena. First, interested participants find counterparties currently used by other participants more viable (*herding*). Second, the nature of the competition is more like a tournament, where the strongest prevail (*survival of the fittest*). Institutional fitness can encompass different dimensions, such as efficiency, size, connectedness, systemic importance, reputation, and market power.

More recently, network science, particularly financial networks, has focused on multilayer networks (Kivela, y otros, 2014), (Berndsen, León, & Renneboog, 2018). A multilayer framework considers that relationships among participants may be categorized using relevant information, thus creating a so-called "network of networks." These different categories among nodes provide additional dimensions to the relationships. In the context of DeFi networks, we primarily consider two additional dimensions: time and the token used for transactions. However, this does not exclude the possibility of considering other categories to identify different layers. Among the prominent types of multilayer networks are multiplex networks and interdependent networks.

Multiplex networks consist of multiple layers of connections that coexist and interact. Each layer represents a distinct relationship or interaction among the same set of nodes. In other words, the nodes are aligned and connected between layers, so each layer is often associated with its own set of properties, such as different strengths of ties or varying dynamics. The inter-layer connectivity enables the study of cross-layer interactions and their influence on various network properties and dynamics. For example, one can investigate how the structure of different types of financial exposures (derivatives, securities, foreign exchange, and loans) can affect the estimation of systemic risk in banking (Poledna, Molina-Barbosa, Martinez-Jaramillo, van der Leif, & Thurner, 2015) . In our case, such financial exposures are characterized by the transactions performed by participants using different tokens.

Interdependent networks represent a network where the functionality of nodes in one layer depends on the availability and proper functioning of nodes in other layers. Unlike multiplex networks, interdependent networks focus on the dependencies between layers (dependence links) rather than capturing different types of relationships (connectivity links). Interdependencies can arise due to various factors, such as resource sharing, information exchange, or functional reliance. In an interdependent network, failure or disruption in one layer can propagate through interdependencies and affect the functioning of other layers, leading to cascading failures. For example, financial institutions interact with other institutions through different types of financial market infrastructures that are used to settle the exchange of different types of assets (Berndsen, León, & Renneboog, 2018). Financial market infrastructures are the backbone for the transactions to flow across financial markets.

In this paper, our focus is on examining the connectivity links among participants in the DeFi network. To map these relationships, we utilize both single-layer and multiplex networks. Single-layer networks are employed when we analyze the interrelations among participants at a specific point in time (e.g., within a month) using information related to a single token. Conversely, when we aggregate data across multiple tokens or over time, we construct a multiplex network by combining the individual single-layer networks. Furthermore, we express all transactions and balances in USD to facilitate the aggregation process. By doing so, we can aggregate the data over various tokens, resulting in a multiplex network where nodes enhance their connectivity or the weight of their connections by considering all tokens. Most metrics we present are based on this type of multiplex network, which involves aggregating data across tokens unless explicitly stated otherwise.

Furthermore, it is worth noting that we can aggregate data across all observed months. However, this aggregation is solely employed for visualization purposes (see Figure 2) and does not influence the metrics and analyses based on the multiplex network formed by aggregating over tokens.

We use the network information to estimate different statistics and characterize the connectivity patterns (density, moments of the degree distribution, degree correlation, geodesic distance, clustering coefficient) and the hierarchical structure (local clustering coefficient, clustering concerning the average degree) (León

& Berndsen, 2014). For the first set of statistics (Table 1), each edge represents a flow between protocols or EOAs. The number of nodes and edges increased consistently over the two years after the DeFi summer (June 2020) until the collapse of the crypto asset market in late 2022.

