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BLOCKCHAIN ECONOMIC NETWORKS
Economic Network Theory: Systemic Risk and Blockchain Technology
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This chapter discusses how the widespread adoption of blockchain technology (distributed ledgers) might contribute to solving a larger class of economic problems related to systemic risk, specifically the degree of systemic risk in financial networks (ongoing credit relationships between parties). The chapter introduces economic network theory, drawing from König and Battiston (2009). Then, Part I develops Payment Network Analysis (analyzing immediate cash transfers) in the classical payment network setting (Fedwire (Soramäki 2007)) synthesized with the cryptocurrency environment (Bitcoin (Maesa 2017), Monero (Miller 2017), and Ripple (Moreno-Sanchez 2018)). The key finding is that the replication of network statistical behavior in cryptographic networks indicates the robust (not merely anecdotal) adoption of blockchain systems. Part II addresses Balance Sheet Network Analysis (ongoing obligations over time), first from the classical sense of central bank balance sheet network analysis developed by Castrén (2009, 2013), Gai and Kapadia (2010), and Chan-Lau (2010), and then proposes how Blockchain Economic Networks might help solve systemic risk problems. The chapter concludes with the potential economic and social benefits of blockchain economic networks, particularly as a new technological affordance is created, algorithmic trust, to support financial systems.

Systemic Risk is an Unsolved Social and Economic Problem in Financial Networks
Economics is a domain that has long been recognized as a complex system that should be investigated with network science, particularly by Potts (2001), Newman (2003), Barabási & Albert (1999), and Kirman (1997). Economic systems are socially-constructed, which means that it can be difficult to understand the connections between individual behavior and overall system change. Traditional microeconomic and macroeconomic approaches have proven insufficient for understanding economic networks (Schweitzer, 2009). This is because on one hand, the microeconomic approach tends to focus on modeling individual agent incentives and actions (such as with game theoretic Nash equilibria and Schelling points), but is not good at predicting macro events. On the other hand, macroeconomic approaches may be able to identify complex system-wide forces, but have difficulty linking these influences to the micro level of individual agent behavior. Thus, network analysis is a method which attempts to incorporate aspects of both in order to identify patterns and understand behaviors which may drive the overall economic system at both the micro and macro level.

Systemic risk and the potential for catastrophic failure appears to be an unfortunate feature of the large-scale systems that enable modern life. These systems include epidemics, climate change, species extinction, power grids, and global financial risk. Financial risk is a particularly challenging problem to address. A 2007 U.S. Fed report surveyed industry leaders in various fields (Kambhu, et al., 2007). The study found that comparatively little was being spent on overall systemic risk as compared with risk management for individual firms, even though firms acknowledged the high social and economic expense of systemic risk events to both the national and global economy. Examples of systemic risk events are disruptions to the financial system such as terrorist attacks (9/11; September 11, 2001), U.S. power blackouts (August 14, 2003), and financial crises (1987, 2008, and the 1998 Russian loan default and subsequent collapse of the hedge fund Long-Term Capital Management).

Despite the recognition of the high social and economic cost of systemic risk in financial networks, it is not clear how to solve the problem. One way the problem has been intractable is the inability to effectively model and predict risk events. This is because data have not been available, and there have not been secure and private ways to share data. Simultaneously, there are claims that risk has increased at both at the individual and systemic level as financial networks have become more complex. Both the nature of contracts between parties has become more complex, and the overall structure of contracts in the economy has become more complex (Battiston et al., 2016). Thus, it is more difficult for regulators and market participants to estimate the probability of individual and systemic default than in previous years. The effect of higher complexity means that the economy is less robust and more vulnerable to potential shocks. For these reasons, estimating systemic risk in financial networks is a significant challenge for financial policy making. This chapter examines how economic network analysis, particularly in the context of blockchain technology, might be employed to address systemic risk in financial networks, and reduce the social and economic cost of their impact.

Economic Network Theory

Networks are ubiquitous in economic and social phenomena, and there is a research precedent for studying them with network science methods (Jackson, 2008). A network is defined as a group or system of interconnected people or things. Economic network theory is the application of graph theory methods (using mathematical structures to model pairwise relations between entities and their interactions) to study the relational connections between economic agents in networks. Standard models of economic theory are incomplete because they assume perfect conditions and do not take into account the dynamical and evolutionary aspects of real-world interactions. Instead, economic network theory may provide an improved method for modeling and understanding the behavior of economic agents and the overall economy. König and Battiston discuss the progression in modeling economic network behavior from standard economic theory to game theory to economic network theory as follows (2009).

Standard Economic Theory

The standard neoclassical model of the economy assumes perfect competition, available information, rational behavior, and price flexibility (Hausman, 2003). Ideally, these conditions result in market equilibria with an efficient allocation of goods and services. In such a general equilibrium framework, individual decision making is represented as maximizing a utility function. A utility function is a way of quantifying options so that higher-preference choices rise to the top. As individuals transact based on these preferences, economic equilibria are found.

However, these laboratory-like conditions do not accurately model real-life situations. In practice, competition and information may be imperfect, behavior may not be economically rational, and price discovery may be difficult. Competition is imperfect since agents or firms only tend to interact with a few others out of all of those present in the economy. Information is costly to obtain, particularly related to price discovery and valuation. Thus, decision making may not be fully rational from an overall market perspective. In addition, economic systems have a living feedback loop in that individual agents are not merely isolated parties reacting to the situation, but may be having an impact on the market through their behavior and by cooperating directly or indirectly with other agents to influence supply and demand, and price and quantity.

Game Theory

Game theoretic approaches have been added to standard economic theory to overcome some of its limitations. First, game theory provides a means of incorporating the dynamical aspects of the feedback loop created by agent behavior updating per new learning. Second, game theory tries to account for agent behavior in the real-life situation of limited information and imperfect competition. The premise is that since agents have limited information in actual conditions, they will try to anticipate the actions of others, and adjust their own behavior accordingly. Game theorists therefore attempt to integrate strategically interacting agents (such as individuals and firms) into the general equilibrium framework of standard economics. Specifically, game theorists apply tools to estimate market crossing points such as Nash equilibria (strategically stable positions in which no agent has an incentive to deviate) and Schelling points (natural set points that agents tend to use in the absence of information and communication, for example a round number price of $100). Research advances have enhanced economic network analysis with findings from social network analysis, for example with Bonacich centrality, which is the degree to which the agent is a key player in the network. The two approaches are integrated in the formulation of Bonacich-Nash linkage, in which the Nash equilibrium action of each agent is proportional to that agent’s Bonacich centrality (Ballester, 2006).

Game theory is a useful step forward, but does not address the two other shortcomings of standard economic theory which have to do with the scope and domain of agent activity within the network. First, although game theory allows that information may be imperfect, models often assume that an agent can quickly process this information, which may not be the case. Thus, the rationality of agents should be bounded to the domain of information which they can feasibly obtain and process. Second, game theory may assume that every agent can transact with every other agent, which is unrealistic in large systems. The environment within which individual agents can reason and transact should be delineated. The conclusion from the game theoretic approach is that economic models should specify a realistic scope of information the agent can process, and interactions the agent can have in the trade environment.

Economic Network Theory

Economic network theory is a third step in this economic modeling progression which attempts to overcome challenges with classical and game theoretic approaches, and provide a way to model the economy as a whole. Network economics more realistically corresponds to the actual behavior of economies because it tolerates ambiguity, is comprised of loosely-coupled relations, and incorporates feedback loops. Agents interact with their *neighbors*, who may be similar firms or value chain partners within the same industry (not necessarily those in geographical proximity), and these firms are linked through customers and suppliers to firms in other industries. Through these connections, changes such as new technological innovations, for example, diffuse throughout the network. The rate and extent of diffusion depends on two factors: the structure and the connectivity of the network. An economy is comprised of a variety of agents (individuals, firms, regulators, governments, investors, and other entities). These agents interact in different ways, and learn over time to adapt their interactions, meaning strengthen profitable relationships and eliminate costly interactions. The system co-evolves in that not only is the system architecture evolving, but also the agents' learning as a contributing factor to this evolution, thus creating an endogenous feedback loop. Network evolution that is dynamical and based on both the structure and the connectivity of the nodes may be an improved approach over microeconomics or macroeconomics, or classic or game theoretic analysis alone.

