Economic Networks: The New challenges

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Abstract We examine the emergent field of economic networks and explore what can or cannot be predicted and controlled in a global economy of transnational credit and investment networks, trade relations, and supply chains. New approaches to the study of economic network structure and dynamics need to go well beyond the systems used in economics that fail to take into account the interplay between agents, and the multiple sorts of entities and networks which they construct. These different elements interact to produce metastabilities, system crashes, and emergent structures that will initially be poorly understood. There are new challenges to much needed inquiry that combine time series analysis, complexity theory, and simulation with theorems drawn from graph and matrix theory and also some that need to be extracted from current simulations to reach a more general unification of theory and data models.

The current economic crisis illustrates a critical need for new and fundamental understandings of the structure and dynamics of economic networks. The problems that have initially emerged in discussion in the media on the global economic crises include considerations related to the separation of banking and investment, lack of transparency in exposing or hiding financial balance sheets and problems in a failure to limit excessive leveraging, to name but a few. Inherently involved even at this level are factors related to the structure and dynamics of economic networks of all sorts: production markets and stock, financial balance-sheet, and commodity trading networks, among many others.

In addition, the gaps in information are augmented by the rapidity of today's systems of electronic communication across national and globally networked markets, with variable intensity of ties and of scale, making attempts to understand or control
various properties of the emergent networked system difficult enough to identify let alone predict [9]. The danger of cascading network failures (33) is greater today than ever. Yet, even the simplest principle of increasing returns to scale—as a network phenomenon—was only recently accepted after it was hard fought in economics. Given the goals of the present discussion we review some of the approaches to the study of economic network structure and dynamics that have been taken and are being undertaken even as we write, but also briefly note past impediments to needed inquiry. \(^1\) In this context we examine aspects of economic networks that can or cannot be predicted and controlled in a global economy of transnational credit and investment networks, trade relations, and supply chains.

The current crisis poses opportunities to apply network approaches that revise and extend various established paradigms in economic theory. In this context we address new perspectives on the possibilities and need for network sciences to identify principles as to what makes make economic networks robust and efficient (i.e., maximizing benefits) in the face of network complexity. Causal analysis of time series will be needed if better policies, e.g., both to reduce conflicts between individual interests and the risk of global failure, can be designed. Network simulations of the dynamics of innovation involving transfer and growth of knowledge shows that network formation is inefficient if the time to evaluate new links is too short [8], which matches findings about time-lags for assimilating new knowledge and innovation in knowledge industries [24].

At this point in network sciences, predictions are often at the aggregate level. For example, the finding that European firm-to-firm foreign direct investment (FDI) stock is power-law distributed with number of employees in the investing firm and in the firm invested in, and with the number of incoming and outgoing investments of both firms [19] (single time-point data were collected in December 2004 from the Amadeus database of Bureau Van Dijk). This allows single time-point “predictions” about the investments that regions will receive or make, based on the activity and connectivity of their firms. Thus, firm activity and attractiveness are consonant. Temporal dynamics would need to be studied to see how these variables alter the probability of future activity and attraction in the short and the long run. Data models for networks and the attributes

\(^1\) New calls for research on these issues might be mentioned – by NSF in the US and by European agencies.
of their nodes and links need to be specified as to key elements and relations extrapolated from appropriate raw data to create a correspondence with theoretical variables so that theories can be tested.

Structural properties of networks generated with different stochastic algorithms (e.g., random, scale-free or small world networks) have been calculated for real complex networks, including those in biology (e.g., metabolic and genetic networks), to infrastructure (road networks and power grids), communication (internet and mobile phone) and social interaction (e.g., collaborations) (6;12;13). The comparison of network structures from these different disciplines suggests that various universality classes can be identified for economic networks, such as now the degrees (number of links) of nodes vary in frequency. Indeed, the degree distribution scales with a power law for the connections of banks in an interbank network (15;16), where the fat tail indicates that only few banks interact with many others. In this example banks with similar investment behavior form clusters in the network. Similar regularities also can be traced for the international trade network (ITN) (17;18), regional investment or ownership networks (19;20), among many potential examples. Regularities observed on the aggregate level, however, like a degree distribution that follows a power law (10), do not imply a specific underlying dynamics of the agents such as preferential attachment (10) to better-connected banks or countries, for example. Preferential attachment is just one of many generative processes for a power-law distribution.

The universality scaling properties of certain networks, such as power laws, thus provide only a first-order classification that emphasizes the role of fluctuations and randomness. We predict that the next generation of research will be challenged to measure causality in time series and deviations from universality and allow us to identify the idiosyncratic mechanisms associated with individual agent dynamics and their decision-making processes. This combination should eventually allow us to predict and propose economic policies that favor desired network structures such as those that show themselves more robust to economic shocks. Oversimplification, however, is the casualty of much prior work on universality classes in the topology of networks. Simply put: there has been too much spurious inference from forms of distributions to their generating
functions, and without testing through time-series analysis whether these are the actual
time-lagged generative processes.