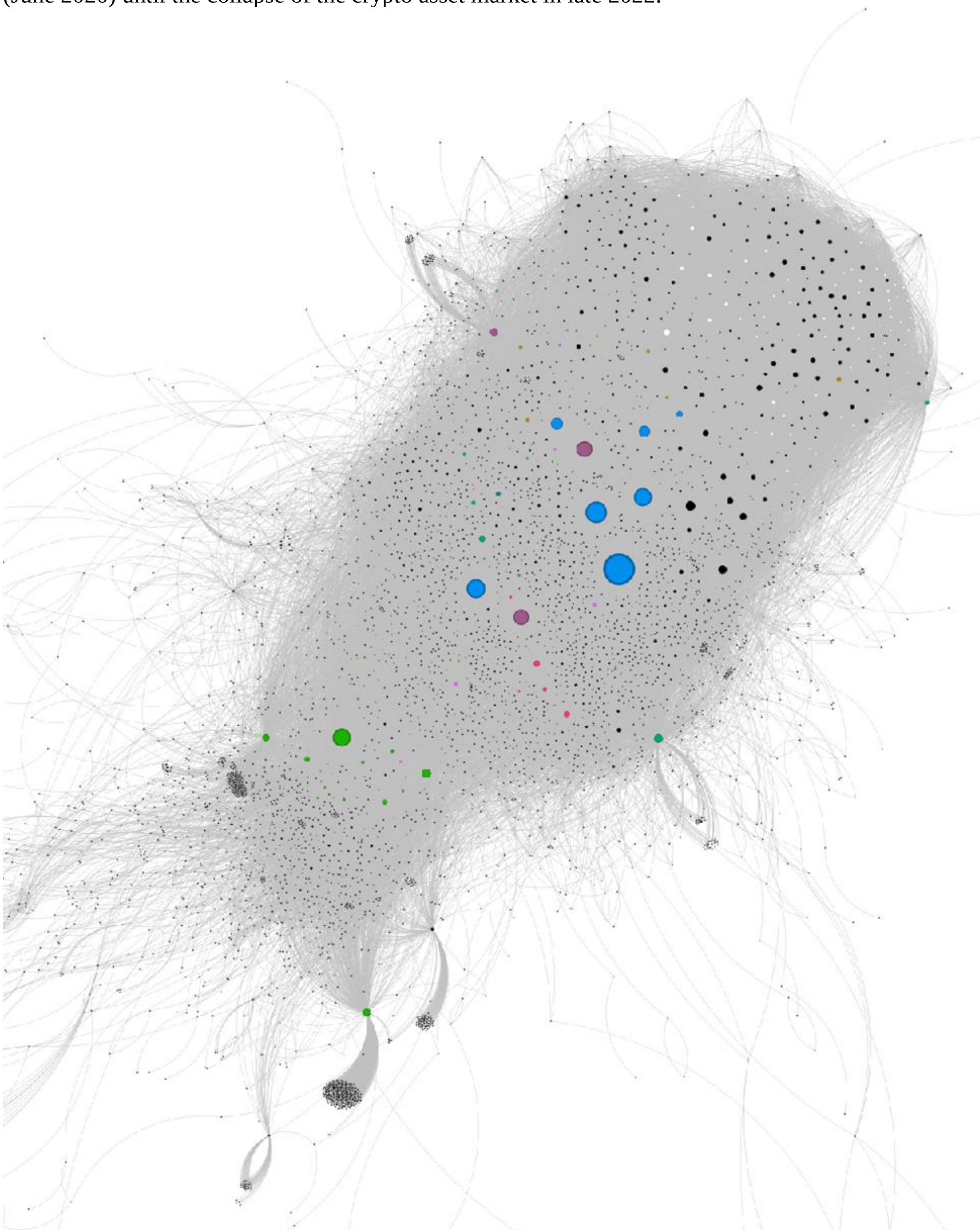

Figure 2: Weighted graph from June 2020 through December 2020.
The node size is given by USD exposure and the colour by type of institution. The edges are determined by the USD transaction amounts.

	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	621	1208	1353	1432	1584	1121
edges	2382	6980	7585	8322	8244	4434
degree	7.48	15.38	16.81	15.03	14.92	9.16
in-degree	3.50	7.36	7.83	7.21	7.03	4.37
out-degree	3.99	8.01	8.98	7.82	7.89	4.79
degree-std	20.54	51.07	52.68	48.91	49.85	32.14
in-degree-std	9.27	23.83	24.14	22.92	23.24	15.22
out-degree-std	12.14	27.98	29.75	26.91	27.50	17.68
density	0.006	0.005	0.004	0.004	0.003	0.004
reciprocity	0.56	0.64	0.62	0.61	0.61	0.57
assortativity	-0.34	-0.28	-0.29	-0.24	-0.25	-0.26
in-assortativity	-0.36	-0.29	-0.29	-0.25	-0.27	-0.27
out-assortativity	-0.02	0.60	-0.05	0.06	0.01	-0.27
clustering	0.08	0.08	0.11	0.13	0.10	0.11
distance	1.26	1.34	1.56	1.46	1.57	1.10
tail index	1.38	1.18	1.45	1.60	1.44	1.23

Table 1 Basic statistics of the network of EOA and protocols.
Degree: average and std of degree (in+out), density, reciprocity, assortativity (in+out), average clustering coefficient, average path length, tail index.

We provide snapshots of network statistics for seven semi-annual periods: June 2020, December 2020, June 2021, December 2021, June 2022, and December 2022. The metrics in Table 1 indicate that the DeFi networks share similar scale-free properties as those of other networks (interbank financial, biological, and social). The networks are sparse: the average degree is significantly smaller than the number of nodes, and density is also relatively small, around 0.004, far from a wholly connected network. This sparseness is evident in Figure 2, with the black dots representing EOAs. Instructions in the Ethereum blockchain are sent via EOAs, so it is not surprising that the network spokes terminate at EOAs. The degree distribution has a large variance and is strongly right-skewed, indicating a heavy-tailed distribution.

We use the Hill estimator to get an estimate of the tail index between 1.2 and 1.6. As the value is below 2, the degree distribution is characterized by extreme events. Although the statistical test rejects the null hypothesis that the empirical distribution is the power-law distribution, the results are consistent with what is found in (Kitzler, Friedhelm, Saggese, & Haslhofer, 2022), indicating super weak-scale free properties (tail index close to 1). Toward the end of the sample, there is a reduction in the average degree distribution and the tail index, meaning that the surviving nodes most likely maintained a strong level of connectedness in line with the survival of the fittest phenomena. We will try to confirm this when we look at centrality measures.

