Mind Soc
DOI 10.1007/s11299-015-0167-y

Network science: a useful tool in economics and finance

Dror Y. Kenett[1] **· Shlomo Havlin**[2]

Received: 18 December 2014 / Accepted: 17 April 2015

Abstract The increasing frequency and scope of financial crises has made global financial stability one of the major concerns of economic policy and decision makers. Under this highly complex environment, supervision of the financial system has to be thought of as a systemic task, focusing not only on the strength of the institutions but also on the interdependent relations among them, unraveling the structure and dynamic of the system as a whole. In recent years, network science has emerged as a leading tool for the investigation of complex systems. Here we review several applications of network science in finance and economics, and discuss existing challenges and future directions which will substantiate network science as a key tool for financial academics, practitioners, and policy and decision makers.

Keywords Network science · Financial networks · Contagion · Interdependence · Financial stability · Percolation theory

1 Introduction

Network science has grown exponentially as a novel tool for the study of complex systems. A huge number of results have established this approach as a new kind of science, where theoretical results are integrated with empirical big data analysis. Many unexpected phenomena of real world systems have been discovered, and increasingly sophisticated system structures are studied. Examples include linked

✉ Dror Y. Kenett
drorkenett@gmail.com

Shlomo Havlin
havlins@gmail.com

[1] Department of Physics, Center for Polymer Studies, Boston University, Boston, MA, USA

[2] Department of Physics, Bar-Ilan University, Ramat Gan, Israel

Published online: 05 May 2015

molecular or cellular structures, climate networks, communication and infrastructure networks, but also social and economic networks. An understanding of the growth, structure, dynamics, and functioning of these networks and their mutual interrelationships is essential in order to find precursors of changes, to make the systems resilient against failures, or protect them against external attacks. The interrelationship between structure (topology) and dynamics, function and task performance in complex systems represents the focus of many studies in different disciplines of research with important scientific and technological applications. Complex networks have been recognized as the leading framework to describe the behavior of physical, chemical, biological, technological and social networks.

Network science has greatly evolved in the twenty-first century, and has become one of the most active fields of interdisciplinary science (Newman 2009; Boccaletti et al. 2006; Newman et al. 2011; Cohen and Havlin 2010; Havlin et al. 2012; Barabási et al. 2014; Barrat et al. 2004; Helbing 2013; Caldarelli 2007; Song et al. 2005). Famous examples include the network of sexual partners (Liljeros et al. 2001), internet and WWW (Faloutsos et al. 1999; Barabási and Albert 1999; Cohen et al. 2000; Pastor-Satorras and Vespignani 2007), epidemic spreading (Pastor-Satorras and Vespignani 2001), immunization strategies (Cohen et al. 2003), citation networks (Radicchi et al. 2008), structure of financial markets (Bonanno et al. 2003), social percolation and opinion dynamics (Solomon et al. 2000; Shao et al. 2009), dynamics of physiological networks (Bashan et al. 2012), protein networks (Milo et al. 2002; Sendiña-Nadal et al. 2011), organization and functioning of the brain (Reis et al. 2014), structure of mobile communication network (Onnela et al. 2007), climate networks (Yamasaki et al. 2008; Ludescher et al. 2014), transportation systems (Li et al. 2015) and many others. Among the phenomena that have been shown to fall in this conceptual framework are: cascading failures, blackouts, crashes, bubbles, crises, attacks and defense against them, introduction of new technologies, understanding measuring and predicting the emergence and evolution of networks and their stylized features, spreading phenomena and immunization strategies, as well as the stability and fragility of airline networks (Cohen and Havlin 2010). Current and past research has shown that in real life systems, there is a strong feedback between the micro states and macro states of the system. This description of nature can be well represented by network science—in which the micro is represented by the nodes of the network and the links between them, and the macro by the network itself, its topology, dynamics and function. Thus, network science is a leading framework to investigate real life systems. For example, as opposed to physical systems where the dynamics is usually bottom-up, in social and economic systems there are interplays on all levels with singular top-down feedbacks. Thus, in many practical realizations, in addition to the bottom-up contagion propagation mechanisms one finds that there is a global-to-local feedback: individuals, their interdependence and behaviors build up the system's cooperative behavior that finally affects back on individuals' choices. It has been proposed that the bottom/up–top/down feedback has the capability to change completely the character of a phase transition from continuous to discontinuous, thus explaining the severity of the economic crises in systems where the collective interacts as such with its own components (Cantono and Solomon 2010) [see extended discussion in Havlin et al. (2012)].