There is evidence in support of network analysis modeling is that standard economic analysis and game theory have not been able to reproduce statistical regularities that have been observed empirically in network structures (Schweitzer, 2009). Therefore, complex systems methods may be better for making predictions in large-scale networks. The way that network theory makes predictions is by positing and testing the stochastic rules that affect link formation. Specifically, network modeling assesses the characteristic features of agents and their interactions. Two of the principal measures are connectivity and centrality: the nodes' degree of connectivity (number of links) and centrality (measurement of the importance of the node), which can be impacted dynamically and with some degree of randomness. Another important measure for understanding the structure of link formation is analyzing how agent incentives and network formation rules arise endogenously within the system, and not as a function of exogenously applied rules (Albert & Barabási, 2002).

In network theory models, agents (individuals, firms) are designated as nodes or vertices, and are the key compositional elements of the network. Their interactions are called edges or links, and capture the relational content of the system. The nodes may exist in different states, which can be modeled as probabilistic distributions of state variable values. The overall quantity to be measured in the system is called the performance measure (similar to a dependent variable in a regression analysis), which could be a quantity such as liquidity, default risk, or growth. As mentioned, there are two levels of co-evolution in a network: how the content exchanged in the links evolves over time, and how the overall network structure of links evolves over time. A heuristic for this is form and content. The content is the contents of the relational links between agents, and the form is the overall network structure of links. The two evolve at different rates. The link content is more likely to update and reach a new equilibrium state quickly as conditions change, whereas the network structure (the presence of links) takes longer to evolve as nodes and edges are added to and subtracted from the overall network structure.

Co-evolution and Dynamic Process Coupling

The two levels of network processes (content exchanged in the links and the overall network structure of links) are coupled and co-evolve. The evolution of the link structure is dependent on the agents' experience from using the links available to them (their contacts and network neighbors). Agents learn and adapt their behavior within their content links, which leads to an evolution of the overall network structure as agents form and sever links (König and Battiston, 2009, 25). This is how the co-evolutionary coupling occurs between agent link use (content) and the network structure (form). The coupling of the fast and slow dynamical processes in a network system is further indicated in a phenomenon called the "slaving principle" (Haken, 2004, 228, 330). The dependent coupling can be seen in the network modeling of R&D networks. For example, one simulation found that the gross return of an agent was proportional to the agent's knowledge growth rate, which was a function of the knowledge levels of the agent's neighbors (König and Battiston, 2009, 57-8). A secondary effect was that knowledge may be transferred not only along the shortest network path, but along all paths, so that the number of agents to which a given agent is connected can boost the agent's return. Rather than hampering network processes, dependent coupling may serve as a self-organization principle for the system (Gross and Blasius, 2008, 4).

Network Construction and Limitations
Considering limitations, since a model is an abstract representation of an underlying phenomenon, there are issues that arise regarding the correspondence and fit of the model, with resulting adjustments to be made for how accurately a model instantiates the actual situation. Network construction entails the abstract conceptualization, representation, and interpretation of a phenomenon. Brandes underlines the importance of conceptualizing a phenomenon first before trying to represent it, and that "a network model should be viewed explicitly as yielding a network representation [e.g. not a direct representation] of something" (Brandes, 2013, 3). Network construction is thus a crucial step including because there might be different ways to set up the network to measure the quantity in question such as default risk, economic growth, or agent choice in economic networks. A related field, cliometrics, uses network models to focus specifically on the performance measure of intangible social goods created in human political and economic systems. Diebolt has a review of 50 such studies (2012).

Considering the different ways to construct a network, the canonical method is the Kauffman NK model (Kauffman and Levin, 1987). In this model, N is the number of components (nodes) in the system, and K is the degree of interaction between the components (edges). Table 1 has an example of the NK Model applied to a gene network. The system is the genome, the N components (nodes) are genes, their K interactions (edges) are relations, the states the nodes might be in are having a mutation or not, and the performance measure of the overall system is the fitness of the organism. The focus is on the states that the genes might be in (mutated or not), and how mutation occurs and gives rise to the overall performance measure, fitness.

Table 1. Kauffman NK Model of Network Structure.

System	**Components (N)**	**Interactions (K)**	**States**	**Performance Measure**
Genome	Nodes: Genes	Edges: Relations	Gene Mutation (Y/N)	Fitness

In economic network analysis, the nodes are often human-based entities. This could be individuals, firms, trading regions, or countries. Economic networks analyzed in trade, ownership, R&D alliances, and credit-debt relationships have typically followed this structure. The method of network construction used is to identify the action-taking parties (nodes) in the network, and map their relations to each other in a network structure with one-way arrows. In other approaches, notably computer science (possibly flowing more directly from graph theory), the nodes are literally network nodes. For example, in the network modeling of the internet, the routers and computers that make up the network are the nodes. For the cryptocurrencies analyzed in this chapter, the software wallets are the nodes. Another network construction method uses events as nodes and activities as edges. There could be a more extensive application of network principles in network construction that does not always feature human decision-making agents as nodes and their interactions as edges. Instead, the network might be architected with goods and their flows, values and their amplitude, and business model changes and their diffusion in efforts to evaluate different performance measures. In an alternative assessment of systemic risk, nodes might be contracts, and edges might be exposure risk or credit quality. Table 2 illustrates some examples of network construction in different domains.

Table 2. Network Construction Examples.

	System	**Nodes**	**Edges**	**Performance Measure**	**Reference**
1.	General economy	Agents	Interactions	Degree/quality of interaction	König & Battiston, 2009
2.	Financial credit industry	Firms	Contractual relations between firms	Change in financial condition (assets, solvency ratio)	König & Battiston, 2009
3.	nanoHUB (online R&D collaboration)	Programmers	Contributions, participations	Citation impact	Brunswicker et al., 2016
4.	Enterprise software (BioPharma industry)	Operating components: business, infrastructure, software	Relations	Propagation cost, network structure	Lagerstrom et al., Jun 2013
5.	Brain	Brain regions	Connections: anatomical, functional, and effective	Signal transmission	Rubinov et al., 2010
6.	Human musculoskeletal network	Bones (point masses)	Muscles (springs)	Compensatory injury risk	Murphy et al., 2018

Specific economic network examples are cited on Lines 1-2 of Table 2. In economic networks, the goal is to quantify how much of the performance measure (such as wealth, knowledge, or output) is generated, propagated, or diminished by the agents acting in the system. In the first example (Line 1), nodes are agents and the performance measure is their utility. This could be the degree of an individual's wealth, a firm's output, or an agent's knowledge in R&D collaborations. The second example (Line 2) models the coupling of a dynamic network in the context of credit relations between firms. In this network, links (edges) are contractually-established credit relations between firms. Financial variables (such as total asset value or solvency ratio) of one firm are affected when they change in connected firms. Despite that, relations maybe fixed until the expiration of contracts, and network link updating cannot occur. Therefore, while links may be modified on a time scale of months, financial variables may vary on a time scale of days. Therefore, the two network processes happen at different rates. The values of the link contents change quickly (coming to a new equilibrium) as information becomes available (e.g. asset value) and is transferred between agents. However, the network structure takes longer to update as links stay in place due to contractual relations that obligate one firm to another for a period of time even if conditions have changed. The content of the links updates faster than the structure of the links. The two processes are coupled in that the network structure evolution lags, yet slaves, the content updating process.