The concepts of reciprocity and assortativity provide valuable insights into the relationships among nodes and their neighbors within the network. Our analysis reveals that reciprocity levels are relatively high, exceeding 0.5, indicating that a significant portion of the links in the network is bidirectional. This finding suggests a mutual dependence among participants within specific protocols, aligning with the earlier discussed notions of DeFi compositions or DeFi Lego. As we proceed with our analysis, we will exclude externally owned accounts (EOAs), and this exclusion is expected to elevate the reciprocity metric further as our focus narrows down exclusively to the network of DeFi protocols. In contrast, negative assortativity (disassortativity) among total degrees, in-degree, and out-degree indicates that nodes with higher degrees tend to interact with nodes possessing lower degrees. Although this property may be observed in newly established protocols, in the context of our study, it primarily stems from the inclusion of EOAs, contributing to the previously mentioned network sparsity. This characteristic of disassortativity in the network is unique to financial networks encompassing interactions between institutional participants and individual participants represented by EOAs. Notably, most of the literature on financial networks predominantly focuses on transactions among institutions. Consequently, when EOAs are considered in the network, this metric deviates from the established facts in the existing financial network literature.

The mean geodesic distance is low, around 1.5, meaning some nodes are essential for interactions in the network. However, the clustering coefficient is very low, below 0.15, indicating a very low probability that the neighbors of a node are themselves connected. These two last results reinforce the idea that some participants play a vital role in the network (for example, decentralized exchange protocols highlighted in blue in Figure 2). However, simultaneously, many participants only interact with some parts of the network.

Most of the network metrics are consistent over time, meaning the network properties have been stable over the different phases of initial consolidation (DeFi summer), expansion (2021), and contraction (end 2022). The results are also similar to those in (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023).

	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	47	66	80	86	84	59
edges	171	280	404	395	384	196
degree	5.16	5.94	7.40	6.67	6.94	3.77
in-degree	2.58	2.97	3.71	3.32	3.45	1.90
out-degree	2.58	2.97	3.70	3.35	3.48	1.87
degree-std	5.92	8.70	10.28	9.63	9.97	6.84
in-degree-std	3.11	4.49	5.34	5.01	5.35	3.58
out-degree-std	3.22	4.53	5.39	5.03	5.05	3.48
density	0.079	0.065	0.064	0.054	0.055	0.057
reciprocity	0.65	0.71	0.65	0.62	0.66	0.65
assortativity	-0.02	-0.12	-0.10	-0.08	-0.18	-0.11
in-assortativity	-0.10	-0.16	-0.14	-0.11	-0.22	-0.15
out-assortativity	0.60	0.72	-0.05	0.75	0.54	0.69
clustering	0.23	0.27	0.30	0.29	0.28	0.29
distance	1.30	0.95	1.26	1.19	1.34	0.77
tail index	1.48	1.45	1.55	1.53	1.55	1.29

Table 2 Basic statistics of the network for protocols.
Degree: average and std of degree (in+out), density, reciprocity, assortativity (in+out), average clustering coefficient, average path length, tail index.

The second set of statistics (Table 2) focuses on the DeFi protocols; hence, they exclude EAOs and MEVBots from the network. From the 5,168 nodes, the sample is reduced to 108 unique nodes, with 31 centralized exchanges (28.7%), 20 funds (18.5%), 13 staking protocols (12%), 10 decentralized exchanges (9.3%), 9 bridges (8.3%), 7 derivatives protocols (6.5%), and 5 lending protocols (4.6%). With the sample reduced to protocol-to-protocol interactions, the results will be more relevant for DeFi compositions.

The results demonstrate a general similarity to the metrics observed for the full network (Table 1). The network density remains close to 0, indicating a high sparsity level. Furthermore, the tail index is closer to 1.6, suggesting a heavy tail in the degree distribution and a better fit to a power law distribution than the full network results. The metric of reciprocity exhibits an increase, surpassing 0.65, indicating a stronger interconnection among protocols, as expected in the context of DeFi compositions. Interestingly, this reciprocity measure shows an increasing trend throughout the sample period and appears unaffected by the recent turmoil experienced in 2022. The network's tightness is reflected in the decrease in negative assortativity and a substantial increase in the average clustering coefficient. Specifically, the significantly negative assortativity observed in Table 1 is reduced to -0.1 overall, and in the case of out-degrees, the measure becomes strongly positive, surpassing 0.5, as shown in Table 2. This transformation in assortativity is a consequence of excluding EOAs from the network. In the protocol network, the positive assortativity can be attributed to a core/periphery structure, where well-connected protocols in the core facilitate transactions with less-connected protocols in the periphery. These highly connected protocols are pivotal in reducing the average distance between nodes, as evidenced by the average geodesic distance of 1.17 in the sample.

We include the network statistics of all addresses involved in the transactions among the tokens considered, Table A2 in the Appendix for comparison. The number of nodes exponentially increases to more than one million per period, and the number of edges is more than two million. The ratio of edges to nodes increases as we restrict the sample, and the network is more sparse than the screened network. As expected reciprocity is now below 0.18, meaning a lower probability that there is a link between two nodes. The tail index is now very close to 1, indicating that the degree distribution has a very heavy tail and re-enforcing the super weak scale-free property of the network.

In summary, the properties observed in these networks align with those typically found in traditional financial network literature, such as sparsity, high clustering, and strong evidence of heavy tails in the degree distribution. Nonetheless, a notable distinguishing characteristic arises from including non-institutional participants (EOAs) within the network, which impacts assortativity measures.

4. Protocol Network Visualization

The graph visualization of the reduced protocol network is relatively straightforward to understand. The networks for June and December of 2020, 2021, and 2022 are illustrated in Figures 3 to 5, with the relative positions of each node fixed throughout the sample for easy comparison. In addition, the edges for each of the five tokens are shown separately to demonstrate the layers of the relationship. Distinct colors represent the flows of each token. Each node in the network represents a unique named protocol or entity, and node size represents the financial exposure measured as outstanding balances in USD at the end of the corresponding month. The outstanding balances are reconstructed from historical flows between all addresses in the Ethereum network and aggregated over the five tokens. Each node’s color corresponds to the protocol/entity type related to the primary business model.