The latest financial crisis has enhanced the emphasis of the importance of collective connectivity effects in the evaluation of financial fragility and for the probability of default. While traditional evaluations of the probability of default use only global information (general situation of the economic branch to which a company belongs) and point information (companies' balance sheet, profit margins, etc.), the latest events show that effects can and do propagate over many intermediate connections. In fact, the cascading effect has been a crucial element of the fast and devastating impact of the crisis. Thus, it is not realistic to separate the stability of a company from the collective dynamics taking place in its economic neighborhood. Access to time and conditions of capital flows between companies allows one in principle a capability to monitor in detail the working of the economy. One example is to express the fragility of a node in terms of the probabilities of default of its clients and suppliers. By conducting experiments on the network of financial transfers, one can probe the probability and size of such cascading events.

Financial systems are perhaps the best example of a complex adaptive system, in which the micro interacts through bottom-up mechanisms with the macro. This is followed by top-down feedback between the macro and the micro. One immediate example is a market index and the stocks that makeup this index. The stocks represent the micro, while the index represents the macro. Kenett et al. (2011, 2012b) have recently shown that the index has a stronger influence on the stocks than vice versa, which is neither a trivial or intuitive result. Thus, the micro and the macro continuously interact. These interactions are best characterized by network science, one which addresses dynamic and coupled networks. Recent work on individual strategies as subtracted from detailed financial data (Lillo et al. 2008; Mu et al. 2010) enables to identify groups of players on the market and their role in stabilization and destabilization. One of the main sources of the intrinsic instability of financial markets is the almost entire absence of negative feedback loops. Appropriate network models with signed (positive and negative) links will help in finding the optimal balance between stability and liquidity and contribute this way to the solution of the major problem of market regulation.

2 Review of financial network literature

Network theory provides the means to model the functional structure of different spheres of interest, and thus, understanding more accurately the functioning of the network of relationships between the actors of the system, its dynamics and the scope or degree of influence. In addition, it measures systemic qualities, e.g., the robustness of the system to specific scenarios, or the impact of policy on system actions. The advantage offered by the network science approach is that instead of assuming the behavior of the agents of the system, it rises empirically from the relationships that they really hold; hence, the resulting structures are not biased by theoretical perspectives or normative approaches imposed 'by the eye of the researcher'. On the contrary, the modeling by network theory could validate behavioral assumptions by economic theories. Network theory can be of interest to various edges of the financial world: the description of systemic structure, analysis and evaluation of the penetration or contagion effects (Lillo 2010; Kenett et al. 2012a, c; Cont 2013; Glasserman and Young 2015; Li et al. 2014; Garas et al. 2010); studies that assess the impact of the insolvency of one or a particular group of actors in the system, depending on its relevance and connectivity within the structure (Jackson 2010; Battiston et al. 2012); and those that allow to evaluate the impact of liquidity problems at specific times and initiated in different nodes of the system (Haldane and May 2011; Haldane 2009; Cont et al. 2013; Amini et al. 2012; Kenett et al. 2010). In a nutshell, it becomes not only an alternative perspective, but provides tools allowing to compare and to contrast the structure of the systems in a static way and project different dynamic scenarios.

In this sense, the payment system can be seen as an example of complex network, and thus, considered as a network, derive its stability, efficiency and resilience features (see for example Aguiar et al. 2014). Analytical frameworks for the study of these structures are varied, and range from the identification of the type and properties of the network, to the analysis of impact of simulated shocks, in order to quantify the risks inherent in its operations to some extent and design policy proposals to mitigate them. Recent studies by Inaoka et al. (2004), Soramäki et al. (2007), Cepeda (2008), and Galbiati and Soramäki (2012), investigated the interbank payment system using network science. considering the system as a network, these authors were able to uncover the structure of the system and allowed the design of scenarios and the visualization of specific effects. Meanwhile, Iori et al. (2008) analyze the overnight money market. The authors developed networks with daily debt transactions and loans with the purpose of evaluating the topological transformation of the Italian system and its implications on systemic stability and efficiency of the interbank market.

Considering the interbank network (Hüser 2015), there have been considered two main channels of risk contagion in the banking system: (1) direct interbank liability linkages between financial institutions, and (2) contagion via changes in bank asset values. The former, which has been given extensive empirical and theoretical study (Wells 2002; Furfine 2003; Upper and Worms 2004; Elsinger et al. 2006; Nier et al. 2007), focuses on the dynamics of loss propagation via the complex network of direct counterparty exposures following an initial default. On the structural level, the contractual obligations would map out the network of claims and liabilities between institutions, and these types of networks have been extensively investigated in different countries (Boss et al. 2004; Cont et al. 2013; Craig et al. 2014; Langfield et al. 2012; Martínez Jaramillo et al. 2012; Elsinger et al. 2005).