Part I: Payment Networks

Economic Network Analysis: Fedwire Example

A leading example of economic network analysis in payment networks is the Fedwire study. The Federal Reserve Bank of New York commissioned a study of the network topology of interbank payment flows within the U.S. Fedwire service (Soramäki et al., 2006), later published in *Physica A* (Soramäki et al., 2007). The U.S. Fedwire service is a real-time settlement system (instantaneous and irrevocable) operated by the Federal Reserve System amongst member banks. In 2016, Fedwire processed 148.1 million transfers for a total value of $766.7 trillion dollars (at an average of $5.1 million per transaction) for 9,289 banks (U.S. Fed, 2017). The study uses data from the first quarter of 2004. The average value of daily transfers between commercial banks was $1.3 trillion, and the number of daily payments was 345,000 (Soramäki et al., 2007, 319). The average value per payment was $3 million, with distribution highly right-skewed for a median payment of $30,000. Both the value and volume of daily payments indicated periodicity around the first and last days of the month, and on mid-month settlement days for fixed income securities. Overall, 66 banks and 181 links accounted for 75% of the value of daily transfers, and only 25 of the banks were completely connected (having a direct link between them) (Ibid.).

The study uses a directed graph to instantiate Fedwire activity. The nodes are the commercial banks. The edges are the payments sent (a directed link from one bank to another is present in a day if at least one transaction debits the account of one bank and credits the account of another). The average size of the daily network was 5,086 nodes (banks) (Ibid., 321). 710,000 links were found between banks over the sample period, with only 11,000 present on all days. On average the network had 76,614 directed links. In comparison, a complete network of similar size would have 25 million links (if all nodes had one-to-one connections). Thus, the connectivity (the number of links relative to the number of possible links) is low, only 0.3%. The interbank payment network is extremely sparse, since 99.7% of the potential links are not used on a given day. The average reciprocity (two-way links) is 22%, meaning banks having payments going in both directions. However, all large-size links (those with more than 100 payments or more than $100 million of value transfer) were reciprocal. Increased reciprocity on large links could be the result of complementary business activity or the risk management of bilateral exposures.

The average path length (the distance from one node to another) is 2.6. In comparison, the average path length of a similar size classical random network is 3.2. The mean eccentricity (maximum distance to another node) is 4.7, and the diameter (the maximum eccentricity across all nodes) ranges between 6 and 7 depending on the day. The interbank payment network exhibits the small-world phenomenon common to many complex networks, meaning that two nodes might not have a direct connection, but any node can be reached from any other node with only a few steps. This is indicated in that although few nodes connect directly, 41% are within two links of each other, and 95% are within three links of each other. The interbank payment network is comprised of a core of hubs with whom smaller banks interact. It is a sparse network with low connectivity that is extremely compact. The compact nature may be relevant to the efficiency and resiliency of the payment system. On one hand, the shorter the distances between banks in the network, the more easily liquidity can be circulated between banks. On the other hand, a payment system in which liquidity can flow rapidly such as Fedwire might also be more vulnerable to disruptions in these flows.

The average degree (the number of connections a node has to other nodes) in the network is 15.2. However, the payment network is a hub system in which most banks have only a few connections, and a small number have thousands of links to other banks. Almost half of the banks have 4 or fewer outgoing links and 15% have only one outgoing link. The degree distribution is the probability distribution of the degrees (connections) over the whole network. For degrees greater than 10, the out-degree distribution follows a power law with a coefficient of 2.1 (Ibid., 325). The in-degree distribution also has a power law coefficient of 2.1. Researchers find similar evidence of scale-free distributions in the Japanese interbank payment system (BOJ-NET) (Inaoka et al., 2004, 20), and the Austrian interbank market (Boss et al., 2003, 3). The BOJ-NET has a power law tail of 2.3 for degrees greater than 20, and the Austrian interbank market has a coefficient of 3.1 for out-degree distribution and 1.7 for in-degree distribution. A similar analysis was performed for Canada's Large Value Transfer System, which did not compute the power law coefficient but did compare other similar network measures (Embree and Roberts, 2009, 10). Authors suggest that a degree distribution following a power law distribution with a coefficient in the range of that of the U.S. and Japan (2.1 and 2.3) might be a norm of economic stability in national interbank payment systems.

The correlation coefficients also indicate that the Fedwire network is highly disassortative. This means that nodes of low degree (having few connections) are more likely to connect with nodes of high degree (having many connections). In the disassortivity analysis, the correlation of out degrees is -0.31 (Soramäki et al., 2007, 326). The property of disassortivity is common in technological and biological networks, but not in social networks which tend to exhibit assortative properties (people connecting with others who have similar characteristics) (Newman, 2003). The implication for economic networks is that assortative networks may be more robust to node removal than disassortative networks, and percolate (loosely, diffuse) more easily (Ibid.).

Another parameter, the average clustering coefficient of the network (the probability that two nodes which are the neighbors of the same node, themselves share a link), calculated using the successors of a node is 0.53 (Soramäki et al., 2007, 326). This is 90 times greater than the clustering coefficient of a comparable random network. The high clustering coefficient for the network as a whole conceals the fact that the clustering across nodes is highly disperse. There are many low degree nodes (those having few connections). When omitting nodes with a degree smaller than three, the average clustering coefficient increases even more to 0.62. A high level of clustering is observed in many other real-world networks. In a payment network, the clustering coefficient measures the degree of payment activity between a bank's counterparties. Therefore, disruptions in banks with a high clustering coefficient might have a larger impact on their counterparties, as some of the disturbance may be passed on by the bank's neighbors to each other, in addition to the direct impact from the source of the disruption.

Summarizing, the Fedwire network has both a low average path length (2.6) and low connectivity (0.3%). The low connectivity is characterized by a relatively small number of strong flows (transfers) between nodes, with the vast majority of linkages being weak to zero (few or no flows). On a daily basis, 75% of the payment flows involved fewer than 0.1% of the nodes, and only 0.3% of the observed linkages between nodes (which are already extremely sparse). The unevenness in link strength (most links are weak) may stabilize the network. The interbank payment network is disassortative and scale-free. The network has a tightly-connected core of banks to which most other banks connect. Large banks are disproportionately connected to small banks, and vice versa; the average bank is connected to 15 others, but this does not give an accurate idea of the reality in which most banks have only a few connections while a small number of hub nodes have thousands.

The Fedwire network performance was studied during the disruption of 9/11 (Soramäki et al., 2007, 229-330). There were significant changes to the network topology, but it remained resilient. The number of nodes and links in the network decreased, 10% among the most strongly connected nodes (from 5,325 to 4,795) and 5% overall, thereby reducing network connectivity from 0.30% to 0.26%. The average path length between nodes increased from 2.6 to 2.8. The clustering coefficient decreased from 0.52% to 0.47%.

Economic Network Analysis: Cryptocurrency Examples

Digital cryptocurrencies are an emerging sector that is evolving rapidly. Since cryptocurrencies entails the notion of operating a monetary system on a computing graph, network science is a natural mode of analysis for such digital financial networks. What follows is a discussion of contemporary research applying network analysis to cryptocurrencies. Cryptocurrencies are especially amenable to network analysis since currently (unlike fiat currencies), cryptocurrencies have a database of all transactions since their inception. Although known for their decentralized nature, running on distributed networks and not requiring intermediaries such as banks and governments, ironically, cryptocurrencies are also centralized in that there may be a consolidated transaction record, which is not available in traditional financial systems. Table 3 shows the three projects discussed here, and their network construction.

Table 3. Cryptocurrency Network Analysis Summary.