The locations of the nodes suggest that similar types of protocols tend to be closer to one another. For example, centralized exchanges (green nodes) tend to be on the left side of the graph, while decentralized exchanges (blue nodes) are on the right. Funds (Fuchsia nodes) tend to be in the middle or toward the left, near centralized exchanges, while bridges (magenta nodes) tend to be at the bottom. Other DeFi protocols, such as lending and staking, tend to be closer to decentralized exchanges (which are also protocols) than centralized exchanges.

The network graphs look increasingly complex as the number of nodes increases from June 2020 to December 2021. The number of nodes will decrease in 2022, which is not surprising given the fall of the Terra UST stablecoin and its blockchain ecosystem in May 2022 and the collapse of FTX in November 2022. However, the network statistics in Table 2 suggest that the network structure remains relatively stable. Remarkably, the density, reciprocity, and clustering remain essentially unchanged.

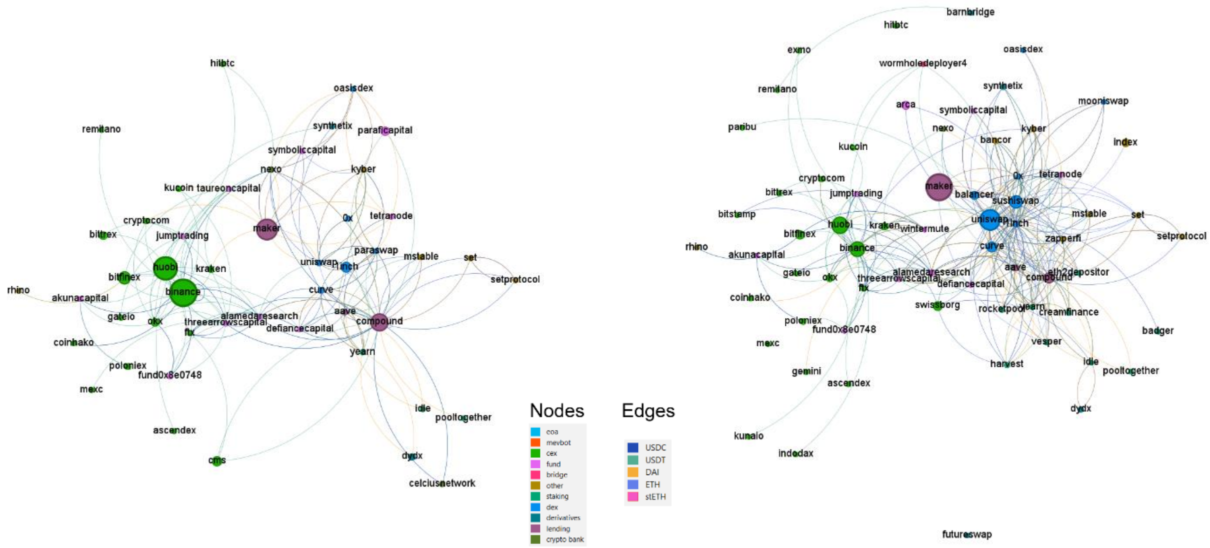

Figure 3: Protocol graph June 2020 (left) and December 2020 (right).
The node size is given by USD exposure and the color by type. The edge color corresponds to a particular token.

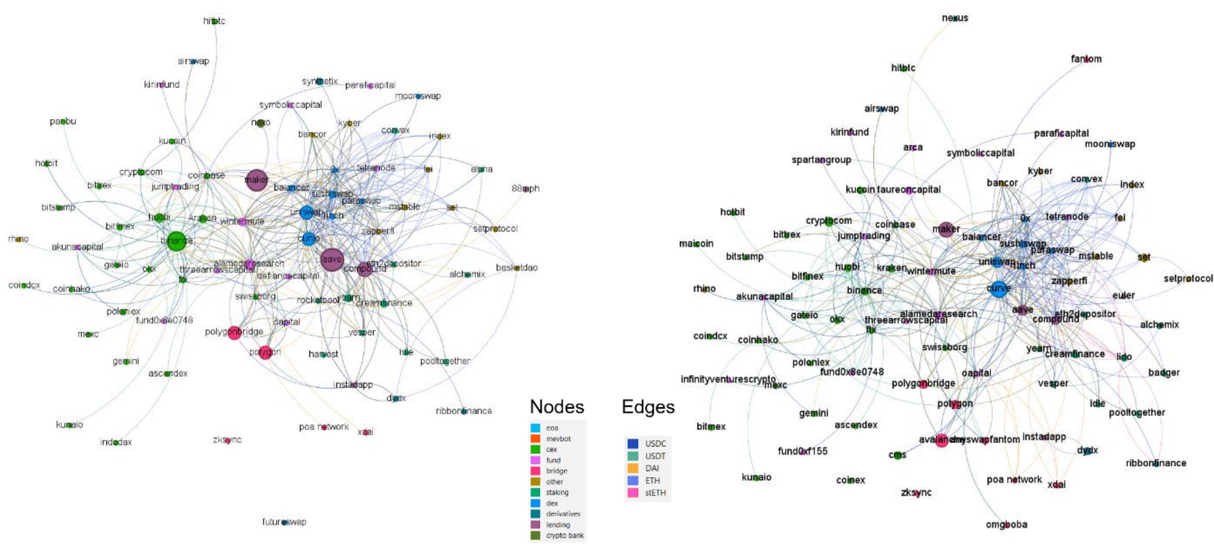

Figure 4: Protocol graph June 2021 (left) and December 2021 (right).
The node size is given by USD exposure and the color by type. The edge color corresponds to a particular token.