In regards to flow of goods or money between industries of different economic activity, it is possible to use input–output tables to present such flows as a network of industries. Based on the supply of the product for each industry, it is possible to construct a directed product supply network, or alternatively have the network represents the money outflow from one industry to another. In such a network, the nodes represent the different industries, and the links the flow of goods (or money value equivalent) between them. Using such data, Li et al. (2014) have introduced a network based methodology to rank the economic importance and influence of economic industries or countries. This methodology uses the uncovered network structure to identify and rank the influence of the individual industries (nodes).

Focusing on liquidity, Minoiu and Reyes (2011) explore the properties of the network of global banking using information from bilateral loans from 184 countries and their direct investment flows (quarterly). Coinciding with several papers on capital flows, they conclude that advanced economies are the major players in the global banking market with 10 times more flows between them than to developing or emerging countries, making up the core of the network with other countries in the periphery. After describing the topology of the network and evaluating its dynamics in the period 1978–2009, they found volatility in the network topological properties: the interconnection between nodes is unstable and connectivity tends to decrease during periods of crisis.

Considering the problem of contagion, Allen and Gale (1998) study how shocks can spread in the banking system when it is structured in the form of a network. Drehmann and Tarashev (2013) develop a measure that captures the importance of an institution, in term of its systemic relevance, in the propagation of a shock in the banking system. More recently, Acemoglu et al. (2013a, b, c) develop a model of a financial network through its liability structure (interbank loans) and conclude that complete networks guarantee efficiency and stability, but that when negative shocks are larger than a certain threshold, contagious prevails and so the systemic instability.

Recently, Huang et al. (2013) presented a bi-partite network model for the investigation of bank balance sheet data. Using this bank-asset network model, it is possible to test the influence of each particular asset or group of assets on the overall financial system. This model has been shown to provide critical information that can determine which banks are vulnerable to failure and offer policy suggestions, e.g., requiring mandatory reduction in exposure to a shocked asset or closely monitoring the exposed bank, to prevent such failure. The model shows that sharp transitions can occur in the coupled bank-asset system and that the network can switch between two distinct regions, stable and unstable, which means that the banking system can either survive and be healthy or collapse. Because it is important that policy makers keep the world economic system in the stable region, it is suggested that this model for systemic risk propagation might also be applicable to other complex financial systems, e.g., to model how sovereign debt value deterioration affects the global banking system or how the depreciation or appreciation of certain currencies impact the world economy. The model has recently been expanded to a dynamical version by Levy et al. (2014), to provide novel macro-prudential information on the vulnerability of the banking system.

Finally, it is important to discuss a large body of work that focuses on the use of correlation based networks in finance. The underlying principle is the use of empirical financial time series, from which a correlation (or covariance) matrix is estimated, that is than used to construct a network. This methodology has been found to uncover important information about financial systems, and has shed new light on their underlying structure and dynamics (Bonanno et al. 2003; Kenett et al. 2010, 2012b; Mantegna 1999; Tumminello et al. 2007a, b, 2010; Onnela et al. 2003a, b; Garas et al. 2008). One main application of correlation based networks is the identification of lead–lag relationships, or causal-like relationships, and as such alternative similarity measures have been recently proposed (Billio et al. 2012; Curme et al. 2015; Sandoval and Franca 2012; Sandoval 2014).

3 Challenges and future directions

Despite its great success in the investigation of many real world social, technological and natural systems, network science has seen a slower acceptance rate in economics and finance. While some researchers in the community have begun realizing its usefulness in understanding the complexity of the economy, there exists a suspicion amongst many others about the applicability of network science in such discipline. In this section we address the key issues that stem from such criticism, which future developments in network science will need to address in order to solidify its usefulness as a theoretical, analytical and application framework for these domains.

3.1 Memory of flow in networks

An important issue in finance is the credit worthiness of the source of the asset that is transferred. As a given asset, or financial quantity, is transferred and flows along the links of the network, its value can change depending on the nodes that is passing through. More importantly, some financial assets, such as collateral, can flow on the network, and then required to travel back the same path to its original source. Such dynamical processes on networks are currently lacking, and need to be addressed in order to provide an understanding of the dynamics of flow on the network. For example, in regards to the flow of collateral, which can be reused and be transferred from one node to another, how to model what will happen when the original node (entity) asks for it back? How will the backwards flow of the collateral, which can be considered as an unwinding of a daily chain, have an effect on the nodes that it passes? Answering such questions is very important in order to map and model the operational flows in the financial system. To answer such questions, new models of flow dynamics on networks need to be developed. Furthermore, existing models of cascading failures in networks need to be adapted to include the presence of memory, which will effect the propagation and the spread of the damage throughout the network.