System	**Nodes**	**Edges**	**Performance Measure**	**Reference**
Bitcoin	Bitcoin addresses	Transactions	Node richness (balance and connectivity)	Maesa et al., 2017
Monero	Spending inputs and outputs	Spend relations	Privacy	Miller et al., 2017
Ripple	Wallets	IOU credit transfers	Liquidity, Privacy	Moreno-Sanchez et al., 2016, 2017

Bitcoin

Maesa et al. (2017) performed a network analysis of bitcoin data cumulative through December 2015. Theirs is one of the few peer-reviewed journal publications. There are other network analyses of bitcoin, mainly presented as conference papers, which have a variety of potential issues as diagnosed by Maesa (Ibid., 2-3). In particular, Maesa et al. take into account the fact that any one user may have several addresses. The team uses a weighted directed multigraph in their analysis. In the first instantiation of the network, a transaction graph is created. The nodes are bitcoin addresses. The edges are transfers between addresses (transactions). Then, in a second phase of analysis, the users graph is derived from the transaction graph by a clustering process. Since each user may control several addresses, bitcoin addresses are initially grouped in single clusters. Then a new graph is defined from this, the users graph, whose nodes correspond to the users and whose edges correspond to value transfers between users. The performance measure is node richness (measured based on account balance and node connectivity). The out-degree distribution is 2.3, and the in-degree distribution is 2.2 (Ibid., 10). The average path length is 4 (Ibid., 16). Other metrics are not quantified specifically, but the team claims to have evaluated a full suite of graph properties such as density, clustering coefficient, and centrality, and that the results are similar to those reported for other complex networks.

The main finding of the study is that the bitcoin network is observed to have a rich-get-richer property (a concentration of the performance measure, node value or richness, in active network nodes over time). The clustering coefficient is constant over time and similar to that of social networks. The diameter of the nodes was 2050, more constant and much longer than that of other real-world networks, for example Facebook, which has a higher number of vertices and a diameter of 41 (Ibid., 9). The authors theorized that this might be due to the fact that transactions are used not only for payments but also to merge and split user funds. The team concludes that despite having a high diameter, the network’s slow decrease over time of the low average distance, together with a relatively high clustering coefficient, suggests a small-world phenomenon (Ibid., 10). The benefit of using network analysis as a method was that it allowed certain topological properties to be observed in the graph which could be translated into emerging economic trends such as the rich-get-richer property. Topological analysis also revealed anomalous behavior such as artificial transactions, possibly from malicious users, and thus might be useful for cybersecurity purposes.

Monero

Research is revealing cryptocurrency transactions to be less private than might have been thought given the domain’s pseudonymous wallet addressing system. For example, blockchain analytics firm Chainanalysis claims that since information related to 25% of bitcoin addresses is tied to real-world identities, it can account for approximately 50% of all bitcoin activity (Friedman, 2017). Thus, for truly confidential transactions, there is demand for a higher degree of privacy that more fully protects user identity. One mechanism for confidential transactions is zero-knowledge proofs. Zero-knowledge proofs hide the three data elements that can typically be seen in some blockchains: sender address, recipient address, and transaction amount. Zero-knowledge proofs are a key feature of privacy-enhancing blockchains such as Monero and Zcash, and have been announced as a feature that will be available in Ethereum (Buck, 2017). Zero-knowledge proofs are a cryptographic software function which confirms but masks the data elements of sender and recipient address and transaction amount. However, unless actual transactions are mixed with false transactions in simultaneous channels, or using other methods, these ‘private’ transactions may also be deanonymizable. Blockchain services offering Service

Level Agreements (SLAs) could emerge to provide cryptographic proof of claims of privacy and confidential transactions.

A working paper from Miller et al. (2017) applies network theoretic methods to deanonymize Monero transactions. By mapping the Monero transaction flow onto a directed graph, they find that outputs can be linked back to inputs, which makes the blockchain less private than advertised. The study uses data from the Monero blockchain from its inception to January 31, 2017 (block 1236196). The nodes are transaction inputs and outputs. The edges are spend relations, in which an input may be spent in an output. The performance measure is privacy (transaction deducibility). The Monero blockchain is imported as a graph with two kinds of nodes, Inputs and Outputs, with directed edges linking them. The edge relation (spending) is iteratively mapped from a status of UnknownSpend to a Spend amount as transactions are back-calculated. The output node states can register as spent, unspent or UnknownSpend. The Neo4J Cypher query language is used to describe the patterns in the graph.

The study finds that approximately 62% of Monero transaction inputs can be linked back to their originating outputs (Ibid., 7). The vulnerability of Monero transactions to deduction analysis varies with the number of mixins (decoys) chosen. Part of the privacy mechanism is that each transaction input can contain decoy links called “mixins.” The idea is to mix in many false transaction inputs and outputs with the bonafide transaction inputs and outputs, such that the real transaction is hidden. In a simple example, each input might have six mixins (seven links in total, including the real one). The decoy outputs are dead ends since there will not be any further spend from the fake transactions directed toward them. However, this kind of privacy has a fixed temporal window because it expires. Although there might be full privacy at the time of the transaction, confidentiality erodes over time. This is because while it is impossible to distinguish between mixin input links and bonafide input links initially, over time it becomes possible to guess which links are mixins since the outputs are not used as inputs in subsequent downstream transactions as are real transaction outputs. The overall findings of the study are that in general, transactions with more mixins are less vulnerable to deducibility, and also transactions using later versions of the Monero software.

Ripple

Ripple Overview

Ripple is a real-time gross settlement system, currency exchange, and remittance network initially released in 2012. It handles both immediate cash payments and credit transactions over time. As of January 2018, it was the fourth largest cryptocurrency, with a market capitalization of $51 billion. Ripple is built on a distributed open source internet protocol, consensus ledger, and native cryptocurrency called XRP (ripples). The shared public database (ledger) uses a consensus process with validator nodes (credentialed external parties such as MIT) confirming the payment, exchange, and remittance transactions. Transactions may be denominated in traditional fiat currencies, cryptocurrencies, and user-defined currencies such as frequent flier miles or mobile minutes. Ripple’s goal is to enable secure, instantaneous, very low-cost global financial transactions of any size with no chargebacks. Ripple is different from other cryptocurrency projects such as Bitcoin, Ethereum, and Monero in that it targets financial institutions, and might possibly be a successor to SWIFT, the current global payment system used among financial institutions.

As of October 2017, over 100 worldwide financial institutions were participating in the Ripple network. Members include 12 of the world's top 50 banks such as Santander, BBVA, and Standard Chartered (Meyer, 2016). Ripple has been received favorably by an initiative of the U.S. Fed, the Faster Payments Task Force, which calls for next-generation global payment systems. A McKinsey study reviewing projects for the Fed task force cites the Ripple network's ability to allow financial institutions to operate cross-border payments much faster than the 2-4 days that is common today, while providing end-to-end transaction visibility and settlement confirmation to banks (Ripple, 2017a). The capability for banks to perform cross-currency transactions in a matter of seconds for a small fee in a publicly verifiable manner could substantially improve financial institution cost and risk profiles. Doing business internationally often requires financial institutions and corporations to pre-fund local currency accounts around the world to quickly send payments in a given market. Ripple estimates that $5 trillion in capital is unproductively committed this way and might be freed for other business uses by using the Ripple network (Ripple, 2017b).

Ripple is distinct as a cryptocurrency both technically and conceptually. Technically, propagation through the credit network is orchestrated by path-based settlement. This means that transactions literally flow through the network in a dynamic debiting-crediting path between available network computer nodes from sender to recipient. This is different from bitcoin and other similar cryptocurrencies, in which submitted transactions are sent to the memory pool on each mining client machine to be confirmed and packaged into transaction blocks that become part of the permanent ledger. Conceptually, Ripple encompasses both the standard notion of cryptocurrencies as a real-time payment system, *and* more fundamentally, a new class of financial network. Ripple is a credit network in which ongoing trust relationships are maintained between parties on the network with a specific financial value attached to them. Ripple is a mesh network of open IOU credits. The name Ripple refers to *rippling*, the idea that transactions can ripple, or flow automatically, across open nodes in the network to their destination, debiting and crediting intermediary wallet nodes without requiring human intervention. As such, Ripple is a credit graph and stores live credit availability in the edges that connect the network nodes. Credit remains resident in the live credit network, which presupposes trust in its on-demand future availability and redemption.