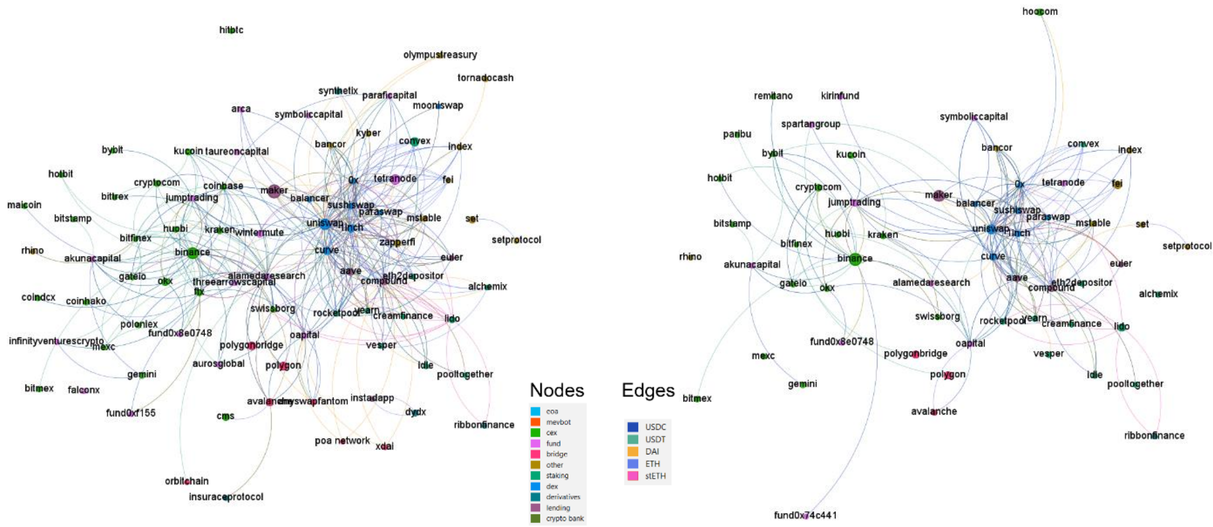

Figure 5: Protocol graph June 2022 (left) and December 2022 (right).
The node size is given by USD exposure and the color by type. The edge color corresponds to a particular token.

5. Higher-Frequency Changes in Centrality

In financial network analysis, various centrality measures are employed to understand the importance and influence of nodes within the network. Here, we compare five commonly used centrality measures: closeness centrality, betweenness centrality, eigenvector centrality, Katz centrality, and PageRank.

Closeness centrality quantifies how quickly a node can reach other nodes in the network. Nodes with high closeness centrality have short average distances to all other nodes, indicating their potential to disseminate information or resources efficiently. For example, in financial networks, nodes with high closeness centrality can be considered influential players who have direct access to a large portion of the network and swiftly transmit information or affect the market.

Betweenness centrality identifies nodes that act as intermediaries or bridges between other nodes. It measures the number of times a node lies on the shortest path between pairs of other nodes. Nodes with high betweenness centrality play a crucial role in the information or resource flow within the network. These nodes are significant in facilitating communication and transactions between different entities in financial networks.

Eigenvector centrality assigns importance to nodes based on their connections to other high-scoring nodes. It considers not only the number of connections but also the quality of those connections. Nodes with high eigenvector centrality are connected to other important nodes, reflecting their influence and prominence in the network. In financial networks, nodes with high eigenvector centrality often represent well-connected entities that can significantly influence the overall system.

Katz centrality measures the influence of a node by considering not only its direct connections but also the contributions from its neighbors. It assigns higher importance to nodes that have connections to other important nodes. In financial networks, Katz centrality captures both the direct and indirect influence of nodes, enabling the identification of nodes that can transmit information or resources effectively.

PageRank is a centrality measure inspired by Google's web page ranking algorithm. Similar to Katz centrality, it classifies a node as important if it is highly linked to other nodes but also emphasizes the quality of the incoming links. It assigns importance to nodes based on the number and quality of incoming links from other important nodes. Nodes with high PageRank are considered influential in the network. In financial networks, PageRank can be applied to identify nodes highly connected to other influential nodes, potentially impacting the overall system.