3.2 Function and transformations

While most studies using network science to investigate the properties of the financial system look at the individual nodes (e.g., banks, companies, countries) as a closed box, in reality these nodes perform one or several actions, or transformation, on the value (funds, collateral, assets, debt, etc.). The recent work by Aguiar et al. (2014) has presented the first methodological framework that addresses this issue, and serves as a blueprint for future work. The authors present a mapping of the flow of funding in the financial system, and instead of looking at the banks as a single entity, they treat them as a collection of sub-units, which play different roles in the network. Financial entities have different functions, ranging from single to multiple, depending on the type of activity they are involved in. This feature of the financial system is a very important one, and is needed to be incorporated in the existing network models and tools, to produce a thorough and realistic characterization and investigation of the financial system using network science (see for example Bookstaber et al. 2015). For example, the feature of node function and transformation needs to be included in current research on dynamical cascading processes in networks, in order to make them more realistic and applicable in the case of economics and finance.

3.3 Time evolution

To understand the functions of the network, one must study its dynamical properties (Arenas et al. 2008), and much work is needed in this direction. The dynamics of links and nodes can change completely the properties of the networks and thus, fundamental questions that have been extensively studied in static networks are still open for dynamical networks (Nardini et al. 2008; Iñiguez et al. 2009; Parshani et al. 2010b; Majdandzic et al. 2014). By studying the dynamical properties of the network, one can uncover its underlying function. It is quite reasonable to claim that the there is a strong link between the dynamics and the function in a given network. Thus, to better understand the network function, it is crucial to study how network structures evolve in time. New tools are necessary to understand the relationship between the dynamics of the network, and its topology and function. In particular, when the system is in a critical state (i.e., at the edge of disintegration, such as a financial crisis), addition or deletion of even a minute number of links can push the system into different phases. Initial observations have shown that the problem of temporal connectivity in a network can be directly mapped onto a directed percolation problem, where the direction represents the time (Parshani et al. 2010b). Thus, the knowledge of directed percolation could be used to understand dynamical networks, and vice versa. Since percolation is related to epidemics, and immunization is related to removing nodes, percolation approaches will be developed to study dynamical systems. Considering the highly adaptable nature of financial markets, and the quickness of change in economical and financial system, this is a crucial issue network science needs to address in order to fully capture the dynamical properties of such systems.

3.4 Interdependent financial networks

The case of a *single* network that is isolated and does not interact with or depend on other systems rarely occur, just as non-interacting particles in statistical physics. In reality, most network systems continuously interact with other networks, especially since modern technology has increased the dependency between networks. Only few and preliminary studies have attempted very recently to face questions relevant to such systems, but they have mainly been qualitative and focused on specific examples. Understanding the interconnections of networks and their effect on the structural and functional behavior of the coupled system is crucial for properly modeling many real world systems. Introducing coupling between networks is analogous to the introduction of interactions between particles in statistical physics, which led to new cooperative behavior with rich phenomena such as phase transitions. The mathematical models (Buldyrev et al. 2010; Parshani et al. 2010a; Gao et al. 2012) show that analyzing complex systems as a network of networks may alter the most basic assumptions that network theory has relied on for single networks. While significant progress is being made in the area of interdependent networks (Kenett et al. 2014) and multilayer networks (Boccaletti et al. 2014), there are still very few applications of these frameworks in economics or finance. One recent example is the work by Bargigli et al. (2015), which investigated a unique database of supervisory reports of Italian banks to the Banca d'Italia that includes all bilateral exposures broken down by maturity and by the secured and unsecured nature of the contract. Investigating this database as a credit multilayer network, the authors found that layers have different topological properties and persistence over time. While this is an important step forward in characterizing the financial system as a multilayer interdependent network, the authors did not consider the interactions between the different layers, and only performed a comparison of them. Future steps would require mapping the different layers of the financial system, and investigating the interconnections and interdependencies between them (Bookstaber and Kenett 2015). Furthermore, the multilayer network framework can be leveraged for the development of new methodologies to investigate the dynamics of networks (Boccaletti et al. 2014), thus provide new insights into the challenges discussed in the previous section.

3.5 Networks and agent based models

Financial networks are formed by the interaction of different financial entities (individual traders, banks, financial companies, financial instruments, countries, etc.). As such, understanding the network properties provides important information on the relationships and interactions, but not the underlying decision rules. This can be resolved and complimented by agent based models (ABM) (Tesfatsion 2002, 2003; LeBaron 2006; Amman et al. 2006). For example, once the payment system can be mapped as a network, such as the recently introduced funding map (Aguiar et al. 2014), then the structure of the network can be used as input for models that simulate the dynamics of the system (Bookstaber et al. 2014). Combining the frameworks of network science and ABM will lead to a framework that captures both micro (decision rules, through the ABM) and macro (relationships and interactions, through network analysis) properties of the underlying financial system. As the system evolves in silicon and the agents update and form interactions with each other, the resulting network of interactions evolves. Thus, future work should expand existing ABM, such as that proposed by Bookstaber et al. (2014) with a layer of network analysis.