Ripple Network Structure

The Ripple network structure is comprised of gateways, market makers, and users (Moreno-Sanchez et al., 2017). A *gateway* is a well-known business wallet (such as Standard Chartered Bank) that can authenticate and bootstrap credit links to new wallets who want to join the network. Gateways are the Ripple counterparts of commercial banks and loan agencies in the traditional credit model. Gateway wallets maintain high network connectivity. A newly created Ripple wallet that does not have any trust relationships with other wallets can create a credit link to a gateway, and through this relationship, interact with the rest of the network before forming direct links to other wallets. Gateways may likely enforce a known-identity credentialing process for new wallets for regulatory purposes (e.g. KYC-AML compliance) and to mitigate risk. Ripple wallet identities (though possibly known to their initial gateway) are pseudonymous to the overall network. The identification process before a new credit link is created and funded may reduce the number of credit links in the Ripple network, and gives rise to a regional geographical structure to the network. This results in a slow-mixing, unclustered, disassortative network. The slow-mixing property is similar to that of other networks where link creation requires establishing trust, and possibly physical interaction (Dell Amico & Roudier, 2009). A *market maker* is a wallet that conducts currency exchange. It receives a certain currency on one of its credit links, and exchanges it for another currency on another link, charging a small fee. Transfers between users and gateways are typically executed without any fee.

There are two kinds of Ripple transactions: direct XRP payments between parties and path-based settlement transactions (Moreno-Sanchez et al., 2016). Path-based settlement transactions transfer any kind of credit (fiat currencies, cryptocurrencies, or user-defined currencies) between two wallets having a valid credit path between them. A valid credit path is a network path through wallets that have pre-established lines of credit extended from one wallet to another. A credit path allows transactions to ripple across the network (e.g. flow through a progression of nodes). Edges are undirected in the sense that a dynamic path can be found through network nodes between sender and receiver at the time of the transaction. In the course of the transaction, the credit value on each edge of the path from one wallet to another is updated directionally. Edges in the direction from the sender to the receiver are increased by the amount of IOU credit being transferred, and reverse edges are decreased by the amount, almost simultaneously as the transaction propagates. Edge weights (i.e. the amount of credit availability) must accommodate the amount of the transaction being transferred. A settlement transaction can be split ("packetized") into multiple paths as long as credit is available. The existence of a valid credit path between a pair of wallets is enough to execute a settlement transaction between them. Thus, settlement transactions are possible between arbitrary pairs of wallets, even if they have not extended direct credit links to each other.

Ripple Network Research Studies

At least three studies provide insight into the Ripple network. Armknecht et al. (2015) presents an overview of the Ripple network and examines the Ripple consensus process. The study uses Ripple ledger data for the period January 2013-January 2015. The team argues that at that time, counter to developer claims, the consensus process would not prevent the occurrence of forks (the ability to diverge the software protocol and possibly redirect funds). The specific finding was that the size of the intersection set between the Unique Node List of any two validating servers would need to be more than 40% of the maximum set size in order to prevent forks, and that this was not always happening in the consensus validation process (Ibid., 178). The Ripple consensus process has since been updated, and it is presumed that the study's claim is no longer a concern.

Moreno-Sanchez and colleagues have a number of studies and ongoing research in the field. Results from two studies are discussed here, the first (2016) examines the full transaction ledger (direct payments in XRP and path-based settlement transactions) and the second (2017) focuses specifically on the path-based settlement transactions (about half of total transactions). The 2016 study finds that the transaction network is much less private than thought, as they were able to deanonymize 78.7% of the total transactions considered in the representative sample (85,962 XRP payments and 649,640 settlement transactions) (Ibid., 449).

The 2017 study conducts a network analysis of the credit transactions executed through path-based settlement. The Ripple credit network is instantiated as a weighted directed graph of IOU credit links. The nodes are wallets. The edges are credit balances available for path-based settlement. Transaction-splitting is not allowed. The network performance measure is liquidity, in the form of credit availability and transfer. The study uses data for the four and a half year period January 2013-August 2017. There were a total of 181,233 wallets, with 352,420 credit links between them (i.e. far from being completely connected with direct links between each of them), and 29,428,355 total transactions (roughly half XRP direct payments and half credit settlement transactions). To study path-based settlement specifically, data were pruned for XRP transactions, anomalous transactions (spam), and older transactions (wallets not used in 2017). This left 8,461,439 transactions.

Ripple Network Study Results
A path-based settlement graph is constituted using the credit settlement transactions. Directed edges are labeled with a dynamic scalar value (weight) indicating the amount of unconsumed credit that one wallet has extended to another wallet. The default wallet setting for making credit available on an edge is lower-bounded by 0 and upper-bounded by infinity, but a stricter upper bound can be specified. The positive weight on an edge represents the amount that one node owes to another. The number of new credit links in the Ripple network grows linearly with the number of wallets, which means that the network density decreases over time, and indicates a sparse graph.

For the credit transactions (not the immediate XRP payment transactions), the study calculates standard network measures for the 2017 network slice such as an average degree of 3.88, clustering of 0.07, assortativity of -0.13, and density of 1.0×10^{-5} (Moreno-Sanchez et al., 2017, 3). The average path length is two, with 95% of transactions completing within three hops and 99% within five hops (Ibid., 4). The study employs a new method, network motif elicitation, based on the premise that three-node subgraphs may reveal higher-order connectivity patterns. The most frequently occurring three-node motif is the structure of user-gateway-user (which occurs 67.8% of the time out of all of the possible three-node motifs). This further underlines the central role of gateways in the network and is also in line with the low clustering coefficient and disassortativity properties found in the network.

The study finds a slow mixing time, which is not surprising given the small clustering coefficient. The lower bound on the mixing time is 730 (for an Eigenvalue=0.10 of the transition matrix of the graph) (Ibid., 3). Mixing time is a measure of the time it takes a random walk on the graph to approach the stationary distribution of the graph. The stationary distribution is the distribution that is proportional to nodes' degrees (number of links) from each possible source with a relatively small number of intermediaries. A similarly slow mixing time is also exhibited in social networks, 200-500 (Mohaisen et al., 2010, 4). It was thought that mixing time would be fast in social networks, implying that social graphs are well-connected and that any arbitrary destination would be reachable with a probability driven by the stationary distribution. However, social network mixing time is slow, meaning that any node is not quickly reachable from another node. The social graph is less liquid than thought, possibly due to the expensive process of establishing trust (Dell Amico & Roudier, 2009). Mixing time is important, not only as a possible quantitative measure of trust, but also as a parameter for network security design, in both social and economic networks.

The study analyzed at-risk situations such as network liquidity, resilience to faulty wallets, and the effect of unexpected balance changes. Two risks were identified. First, the study found that, due to the setting of a software wallet parameter, 11,000 wallets, with a total value of USD $13 million (as of August 2017) could potentially be at risk of being redistributed to lower credit quality IOUs (Ibid., 6). The issue is that credit rippling through nodes may not be innocuous since lower credit quality IOUs might be substituted in the process. If wallet parameters are not specified in a certain way, as transactions ripple through nodes, a higher-credit quality IOU might be replaced by a lower-credit quality IOU. Wallet nodes are exposed to credit risk in that the credit quality of the IOU could change over time. This risk can be avoided by setting software parameters a certain way, particularly the *no_ripple* and the *defaultRipple* flags. This points out the need for user knowledge and best practices regarding the new domain of digital financial networks. The second risk the study found is that although the overall Ripple network has high liquidity, newly emerging regions might be subject to disruption since transactions flow through local gateways. The study found that one emerging geographical user base of about 50,000 wallets was prone to disruption by as few as ten highly-connected wallets in the region. Again, the issue can be remedied by user awareness and the application of a higher degree of control in wallet software settings.