Each of these centrality measures provides unique insights into the structure and dynamics of financial networks. For example, closeness centrality emphasizes efficient information transmission, betweenness centrality focuses on intermediaries, eigenvector centrality captures well-connected entities, Katz centrality considers direct and indirect influence, and PageRank identifies influential nodes based on incoming links. The last three are feedback centrality measures; hence they consider the feedback loops within the network to determine the most relevant nodes. We use PageRank as a centrality measure as it has recently been used to study financial networks by (Korniyenko, Manasa, del Rio-Chanon, & Porter, 2018) and (Yun, Jeong, & Park, 2019). Modified versions of this algorithm are also used explicitly to identify systemically important network participants. For example, DebtRank is a version of PageRank that has been adjusted to consider the strength of the counterparty exposures across financial institutions and analyze how defaults cascade, or stresses propagate through a network (Battiston, Puliga, Kaushik, Tasca, & Caldarelli, 2012). A higher value of DebtRank for an institution indicates that the institution is more central in the network and that its default or distress will have a more significant economic impact. We leave for future research to adapt the algorithm to the collateralized lending relations among some protocols and the compositions among protocols to identify systemically important protocols in financial terms.

We examine the temporal evolution of centrality, highlighting the protocols facilitating resource intermediation across the network and serving as core functional components supporting compositions within this technological stack. To assess centrality, we employ the PageRank algorithm, which assigns a score to each node based on the importance of the nodes that link to it. PageRank considers the quantity and quality of incoming links to a node instead of mere proximity. Nodes with high PageRank scores are targets of other highly ranked nodes, indicating explicit or implicit compositions.

Figures 6 and 7 depict the PageRank scores of the most relevant protocols for the 31 months between June 2020 and December 2022, categorized by protocol type. Figure 6 includes EOAs, while the nodes in Figure 7 only comprise protocols. The scores are normalized to the range of [0, 10] for easy comparison. Protocols with high PageRank can be considered core protocols that are the basis for DeFi compositions.

The graphs reveal that Compound was the most central protocol at the beginning of the sample, which is not surprising as it is one of the oldest DeFi protocols and gave rise to the DeFi summer of 2020. However, it quickly lost ground to Uniswap, a decentralized exchange (dex). In general, decentralized exchanges such as Uniswap, SushiSwap, and Curve tend to have higher PageRank than centralized exchanges as they provide the most basic functionality in the DeFi stack and allow crypto assets to be exchanged on-chain. While the rules of exchange may be different in dex compared to cex, (Lehar & Parlour, 2021) show that their performance in terms of price slippage can be similar if there is enough liquidity in the swap pool. In addition, some protocols, such as 1inch, facilitate the transactions by searching for the optimal exchange routes across multiple protocols (Auer, Haslhofer, Kitzler, Saggese, & Friedhelm, 2023), leading to a greater level of protocol connectivity.

The inclusion or exclusion of EOAs can affect network centrality. For example, when comparing lending protocols, we observe that Aave surpassed Compound's importance in June 2021 when considering interactions with EOAs (Figure 6). However, when exclusively considering the protocol network (Figure 7), Compound maintains a lead over Aave throughout the sample.

Some funds, such as Three Arrows Capital and Alameda Research, were highly central and the most significant until their collapse. Three Arrows Capital filed for bankruptcy in July 2022 following the collapse of the Terra blockchain ecosystem, and Alameda Research's affiliation with FTX, which filed for bankruptcy in November 2022, halted their on-chain activities. In the last half of 2022, Jump Trading emerged as an important player in the network. However, their activities are mostly connected to centralized exchanges, likely performing the role of market maker and arbitraging across the exchanges. Alameda Research's centrality spiked in October 2022, just one month before the collapse. During the same period, the centrality of Binance, FTX, Crypto.com, and Huobi spiked relative to other centralized exchanges (cex). Their centralities remained high in November 2022 before receding to previous levels in December 2022. When EOAs are considered, Binance obtains a score ten times higher than the other centralized exchanges.

Changes in protocol centrality can often be linked to critical structural shifts in the market. For example, toward the end of 2022, Lido emerged as a central player, especially considering EOAs. This phenomenon can be attributed to the migration from the proof-of-work consensus rule to proof-of-stake in the Ethereum network. Lido allows participants to stake their Ether in a pool to participate in the proof-of-stake consensus and get a liquid depository receipt (similar to Compound's c-tokens and Aave's a-tokens) that can be traded or deposited elsewhere.

The Terra and FTX events are also critical structural shifts. However, the Terra event beginning in May 2022 appears to have less impact on the network structure than the FTX event in November 2022. In addition, the changes to the network structure were only apparent when viewed at the monthly frequency, as our earlier analysis at the semi-annual frequency from June 2022 to November 2022 presented in Table 2 did not exhibit this change. Nevertheless, this result highlights the high-speed nature of DeFi and necessitates more frequent monitoring of the ecosystem.

Over time, decentralized exchanges have become the most central participants in both networks, with Uniswap holding particular significance since the end of 2020. In addition, decentralized exchanges and aggregator services like 1inch also exhibit increasing importance along with cyclical patterns tied to the appreciation and depreciation of the total value locked in DeFi. On the other hand, protocols that provide derivatives exposure are not as strongly connected throughout the entire sample. This observation is crucial, as it demonstrates that the core DeFi Legos or compositions of financial services offer the primary and necessary function of exchange.