3.6 Benchmark topologies of financial networks

A key element of networks is the interplay between topology and function. Benchmark network topologies include Erdős and Rényi (1959), scale free (Albert and Barabási 2002; Barabási et al. 2014), core-periphery (Borgatti and Everett 2000), modular (Shai et al. 2014), and fully connected networks (Boccaletti et al. 2006). Recent work has found that such financial systems as the interbank network have a core-periphery topology (Fricke and Lux 2015; Boss et al. 2004; Hüser 2015). However, additional research is needed in order to identify benchmark topologies of financial networks. Identifying such benchmark topologies would provide new tools for identifying systemic risk and vulnerabilities, by monitoring how the given financial network is diverging or converging to its given benchmark apology. Furthermore, additional work is needed in order to fully characterize these topologies, and associate them with different financial networks (interbank networks, CDS networks, stock correlation networks, input-output networks, etc.).

4 Summary

Haldane (2009), the Executive Director for Financial Stability at the Bank of England, is famous for having suggested that highly interconnected financial networks may be robust-yet-fragile in the sense that within a certain range, connections serve as shock-absorbers [and] connectivity engenders robustness. However, beyond a certain range, interconnections start to serve as a mechanism for the propagation of shocks, the system [flips to] the wrong side of the knife-edge, and fragility prevails (Acemoglu et al. 2013c). This term reflects the realization and understanding of the usefulness of network science in characterizing and monitoring of economic and financial systems. However, to fully solve this contraction, and to understand the basis of this balance and how to achieve it, there is a need to continue, expand and advance the role of network science in economics and finance. Addressing the challenges highlighted in this paper will result in new insights on the structure, dynamics and function of economic and financial systems, insights that are critical for academics, practitioners, and policy and decision makers.

Acknowledgments We thank Richard Bookstaber and Mark Flood for fruitful conversations and insights related to this paper. We acknowledge financial support from Office of Naval Research (ONR), DTRA, BSF, the LINC (No. 289447) and the Multiplex (No. 317532) EU projects, the DFG, and the Israel Science Foundation.

References

Acemoglu D, Malekian A, Ozdaglar A (2013a) Network security and contagion. Technical report, National Bureau of Economic Research

Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2013b) The network origins of large economic downturns. Technical report, National Bureau of Economic Research

Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2013c) Systemic risk and stability in financial networks. Technical report, National Bureau of Economic Research

Aguiar A, Bookstaber R, Wipf T (2014) A map of funding durability and risk. Off Financ Res Work Pap Ser 14(03)

Albert R, Barabási A-L (2002) Statistical mechanics of complex networks. Rev Mod Phys 74(1):47

Allen F, Gale D (1998) Optimal financial crises. J Financ 53(4):1245–1284

Amini H, Cont R, Minca A (2012) Stress testing the resilience of financial networks. Int J Theor Appl Financ 15(01)

Amman HM, Tesfatsion L, Judd KL, Kendrick DA, Rust J (2006) Handbook of computational economics, vol 2. Elsevier, Amsterdam

Arenas A, Díaz-Guilera A, Kurths J, Moreno Y, Zhou C (2008) Synchronization in complex networks. Phys Rep 469(3):93–153

Barabási A-L, Albert R (1999) Emergence of scaling in random networks. Science 286(5439):509–512

Barabási A-L, Frangos J (2014) Linked: the new science of networks. Basic Books, New York

Bargigli L, Di Iasio G, Infante L, Lillo F, Pierobon F (2015) The multiplex structure of interbank networks. Quant Financ 15(4):673–691

Barrat A, Barthelemy M, Pastor-Satorras R, Vespignani A (2004) The architecture of complex weighted networks. Proc Natl Acad Sci USA 101(11):3747–3752

Bashan A, Bartsch RP, Kantelhardt JW, Havlin S, Ivanov PC (2012) Network physiology reveals relations between network topology and physiological function. Nat Commun 3:702

Battiston S, Puliga M, Kaushik R, Tasca P, Caldarelli G (2012) Debtrank: too central to fail? Financial networks, the fed and systemic risk. Sci Rep 2

Billio M, Getmansky M, Lo AW, Pelizzon L (2012) Econometric measures of connectedness and systemic risk in the finance and insurance sectors. J Financ Econ 104(3):535–559

Boccaletti S, Latora V, Moreno Y, Chavez M, Hwang D-U (2006) Complex networks: structure and dynamics. Phys Rep 424(4):175–308

Boccaletti S, Bianconi G, Criado R, Del Genio C, Gómez-Gardeñes J, Romance M, Sendiña-Nadal I, Wang Z, Zanin M (2014) The structure and dynamics of multilayer networks. Phys Rep 544(1):1–122