Discussion and Implications of Fedwire and Cryptocurrency Network Analysis

Discussion of Fedwire and Cryptocurrency Economic Network Analysis

The economic network analysis studies for both the Fedwire and the cryptocurrency examples find similar evidence of complex network behavior. The Fedwire payment network indicates a scale-free degree distribution, a high clustering coefficient, and the small-world phenomenon. Bitcoin similarly exhibits small-world and scale-free network properties. Monero also indicates complex network characteristics. The Ripple credit network is shown to be slow-mixing and disassortative. The network is sparse and density decreases over time because links expand linearly. There is a low clustering coefficient overall, but the core (10,000 wallets) is highly-connected. For Fedwire and Ripple (both interbank transfer networks), the core is highly-connected, and the rest of the network is highly disperse. The high clustering coefficient for the Fedwire network and the low clustering coefficient for the Ripple network are not directly comparable measures as the Ripple figure is for the credit network (ongoing relationships), and the Fedwire figure is for the immediate payments network. To the extent available, standard network analysis statistics are presented in Table 4.

Table 4. Standard Network Analysis Statistics.

	Fedwire	**Bitcoin**	**Ripple***
Connectivity	0.3%		
Eccentricity	4.7		
Path Length	2.6 (41% (2), 95% (3))	4	2 (95% (3); 99% (5))
Diameter	6-7	2050	
Degree	15.2		3.88

Degree Distribution	2.1 (out & in)	2.3 out, 2.1 in	
Clustering	0.53		0.07
Assortativity	-0.31		-0.13

*Ripple statistics are for the credit network transactions only (i.e. not including payment transactions)

It is not a surprise that the Fedwire and cryptocurrency examples echo some of the same kinds of complex network characteristics. They both model the same underlying phenomenon, real-life payment networks, which are economic networks that have highly-connected cores, and are dissortative, small-world, and scale-free. It is a surprise that cryptographic networks are replicating robust financial processes so quickly. The additional finding in the cryptocurrency domain is that all three cryptocurrencies are less private than was thought.

It is known that complex networks are not usually normally distributed (Gaussian), as are the random networks proposed by Erdös and Rényi (1959). Instead, complex networks are more likely to have a Pareto or power law distribution, in the sense that the number of links originating from a given node exhibits a power law distribution. These kinds of networks are characterized as scale-free networks (Watts & Strogatz, 1998). Nodes in a network tend to connect to nodes which have more links, as Barabási and Albert further formulate in the theory of preferential attachments (2002, 76). This is logical because networks evolve over time, so incoming nodes may prefer to connect to established nodes. A related power law distribution is Zipf's law which is observed in word use frequency, income levels, and city size. Complex networks also exhibit small-world behavior, in that although direct neighbors may not be linked, it may only take a few hops to reach any node (Barabási and Albert, 1999).

Key Findings of the Review of Economic Network Analysis Studies

The key findings of the review of economic network analysis studies are the confirmation that economic payment and credit networks are starting to transition to the digital realm of blockchain networks. The evidence is that cryptocurrency networks are exhibiting the same characteristics as traditional economic networks, which suggests their robustness. The transaction activity is not merely isolated and anecdotal, it is substantial and fully-formed. If activity were not shifting to cryptographic networks in a full-fledged manner, the network statistics would not be similar to those of other economic networks. Thus, traditional economic network statistics may be used as a well-formedness condition for evaluating activity in new economic domains such as cryptographic financial networks. Not only is the digitization of money, payments, and credit underway, it is robust and well-formed, at least insofar as cryptocurrency networks exhibit the same standard characteristics observed in other economic networks. One question is how network measures might change as the blockchain industry continues to develop. The hypothesis is that network statistics over time will start to suggest that blockchain economic networks are more than just a replication of existing real-world economic networks, affording new conveyances as well, which can be observed in network analysis.

The first potential change that may be made as blockchain networks scale is more efficient consensus methods, particularly those using proof-of-stake as opposed to proof-of-work mechanisms. Bitcoin, as the first demonstration example of a cryptocurrency, provides strong cryptographic network security (Nakamoto, 2008). The Bitcoin blockchain has not been tampered with, only the front-end methods used to access the blockchain such as wallet software and exchange companies. However, the consensus mechanism, proof of work, is computationally expensive and consumes a significant amount of electricity. The design goal of next-generation blockchain protocols is to have distributed consensus mechanisms that are still cryptographically robust in terms of network security, but less expensive in resource consumption.

The second potential change in blockchain networks is the nature of the link structure. Two new forms of links could be confidential transactions and payment channels. The distinguishing finding in the cryptocurrency network analysis is less privacy than might have been thought given the pseudonymous nature of the networks. Teams have back-calculated or identified 50% of Bitcoin transactions, 78.7% of Ripple transactions, and 62% of transaction inputs in Monero transactions. Blockchains could become more privacy-rich over time. One implication is that network analysis will become even more crucial as a tool for understanding digital economic networks since activity may be observable only at the aggregate level. The other form of new link structure could be payer-payee interaction through a payment channel, a pre-escrowed deposit against which resources are consumed (Swan, 2017). From a network perspective, parties do not need to know and trust each other in real-life, and thus the network could become less connected at the core, less dissortative, with a faster mixing time and a faster co-evolution as an indication of quantified trust.

The third potential change is a series of potential shifts in the architecture of transaction execution, to streamline and segment blockchain networks. The overall effect could be a further instantiation of algorithmic trust (built into network operations) as opposed to physical-world trust mechanisms for identifying the parties executing transactions. For example, the notion of a blockchain (a sequential block of transactions cryptographically hashed together) is being superseded by some projects calling for “blockless blocks,” in the sense that a distributed ledger may be cryptographically maintained with hashes that call each other without having to have a block structure. A related method is directed acyclic graphs (DAGs) which do not have sequential blocks of transactions. An example of DAGs is the IOTA project, which uses the architecture of a tangle of transactions. Internet-of-things entities (machine-to-machine transactions) using this network do not need the very-high security of financial transactions on the bitcoin network and have a much smaller peer-based proof-of-work consensus mechanism that consumes much less electricity than the bitcoin mining operation. Instead of transactions paying a transaction fee, the network is free and runs via peer-to-peer services. Any node submitting a new transaction for confirmation is asked to conduct a small proof of work to confirm two other random transactions on the network. Another proposed structural mechanism that takes advantage of network properties is path-based settlement, which may provide a more efficient method of transfer with greater privacy (Roos et al., 2017).

Part II: Balance Sheet Networks

Economic Network Analysis of Balance Sheets

Economic networks are comprised of both immediate cash transactions (payments) and contractual obligations (debt and credit relationships) that unfold over time. The two functions are differentiated in Table 5. Payments is the more immediate, tangible, and measurable activity, and is the target of the economic network analyses discussed in Part I. Another form of economic network analysis, balance sheet networks, attempts to model the ongoing credit relationships and mutual financial obligations that link companies in future time periods, and contribute more substantially to systemic risk. Network analysis is needed to understand microeconomic and macroeconomic factors together since it is difficult for policymakers to assess the systemic impact associated with the failure of an individual financial institution, and the influence of an aggregate shock to the system as a whole on individual firms.

Table 5. Immediate Payment Transactions vs. Ongoing Credit Obligations.

Immediate Transactions Time t=0	**Ongoing Contractual Arrangements Time t>0**
Payments	Contracts
Immediate cash transfer	Future obligations (credit/debt)
Spot market	Futures and Options market
Bitcoin Transactions	Ethereum Smart Contracts
Fedwire	Balance Sheets
Cryptocurrency payment networks	Ripple IOU credit network

Balance Sheet Networks and Contagion
A key objective of balance sheet network analysis is understanding contagion. Contagion is the degree to which asset value declines are contagious, how one asset decreasing in value is likely to impact the value of others and the market overall. There is higher contagion in dense highly-connected interdependent financial networks (Jackson, 2008), such as those that comprise a modern economy. Some of the other goals of balance sheet network analysis include quantifying the effects of valuation methods, credit policies, and hedging activities between financial institutions. Balance sheet networks might also be helpful in studying the effects of credit crises, asset bubbles, derivatives, and high-frequency trading.