Figure 6: PageRank centrality for lending, funds, cex, dex, derivatives, and staking for the network of EAO and protocols. The centrality metric is normalized to the range [0,10]

Figure 7: PageRank centrality for lending, funds, cex, dex, derivatives, and staking for the network of protocols. The centrality metric is normalized to the range [0,10]

6. Single Token Single-Layer Networks

In this section, we estimate the network statistics for the five tokens separately and report the results in Table 3. The results of the single-layer networks for each token can be compared to Table 1. There are observable differences in the metrics for each token. For stablecoins, the USDT and USDC networks have lower clustering coefficients and reciprocity than the DAI network but higher average degree centrality and standard deviation. A possible explanation for this difference is that USDT and USDC are more likely to be used as the quoting currency for trading in both cex and dex than DAI. Taken together with the PageRank centrality in Figure 6, this difference highlights the role of USDT and USDC in the crypto asset ecosystem as a means of exchange. While DAI is also a stablecoin, the creation mechanism is different and requires the creation of debt collateralized by accepted tokens facilitated by on-chain smart contracts. They also tend to be used in other DeFi protocols, as documented by (Saengchote, Where do DeFi stablecoins go? A closer look at what DeFi composability really means., 2021).

While the DAI network is more clustered than the USDT and USDC networks, the WETH network is even more clustered with a slightly longer geodesic distance than the other three tokens. This difference is likely because WETH is a tokenized version of Ether (ETH), the native coin that is crucial to the operation of the Ethereum network and is used to pay network transaction fees (“gas”). ETH is fundamentally a different type of digital information in the network, so to use Ether to interact with other DeFi protocols or tokens, developers must write different codes to make ETH compatible. Wrapped Ether solves this complexity by creating a token WETH for each deposited ETH, effectively turning a native coin into a token that can interact more easily with other protocols. Furthermore, WETH can also be redeemed for ETH. In other words, WETH is a more composable version of ETH, and thus the greater connectivity is evident in the degree centrality, density, reciprocity, and clustering coefficient.

Finally, the stETH network is relatively younger than the other networks, as stETH was created in anticipation of Ethereum’s switch from proof-of-work to proof-of-stake. WETH and stETH are tokenized versions of ETH and can be considered derivatives of ETH, but while WETH can be easily redeemed for ETH, stETH cannot. Therefore, users who want to exchange must do so in multiple steps, typically first swapping stETH for WETH in dex, and the redeeming WETH for ETH. Thus, one of the main uses of stETH is to provide liquidity in dex with some other tokens, such as WETH. stETH can also be used as collateral in lending protocols or deposited into yield protocols, and so can WETH. However, there are fewer venues to use stETH compared to WETH, resulting in a network with fewer nodes, smaller degree centrality, density, reciprocity, and clustering coefficient.

Our results from the single-layer networks highlight that tokens in the same category (stablecoins and derivative tokens) can serve very different roles in the crypto asset ecosystem.

A. USDT	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	369	672	700	656	621	497
edges	969	2109	2119	2084	1915	1240
degree	6.44	10.96	11.42	10.49	9.81	7.16
in-degree	2.60	4.73	4.83	4.52	4.27	2.99
out-degree	3.84	6.23	6.60	5.97	5.54	4.16
degree-std	19.63	32.63	31.73	28.70	25.66	19.63
in-degree-std	8.51	14.44	13.29	12.01	11.68	8.42
out-degree-std	12.54	19.59	20.09	17.86	14.89	12.51
density	0.01	0.00	0.00	0.00	0.01	0.01
reciprocity	0.37	0.44	0.42	0.43	0.44	0.39
assortativity	-0.38	-0.35	-0.33	-0.30	-0.27	-0.26
in-assortativity	-0.35	-0.35	-0.30	-0.30	-0.30	-0.25
out-assortativity	0.18	0.43	0.36	0.18	0.29	-0.04
clustering	0.03	0.05	0.05	0.07	0.10	0.09
distance	0.79	0.86	1.44	1.40	1.43	1.01
tail index	1.00	0.95	1.01	1.07	1.13	1.34

B. USDC	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	305	621	750	841	933	631
edges	830	2574	2830	2880	3092	1585
degree	5.81	13.38	14.22	13.12	13.77	7.70
in-degree	2.67	6.22	6.16	5.75	5.74	3.31
out-degree	3.13	7.16	8.06	7.37	8.03	4.39
degree-std	14.36	40.03	40.36	37.07	39.57	23.14
in-degree-std	7.00	18.57	17.60	16.18	16.82	10.07
out-degree-std	7.91	21.79	23.61	21.91	23.81	13.77
density	0.01	0.01	0.01	0.00	0.00	0.00
reciprocity	0.52	0.60	0.53	0.46	0.47	0.42
assortativity	-0.38	-0.30	-0.35	-0.28	-0.26	-0.22
in-assortativity	-0.42	-0.31	-0.36	-0.30	-0.28	-0.24
out-assortativity	-0.12	0.39	0.15	-0.04	-0.06	-0.23
clustering	0.05	0.05	0.05	0.07	0.07	0.07
distance	1.02	1.37	1.39	1.67	1.61	0.95
tail index	1.16	0.96	0.93	1.00	1.04	1.20

C. DAI	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	252	504	480	491	513	313
edges	769	2052	1681	1523	1687	775
degree	6.14	13.14	9.72	8.85	8.67	4.68
in-degree	3.16	6.52	4.55	4.30	4.10	2.38
out-degree	2.98	6.62	5.17	4.55	4.57	2.30
degree-std	14.35	34.04	26.60	24.69	24.87	13.00
in-degree-std	7.57	16.54	12.86	12.02	12.52	6.83
out-degree-std	7.76	17.77	13.95	12.86	12.66	6.43
density	0.01	0.01	0.01	0.01	0.01	0.01
reciprocity	0.53	0.60	0.59	0.56	0.58	0.55
assortativity	-0.38	-0.30	-0.33	-0.28	-0.26	-0.22
in-assortativity	-0.29	-0.29	-0.33	-0.29	-0.29	-0.26
out-assortativity	-0.20	0.16	0.34	-0.12	0.01	0.03
clustering	0.11	0.06	0.08	0.09	0.12	0.14
distance	0.92	1.43	1.19	1.31	1.23	0.68
tail index	1.04	1.15	1.06	1.17	1.14	1.19