Bonanno G, Caldarelli G, Lillo F, Mantegna RN (2003) Topology of correlation-based minimal spanning trees in real and model markets. Phys Rev E 68(4):046130

Bookstaber RM, Kenett DY (2015) The multilayer structure of the financial system (preprint)

Bookstaber R, Paddrik M, Tivnan B (2014) An agent based model for financial vunerability. Off Financ Res Work Pap Ser 14(05)

Bookstaber R, Glasserman P, Iyengar G, Luo Y, Venkatasubramanian V, Zhang Z (2015) Process systems engineering as a modeling paradigm for analyzing systemic risk in financial networks. Off Financ Res Work Pap Ser 15(01)

Borgatti SP, Everett MG (2000) Models of core/periphery structures. Soc Netw 21(4):375–395

Boss M, Elsinger H, Summer M, Thurner S IV (2004) Network topology of the interbank market. Quant Financ 4(6):677–684

Buldyrev SV, Parshani R, Paul G, Stanley HE, Havlin S (2010) Catastrophic cascade of failures in interdependent networks. Nature 464(7291):1025–1028

Caldarelli G (2007) Scale-free networks: complex webs in nature and technology. Oxford University Press, Oxford

Cantono S, Solomon S (2010) When the collective acts on its components: economic crisis autocatalytic percolation. N J Phys 12(7):075038

Cepeda F (2008) La topología de redes como herramienta de seguimiento en el sistema de pagos de alto valor en colombia. Borradores de Economía 513

Cohen R, Erez K, Ben-Avraham D, Havlin S (2000) Resilience of the internet to random breakdowns. Phys Rev Lett 85(21):4626

Cohen R, Havlin S, Ben-Avraham D (2003) Efficient immunization strategies for computer networks and populations. Phys Rev Lett 91(24):247901

Cohen R, Havlin S (2010) Complex networks: structure, robustness and function. Cambridge University Press, Cambridge

Cont R (2013) Networks: introduction. In: Fouque JP, Langsam JA (eds) Handbook on systemic risk, vol 285. Cambridge University Press, Cambridge

Cont R, Moussa A, Santos EB et al (2013) Network structure and systemic risk in banking systems. In: Handbook of systemic risk. Cambridge University Press, Cambridge, pp 327–368

Craig B, Von Peter G (2014) Interbank tiering and money center banks. J Financ Intermed 23(3):322–347

Curme C, Tumminello M, Mantegna RN, Stanley HE, Kenett DY (2015) Emergence of statistically validated financial intraday lead–lag relationships. Quant Financ. doi:10.1080/14697688.2015.1032545

Drehmann M, Tarashev N (2013) Measuring the systemic importance of interconnected banks. J Financ Intermed 22(4):586–607

Elsinger H, Lehar A, Summer M (2005) Using market information for banking system risk assessment. Available at SSRN: 787929

Elsinger H, Lehar A, Summer M (2006) Risk assessment for banking systems. Manag Sci 52(9):1301–1314

Erdős P, Rényi A (1959) On random graphs. Publicat Math Debr 6:290–297

Faloutsos M, Faloutsos P, Faloutsos C (1999) On power–law relationships of the internet topology. In: ACM SIGCOMM computer communication review, vol 29. ACM, New York, pp 251–262

Fricke D, Lux T (2015) Core-periphery structure in the overnight money market: evidence from the e-mid trading platform. Comput Econ 45:359–395

Furfine CH (2003) Interbank exposures: quantifying the risk of contagion. J Money Credit Bank 35(1):111–128

Galbiati M, Soramäki K (2012) Clearing networks. J Econ Behav Organ 83(3):609–626

Gao J, Buldyrev SV, Stanley HE, Havlin S (2012) Networks formed from interdependent networks. Nat Phys 8(1):40–48

Garas A, Argyrakis P, Havlin S (2008) The structural role of weak and strong links in a financial market network. Eur Phys J B Condens Matter Complex Syst 63(2):265–271

Garas A, Argyrakis P, Rozenblat C, Tomassini M, Havlin S (2010) Worldwide spreading of economic crisis. N J Phys 12(11):113043

Glasserman P, Young HP (2015) How likely is contagion in financial networks? J Bank Financ 50:383–399

Haldane AG et al (2009) Rethinking the financial network. Financial Student Association, Amsterdam

Haldane AG, May RM (2011) Systemic risk in banking ecosystems. Nature 469(7330):351–355

Havlin S, Kenett DY, Ben-Jacob E, Bunde A, Cohen R, Hermann H, Kantelhardt J, Kertész J, Kirkpatrick S, Kurths J et al (2012) Challenges in network science: applications to infrastructures, climate, social systems and economics. Eur Phys J Spec Top 214(1):273