Data availability is a key challenge in balance sheet network modeling. The required data are not as readily or publicly available as for payment networks. Regulators would be presumed to have better access to data, as far as the information that firms are willing to disclose to meet compliance requirements. Ripple therefore constitutes an important step forward in the endeavor to calculate systemic risk by providing visibility into ongoing credit relationships in the interbank system, which is information that has not typically been publicly available.

Another challenge with balance sheet networks is evaluating the intricacy of the relationships. One firm's assets are another's liabilities, but risk measures do not cancel to zero. An open question is the right amount of interdependence in an economic network to provide stability and resiliency. On one hand, a bank's ability to make contracts with other banks in the system increases its ability to diversify risk. On the other hand, the resulting complexity of contractual arrangements can mean less transparency and higher risk. A more complex economy makes it more difficult for firms and regulators to evaluate the probability of individual and systemic default. Thus, greater complexity may mean that the economy is less robust and more vulnerable (Battiston et al., 2016).

There is a financial contagion literature (many papers published in the wake of the 2008 financial crisis, particularly as curated by Chaturvedi (2017)). These papers propose different methods of using network models for modeling financial contagion. The straightforward way to construct balance sheet networks is to model interbank counterparty relationships as a directed random graph, with the performance measure as the propagation of financial contagion (Hurd, 2015). Global regulators have explored this method in a variety of publications. In an IMF Working Paper, Chan-Lau (2010) proposes a balance sheet network model as a directed graph to measure the interrelation of assets and liabilities, and how they impact bank capital in cases of economic shock. The graph is constructed so that randomness can be added to either the number of banks (nodes) in the system or the links between them.

Representatives from the Bank of England developed a framework for modelling contagion risk in financial networks in which the actual linkages are unknown, such as in the case of off-balance sheet obligations (e.g. collateralized debt obligations (CDOs)) (Gai & Kapadia, 2010, 22-3). A directed network analysis is performed in which the nodes are banks and the links are interbank exposures. The network is highly-connected and the most significant network metric (similar to the Fedwire study) is the degree distribution of incoming and outgoing links, which correspond to assets and liabilities. The overall finding is that while greater connectivity may reduce the probability of contagion, it might also be more severe when it occurs (Ibid.). Other factors could amplify contagion in a highly-connected interdependent network such as strong aggregate shocks, liquidity risk, and not being bound by counterparty risk (Ibid., 20). The study also advised that the past is not the future, as shocks are heterogeneous. Even if a financial system has withstood crises in the past, it may not be similarly resilient in the future.

The European Central Bank (ECB) has ongoing publications applying network theory to financial contagion. In an ECB Working Paper, Aldasoro & Alves (2016) model the web of balance sheet exposures of large European banks with a similarity and core-periphery network analysis method. Banks are connected through an arbitrary number of layers of instrument type and maturity. The network indicates positive correlation in multiple separate connections between parties, and a high similarity between layers. The systemic risk contribution of each bank is calculated, which could serve as a policy tool for banking regulators and supervisors. Earlier theoretical analysis by Castrén & Kavonius (2009) and Castrén & Rancan (2013) uses a network model to likewise study the web of balance sheet exposures. They point out that the typical snapshot analysis of balance sheet exposures does not provide a full picture of risk, which should also include the accumulation of risk exposures and the ability to transfer them. They demonstrate this by examining shock propagation across the economy as experienced by four constituencies: financial institutions, non-financial firms, governments, and households. The team argues that an important factor in contagion is the degree of accumulated pre-existing risk exposures, which can be easily triggered by sudden bursts of volatility in asset values. To include accumulated risk in balance sheet network analysis, the team calls for the construction of stochastic risk-based balance sheets in accordance with standard accounting principles.

Overall, the status of balance sheet network analysis appears to be that publications have primarily focused on proposing models for how balance sheet network analysis should be undertaken. There is a lack of studies published with actual data, possibly because the underlying data and network analysis efforts are private. However, without empirical evidence, the network characterizations for balance sheet networks are unknown. For example, like payment networks, do balance sheet networks exhibit dense highly-connected cores, and scale-free, small-world, and disassortativity properties? Without results data, it is difficult to gauge activity and progress in this domain. However, blockchain technology may be changing all of this.

Blockchain Economic Networks

This section describes blockchain economic networks, how their implementation might unfold, and how they may address the systemic risk problem left unresolved by balance sheet networks. To clarify terminology, blockchain economic networks and cryptographic economic networks are used interchangeably and mean all varieties of distributed ledgers that include cryptocurrency payment networks and ongoing credit relation balance sheet networks.

Step 1: Digitization of Assets

One implication of blockchain technology is that financial assets and liabilities may be digitized. The new mode of business practice may involve registering assets to blockchains for administration, ownership confirmation, transfer (buying and selling), audit tracking, and compliance. Blockchain land title registry projects are underway (De 2017, 2018; Young 2017), and corporate assets and liabilities, financial and otherwise, might be similarly registered in blockchain inventories. Digitized assets could mean the ability to have a consolidated view of assets at various permissioned levels of detail. This could be at the department-level or firm-level internally within organizations; at the industry-wide level for regulators; and at the economy-wide level for central bankers, systemic risk managers, and policy-makers. Digitized asset ledgers might be used to calculate global financial risk by keeping a real-time tally of aggregate exposures, with the goal of averting crisis, and at minimum detecting early warning signals.

Having an asset registered to a blockchain means that the private key that controls the asset must be used for any transaction involving the asset. Any attempted transactions without the private key would be invalid. Therefore, there is more scrutiny in the audit trail and it is less likely for the asset to be pledged in grey area activities such as undisclosed off-balance sheet obligations. Further, in corporate environments, multiple signatures (multisig functionality) are usually required for asset transactions above certain thresholds, which brings more inspection and audit-tracking to the domain of asset management. These requirements suggest that blockchains may make it more difficult to hide, and perhaps practically impossible to have off-balance sheet transactions such as collateralized debt obligations (CDOs). There is no “off-balance sheet” since all assets are registered to blockchains. Even if executives colluded, it would be impossible to hide off-balance sheet encumbrances from regulators because the assets and their contractual arrangements would be visible in a financial systems audit (to regulators, not to competitors or the public). Counterparties would not agree to non-blockchain registered transactions because they would lack enforcement. Any encumbrance or other contractual arrangement involving an asset would have to be registered to a blockchain otherwise the arrangement could not be enforced.

Step 2: Real-time Asset Valuation and Payment Channels

One consequence of digitized and blockchain-registered assets is that they might be valued with greater ease, and even automatically. Currently, balance sheets are a snapshot of values at a past moment in time and do not reflect present market value. The digital instantiation of assets means that smart contracts or other tools could constantly or periodically value these assets in real time. It has long been possible to see continuous market values for assets such as securities, and now cryptocurrencies. However, for corporate balance sheets, there has not been a means of real-time asset valuation. With digitized assets, it would be straightforward to obtain immediate values for liquid assets. Illiquid assets could be valued different ways, applying GAAP-based (Generally Accepted Accounting Principles) methods to business inventory price data drawn from Amazon, enterprise eMarketplaces, and procurement networks. Smart contracts could consult websites such as LoopNet for commercial real estate prices. Again, blockchain economic networks would be constructed in many layers of private views for the different parties involved. The point is that corporate asset and liability values might be mobilized into having real-time valuations, which could have a direct benefit to firms, and serve as an important input for balance sheet network modeling. The kinds of balance sheet network models proposed by regulators in the previous section could start to be instantiated with blockchain balance sheet networks. The financial claims that firms have on one another might be more readily elicited, valued, and assessed on an aggregate basis for improved systemic risk management.