E. WETH	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	178	346	413	471	499	314
edges	789	2763	3533	4418	3968	2216
degree	9.24	18.38	20.92	23.84	21.47	16.46
in-degree	4.53	9.28	10.65	12.16	10.88	8.34
out-degree	4.71	9.10	10.27	11.68	10.59	8.12
degree-std	16.00	38.98	42.39	46.76	46.58	37.37
in-degree-std	6.84	19.04	21.52	23.81	23.71	18.91
out-degree-std	9.45	20.08	21.20	23.15	23.07	18.57
density	0.03	0.02	0.02	0.02	0.02	0.02

reciprocity	0.68	0.76	0.75	0.75	0.75	0.75
assortativity	-0.38	-0.39	-0.28	-0.25	-0.28	-0.35
in-assortativity	-0.37	-0.39	-0.27	-0.24	-0.29	-0.34
out-assortativity	-0.35	0.70	-0.06	0.06	-0.19	-0.40
clustering	0.17	0.20	0.25	0.26	0.20	0.21
distance	1.62	1.60	1.81	1.61	1.50	0.95
tail index	1.32	0.94	1.24	1.57	1.31	1.00

F. stETH	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes				50	318	153
edges				78	647	245
degree				0.79	5.21	2.41
in-degree				0.41	2.50	1.26
out-degree				0.38	2.71	1.15
degree-std				3.95	20.23	8.00
in-degree-std				1.92	8.94	4.34
out-degree-std				2.06	11.47	3.81
density				0.03	0.01	0.01
reciprocity				0.46	0.44	0.38
assortativity				-0.51	-0.48	-0.45
in-assortativity				-0.47	-0.50	-0.53
out-assortativity				-0.42	-0.18	-0.31
clustering				0.01	0.02	0.03
distance				0.18	1.02	0.72
tail index				1.77	1.25	1.51

7. Final Remarks

The scale-free nature of the DeFi protocol network, akin to other financial networks, suggests that a mechanism such as preferential attachment, as described by (Barabasi & Albert, 1999), may explain its evolution. Investigating how this novel financial infrastructure, characterized by open access and interoperability, influences and shapes the network's generative process can provide valuable insights into the future evolution of the financial system.

(Kitzler, Friedhelm, Saggese, & Haslhofer, 2022) propose that DeFi compositions align with the concept of preferential attachment. The resemblance of the DeFi protocol network to traditional institutional networks, including interbank networks that have been extensively studied and monitored by regulatory bodies, is reassuring and intriguing. On the one hand, this similarity enables supervisors to implement macroprudential tools that have proven effective in traditional finance. Additionally, it offers a fertile ground for academics to deepen their understanding of this ecosystem. On the other hand, it raises new questions about the extent to which technological innovations facilitating access for new participants impact the configuration of players within financial services. Of particular interest is the observation that the first-mover advantage remains important in this ecosystem of free entry. Despite the ease with which new protocols can compete with similar business models based on services offered through smart contracts, existing protocols maintain their significance within the network.

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Appendix

protocols	addresses
1inch	34
aave	182
alamedaresearch	29
alchemix	7
balancer	53
barnbridge	40
binance	23
bitfinex	6
coinbase	4
compound	66
creamfinance	7
cryptocom	5
curve	190
dydx	42
euler	1
ftx	5
huobi	12
instadapp	72
jumptrading	6
kucoin	10
lido	3
maker	204
nexus	24
okx	5
ribbonfinance	2
sushiswap	128
synthetix	273
taureoncapital	1
threearrowscapital	12
uniswap	549
vesper	48
yearn	101
0x	28

Table A1 Number of addresses identified for selected protocols.

	Jun-20	Dec-20	Jun-21	Dec-21	Jun-22	Dec-22
nodes	1240916	1087676	1285561	1276216	918007	1473871
edges	2235917	2497675	2549482	2262974	1752154	2627291
degree	3.60	4.59	3.97	3.55	3.82	3.57
in-degree	1.80	2.30	1.98	1.77	1.91	1.78
out-degree	1.80	2.30	1.98	1.77	1.91	1.78
degree-std	615.27	325.70	332.52	335.24	247.76	571.05
in-degree-std	317.02	135.00	161.30	153.67	125.33	464.48
out-degree-std	326.72	194.66	191.57	219.64	142.45	126.07
density	0.000	0.000	0.000	0.000	0.000	0.000
reciprocity	0.05	0.14	0.16	0.12	0.13	0.12
assortativity	-0.24	-0.14	-0.20	-0.20	-0.20	-0.19
in-assortativity	-0.24	-0.14	-0.18	-0.15	-0.17	-0.13
out-assortativity	-0.18	-0.13	-0.15	-0.17	-0.17	-0.20
tail index	1.00	1.13	0.98	0.99	0.90	0.97

Table A2 Basic statistics of the full network.
Degree: average and std of degree (in+out), density, reciprocity, assortativity (in+out), tail index.