Helbing D (2013) Globally networked risks and how to respond. Nature 497(7447):51–59

Huang X, Vodenska I, Havlin S, Stanley HE (2013) Cascading failures in bi-partite graphs: model for systemic risk propagation. Sci Rep 3

Hüser A-C (2015) Too interconnected to fail: a survey of the interbank networks literature. SAFE working paper no. 91 (available at SSRN 2577241)

Inaoka H, Ninomiya T, Taniguchi K, Shimizu T, Takayasu H (2004) Fractal network derived from banking transaction-an analysis of network structures formed by financial institutions. Bank Jpn Work Pap 4

Iñiguez G, Kertész J, Kaski KK, Barrio R (2009) Opinion and community formation in coevolving networks. Phys Rev E 80(6):066119

Iori G, De Masi G, Precup OV, Gabbi G, Caldarelli G (2008) A network analysis of the italian overnight money market. J Econ Dyn Control 32(1):259–278

Jackson MO (2010) Social economic networks. Princeton University Press, Princeton

Kenett DY, Tumminello M, Madi A, Gur-Gershgoren G, Mantegna RN, Ben-Jacob E (2010) Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market. PloS One 5(12):15032

Kenett DY, Shapira Y, Madi A, Bransburg-Zabary S, Gur-Gershgoren G, Ben-Jacob E (2011) Index cohesive force analysis reveals that the us market became prone to systemic collapses since 2002. PloS One 6(4):19378

Kenett DY, Preis T, Gur-Gershgoren G, Ben-Jacob E (2012a) Dependency network and node influence: application to the study of financial markets. Int J Bifurc Chaos 22(7):1250181

Kenett DY, Raddant M, Zatlavi L, Lux T, Ben-Jacob E (2012b) Correlations in the global financial village. Int J Mod Phys Conf Ser 16(1):13–28

Kenett DY, Raddant M, Lux T, Ben-Jacob E (2012c) Evolvement of uniformity and volatility in the stressed global financial village. PloS One 7(2):31144

Kenett DY, Gao J, Huang X, Shao S, Vodenska I, Buldyrev SV, Paul G, Stanley HE, Havlin S (2014) Network of interdependent networks: overview of theory and applications. In: D'Agostino G, Scala A (eds) Networks of networks: the last frontier of complexity. Springer, Berlin, pp 3–36

Langfield S, Liu Z, Ota T (2012) Mapping the UK interbank system (manuscript). UK Financial Sevices Authority

LeBaron B (2006) Agent-based computational finance. Handb Comput Econ 2:1187–1233

Levy Carciente S, Kenett DY, Avakian A, Stanley HE, Havlin S (2014) Dynamical macro-prudential stress testing using network theory (available at SSRN 2482742)

Li D, Fu B, Wang Y, Lu G, Berezin Y, Stanley HE, Havlin S (2015) Percolation transition in dynamical traffic network with evolving critical bottlenecks. Proc Natl Acad Sci 112(3):669–672

Li W, Kenett DY, Yamasaki K, Stanley HE, Havlin S (2014) Ranking the economic importance of countries and industries (preprint). arXiv:1408.0443

Liljeros F, Edling CR, Amaral LAN, Stanley HE, Åberg Y (2001) The web of human sexual contacts. Nature 411(6840):907–908

Lillo F (2010) Networks in finance. In: Encyclopedia of life support systems (EOLSS), developed under the auspices of the UNESCO. Eolss Publishers, Oxford, UK

Lillo F, Moro E, Vaglica G, Mantegna RN (2008) Specialization and herding behavior of trading firms in a financial market. N J Phys 10(4):043019

Ludescher J, Gozolchiani A, Bogachev MI, Bunde A, Havlin S, Schellnhuber HJ (2014) Very early warning of next el niño. Proc Natl Acad Sci 111(6):2064–2066

Majdandzic A, Podobnik B, Buldyrev SV, Kenett DY, Havlin S, Stanley HE (2014) Spontaneous recovery in dynamical networks. Nat Phys 10(1):34–38

Mantegna RN (1999) Hierarchical structure in financial markets. Eur Phys J B Condens Matter Complex Syst 11(1):193–197

Martínez Jaramillo S, Kabadjova B, Bravo Benítez B, Solórzano Margain J (2012) Systemic risk analysis by means of network theory: an empirical study of the Mexican banking system. Technical report, Banco de México working papers

Milo R, Shen-Orr S, Itzkovitz S, Kashtan N, Chklovskii D, Alon U (2002) Network motifs: simple building blocks of complex networks. Science 298(5594):824–827

Minoiu C, Reyes JA (2011) Network analysis of global banking: 1978–2009. International Monetary Fund