Another consequence of digital assets is the possibility of new forms of financial interaction that make better use of business capital such as payment channels. Since assets are digitized, this means that they may be contractually obligated in ways that provide more assurance and trust to both owner and counterparty. Capital is tied up unproductively in the friction of conducting business, particularly international business. Ripple cites firms having $5 trillion in local cash balances in their countries of operation. $3.9 trillion of working capital is obligated in global supply chains (PWC, 2015). There is an estimated $1.5 trillion global trade finance gap (i.e. trade finance transactions rejected by banks but needed for global distribution) (The Economist, 2017). Business requirements that have traditionally restricted the use of capital might be eased by blockchain technology's ability to transfer payments immediately and instantiate ongoing credit relationships across borders. Further, blockchains enable a lower cost of detailed control which allows new forms of remuneration structures such as payment channels. Digitized assets mean that it is easy to have "an account relationship" with business partners instantaneously because assets can be trustfully pledged on digital networks without having to know the other party (and verify them in an internal vendor/partner qualification process). Payment channels is the idea of contractually obligating an asset (a prepaid escrow of capital or another asset obligation), tracking consumption of a resource against the escrow, and then settling on a net basis in one transaction at the end of the period (Swan, 2017).

Step 3: Business Networks, Shared Business Processes, and Shared Ledgers across Value Chains
One consequence of digitizing operations is that value chains may start to migrate toward single shared business processes for the conduct of operations. Shared business processes in business networks with privacy-specific views is the explicit objective of enterprise blockchain implementations. For example, any party in a certain manufacturer's automotive supply chain might look up an item number in the blockchain-based ID system using the same network-based process. In the implementation of blockchain technologies, business practices might be redesigned and streamlined into shared processes in business networks. The implication of shared business processes is that there could also be shared ledgers which incorporate the economic side of business processes. In the farther future, instead of each firm maintaining its own books, it might have journal entry posting privileges for its activities, and a view of its overall activity in the shared ledger that keeps the books for all activity in the value chain. Firms might continue to run their own books until they fully validate and trust the industry shared-

ledger. The concept is "Ripple for ERP," a single shared set of business processes, accounting books, and legal processes in a value chain (Swan, 2018a). Blockchain implementations are underway in the financial sector for shared business processes and ledgers for securities settlement and clearing, syndicated loan placement, and interbank transfers (Short 2017; Higgins 2017; Chinsky 2017). Blockchains are providing a means of improving the efficiency of existing operations, and also producing even more disruptive change that may force industries to reinvent themselves in new ways. One example of blockchain technology enabling a new business paradigm is that of decentralized stock exchanges, as announced by tZERO (Dale, 2017).

Blockchain Economic Network Analysis: Quantified Trust
A blockchain economic network analysis would seek to demonstrate a variety of performance measures. The broader research claim is that not only does blockchain technology modernize banking, finance, and legal operations (and eventually governance) by digitizing them, it also produces social goods such as surety (i.e. lower risk), value creation, and trust. These claims could be tested and quantified. Specifically, the claims are that there is 1) diminished risk and uncertainty due to asset transfer being instantaneous and cryptographically validated, 2) improved value creation since contribution and reward can be more closely linked, and 3) the production of algorithmically-derived trust from not having to know or trust counterparties, only the software, including from technical features such as hashing and zero-knowledge proofs (Swan, 2018b). These features provide a means of validating information without revealing their contents. Trust is built by the ability to ascertain that assets have been transferred and that other parties have fulfilled their commitments without disclosing the details of the commitments.

Economic network analysis could be employed to quantify the value of the trust creation. A research study could investigate how credit availability decisions are made on the Ripple network. The premise is that the real-money amounts of open credit maintained on the network are a quantitative measure of trust since the credit-extending party assumes that the IOU can be exercised and settled at any future moment. A research question could ask how Ripple wallet owners decide how much credit to make available on their network nodes. Since there are no transaction fees, decision-making may be indirect and game theoretic. Overall, a blockchain economic network theory would seek to demonstrate a beneficial impact, both economically and socially, to blockchain economic networks.

Conclusion

Key Findings
This chapter investigates systemic risk as an unsolved problem in financial networks that has high social and economic costs. Economic network theory is an approach that overcomes issues in both standard economic analysis (by incorporating system dynamics and imperfect equilibria), and some forms of game theoretic analysis (by bounding the scope of realistic agent behavior). Economic network theory is a method that integrates both microeconomic and macroeconomic approaches in economic modeling to identify patterns and behaviors that drive the overall system at both the individual and aggregate level. Economic network levels co-evolve at different but interconnected rates as the relational content transmitted between links updates more quickly than the overall structure of links in the network. There are diverse ways to construct an economic network, by identifying the core compositional features (nodes) and their interactions

(edges), which interrelate to create, distribute, or diminish the network performance measure in question (such as growth, utility, wealth, knowledge, or output).

An examination of network analysis studies of payment networks (Fedwire, and Bitcoin, Monero, and Ripple in the cryptocurrency domain) finds that the banking and the cryptographic networks display similar characteristics: highly-connected cores, disassortativity, scale-free, and small-world network properties. Since the two kinds of networks, banking and cryptographic networks, display the same network statistics profiles, a confirmatory conclusion can be drawn, confirmation that blockchain technology is being adopted robustly in payment networks. Payment networks are concerned with immediate cash transfers; however, balance sheet networks capture the ongoing credit obligations between firms and have a greater impact on financial crises and systemic risk. The problem is that it has been much easier to conduct payment network analysis than balance sheet network analysis due to data availability. Now though, blockchain technology might change this as organizational assets and liabilities could start to become blockchain-registered and digitally transferred.

Future Implications

Blockchain economic networks might greatly improve the ability to manage systemic risk. Digitized credit relationships might be more easily consolidated into interbank risk models by regulators and policy makers. Off-balance sheet obligations could gradually disappear for two reasons. First, it would be practically impossible to have an asset encumbrance or contractual relation that is unknown to the distributed ledger system, because all financial and legal operations of the asset are conducted with the digital ledger. Second, over time, if there is more trust and transparency (in the sense of knowing that other parties are complying, not the specifics of their activity) in the financial system due cryptographically-pledged assets and their immediate transfer, then the need for having off-balance sheet obligations disappears. The financial system could start to have mechanisms to address the risks that prompt off-balance sheet arrangements, and is safer and more transparent as a result.

A further consequence of digital assets and liabilities being blockchain-registered for administration, ownership confirmation, transfer (buying and selling), audit tracking, and compliance is the possibility of real-time balance sheet networks. Not only liquid assets, but all assets and liabilities might be valued more regularly, and even in real-time by smart contracts querying online procurement marketplaces and instantiating standard accounting principles. Real-time balance sheet views could be extremely useful to enterprise and regulators alike. Industry-wide enterprise blockchain implementations could result in streamlined business processes running on private blockchain-based business networks. There could be a single shared set of business processes, accounting books, and legal processes in a value chain, with participating entities having private views of their activity. The farther future of blockchain business networks (for example in the financial services, manufacturing, supply chain, healthcare, and energy sectors) might be instantiation in an enterprise blockchain environment with shared business processes, shared ledgers, and multi-jurisdictional legal and regulatory compliance all embedded in the algorithmic logic of the blockchain economic network infrastructure.

Overall, blockchain economic networks might have a beneficial impact, both economically and socially. The broader possibility is that blockchain technology not only modernizes banking, finance, and legal operations (and eventually governance) by digitizing them, it also produces social goods. Thus, a more modern and efficient world is being created, and also a better world that is more humane though the generation of intangible social goods such as assurity, access, equity, choice, and trust, which are available to more persons globally.

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