Mu G-H, Zhou W-X, Chen W, Kertész J (2010) Order flow dynamics around extreme price changes on an emerging stock market. N J Phys 12(7):075037

Nardini C, Kozma B, Barrat A (2008) Whos talking first? Consensus or lack thereof in coevolving opinion formation models. Phys Rev Lett 100(15):158701

Newman MEJ (2009) Networks: an introduction. Oxford University Press, Oxford

Newman MEJ, Barabasi A-L, Watts DJ (2011) The structure and dynamics of networks. Princeton University Press, Princeton

Nier E, Yang J, Yorulmazer T, Alentorn A (2007) Network models and financial stability. J Econ Dyn Control 31(6):2033–2060

Onnela JP, Chakraborti A, Kaski K, Kertesz J (2003a) Dynamic asset trees and black monday. Phys A Stat Mech Appl 324(1):247–252

Onnela JP, Chakraborti A, Kaski K, Kertesz J, Kanto A (2003b) Dynamics of market correlations: taxonomy and portfolio analysis. Phys Rev E 68(5):056110

Onnela J-P, Saramäki J, Hyvönen J, Szabó G, Lazer D, Kaski K, Kertész J, Barabási A-L (2007) Structure and tie strengths in mobile communication networks. Proc Natl Acad Sci 104(18):7332–7336

Parshani R, Buldyrev SV, Havlin S (2010) Interdependent networks: reducing the coupling strength leads to a change from a first to second order percolation transition. Phys Rev Lett 105(4):048701

Parshani R, Dickison M, Cohen R, Stanley HE, Havlin S (2010) Dynamic networks and directed percolation. Europhys Lett 90(3):38004

Pastor-Satorras R, Vespignani A (2001) Epidemic spreading in scale-free networks. Phys Rev Lett 86(14):3200–3203

Pastor-Satorras R, Vespignani A (2007) Evolution and structure of the internet: a statistical physics approach. Cambridge University Press, Cambridge

Radicchi F, Fortunato S, Castellano C (2008) Universality of citation distributions: toward an objective measure of scientific impact. Proc Natl Acad Sci 105(45):17268–17272

Reis SD, Hu Y, Babino A, Andrade JS Jr, Canals S, Sigman M, Makse HA (2014) Avoiding catastrophic failure in correlated networks of networks. Nat Phys 10:762–767

Sandaval L Jr, Franca IDP (2012) Correlation of financial markets in times of crisis. Stat Mech Appl 391(1):187–208

Sandoval L (2014) Structure of a global network of financial companies based on transfer entropy. Entropy 16(8):4443–4482

Sendiña-Nadal I, Ofran Y, Almendral JA, Buldú JM, Leyva I, Li D, Havlin S, Boccaletti S (2011) Unveiling protein functions through the dynamics of the interaction network. PLoS One 6(3):17679

Shai S, Kenett DY, Kenett YN, Faust M, Dobson S, Havlin S (2014) Resilience of modular complex networks (preprint). arXiv:1404.4748

Shao J, Buldyrev SV, Braunstein LA, Havlin S, Stanley HE (2009) Structure of shells in complex networks. Phys Rev E 80(3):036105

Solomon S, Weisbuch G, de Arcangelis L, Jan N, Stauffer D (2000) Social percolation models. Phys A Stat Mech Appl 277(1):239–247

Song C, Havlin S, Makse HA (2005) Self-similarity of complex networks. Nature 433(7024):392–395

Soramäki K, Bech ML, Arnold J, Glass RJ, Beyeler WE (2007) The topology of interbank payment flows. Phys A Stat Mech Appl 379(1):317–333

Tesfatsion L (2002) Agent-based computational economics: growing economies from the bottom up. Artif Life 8(1):55–82

Tesfatsion L (2003) Agent-based computational economics: modeling economies as complex adaptive systems. Inf Sci 149(4):262–268

Tumminello M, Coronnello C, Lillo F, Micciche S (2007a) Spanning trees and bootstrap reliability estimation in correlation based networks. Int J Bifurc Chaos 17:2319–2329

Tumminello M, Di Matteo T, Aste T, Mantegna R (2007b) Correlation based networks of equity returns sampled at different time horizons. Eur Phys J B Condens Matter Complex Syst 55(2):209–217

Tumminello M, Lillo F, Mantegna RN (2010) Correlation, hierarchies, and networks in financial markets. J Econ Behav Organ 75(1):40–58

Upper C, Worms A (2004) Estimating bilateral exposures in the German interbank market: is there a danger of contagion? Eur Econ Rev 48(4):827–849

Wells S (2002) UK interbank exposures: systemic risk implications. Financ Stab Rev 13:175–182

Yamasaki K, Gozolchiani A, Havlin S (2008) Climate networks around the globe are significantly affected by El Nino. Phys Rev Lett 100(22):228501