Instead, the frontiers of research examining economic networks have been
advancing along two strands: one emanating from economics and sociology, the other
from research on complex systems in physics and computer science. In both, nodes
represent the different individual actors, or agents, such as firms, banks, or even
countries, and links between the nodes describe their mutual interactions, be it trade,
ownership, or credit/debt relationships. The addition or deletion of either agents or the
links between them, and changes in the direction of links, are fundamentals of network
formation. The socio-economic perspective emphasizes understanding how the strategic
behavior of the interacting agents is influenced by —and reciprocally shapes— relatively
simple changes in network architectures. One set of examples is given in a series of
studies by experts from different fields that explore how networks that are bipartite or
disassortative— like generalist and specialist “species nodes” in an ecosystem, or the
pairing of highly connected and less connected nodes in a network or an ecosystem of
plants and pollinators— are thought [A] or shown [15] to lend robustness, within certain
limits, against disturbance to ecosystems or markets, respectively. The alternation of
buyers and suppliers in production chains (avoiding triples and forming hierarchies) also
brings the appearance of structural stability [25]. These types of structures in economic
networks, however, have been shown to be vulnerable to cascades of failure: as when
production chains lack redundancies, certain ranges of flow parameters lead to
insolvencies [36], or problems of pricing created by noncompetitive buyers lead to
instabilities [25]. Bankruptcy cascades may occur from suppliers are not paid by those
who are their suppliers, or by unexpected shocks to revenues. Studies of local interactions
and global network properties go beyond the coupling of global averages, as when more
firms fail, raising the interest rate for all, causing still more to fail [36].

A further level of complexity of disassortative instabilities is shown in the study
of an overnight money market [15]. Here, a disassortative network tendency is induced
by big lenders having many small borrowers, or the reverse. The dominant tendency is
metastable (recurrent alternation without a system crash) where reversals depend on
whether interbank rates toward end-of-month short-term clearing days are decreasing
(favoring big lenders) or increasing (favoring buyers). In the loan network this is reflected by changes in the indegree versus outdegree distributions, where the dominant distribution tends to converge at month’s end to a power law. Thus a macro feature of the network (lending rates) affects disassortativity and a degree connectivity power law emerges from the short-term behaviors of the nodes. Metastable dynamical oscillations between these two disassortative states become unstable, however, when overall density of the network of loans passes a critical threshold. As shown by simulation [D] this is because disassortativity is no longer possible and uncertainty becomes greater for both buyers and sellers. [[ref D could conceivably be omitted because it is referenced in 15]]

Questions of how standing debts and claims between connected financial institutions affects the probability of a systemic failure has generated interesting insights (34;35). The Lehman Brothers failure offer a real world example but to offer a predictive theory here requires that we understand longer run dynamics. Most theoretical and empirical methods are not suited to predict cascading network effects. The assumption that a denser network of interbank loans or securitization would allow for a better diversification of the failure risk of individual nodes is suspect because risk is only transferred to another level. Simulation studies (36;37) suggest that greater aggregate risk may depend on the coupling strength between nodes. Simulations that account for the addition/removal of only single agents to/from the network at each instance of time can produce stable dynamic network models of aggregate risk, but the addition or removal of whole groups of agents to/from the network (e.g., as part of a systemic failure) may result in larger, less predictable effects and drastically change the stability of the system.

These examples show potential micro-macro network linkages where local network behavior interacts with more global network structure, i.e., in the exchange of knowledge, in trade, or investments. With some simplification, the behavioral or micro-perspective focuses on the system elements, and the global or macro-perspective focuses on the statistical regularities observed at the system level. A key challenge is to identify the paths through which the two largely separate strands of empirical research may converge, given that both graph theory and complexity theory [14] contain numerous mathematical proofs of strong theoretical ties between micro configurations and macro properties and structures in networks. The unification of empirical studies on the grounds
of basic theoretical commonalities may create a more unified field of economic networks that coalesces in a manner that advances our understanding and leads to further insight and predictions. The theorems of micro-macro network linkages [B,8] also support closer unification of simulation results and empirical studies, as exemplified here.

Economic networks are often viewed through the lens of a network formation game among competing and cooperating agents. In this regard, agents include firms that collaborate in joint R&D projects [1] or workers who share information on job opportunities [2], and links are added or deleted as the result of purposeful decisions by individual agents that seek to maximize their payoffs. Furthermore, agents must rely on some (generally imperfect and asymmetric) anticipation of what others will do with their (perhaps limited) information about their environment, they frame the problem within some (necessarily bounded) time horizon, and learn from past (and possibly biased) experience of similar situations [31]. These considerations result in a dramatically large number of options (strategies, interactions, etc.) to choose from and agents typically decide among them on the basis of boundedly-rational rules (3;4;5).

Analyzing economic networks of these sorts involves game theory, such as determining the equilibrium among possibly inefficient outcomes, but also examines problems in operations research, such as searching for partners and calculating expected payoffs over finite time horizons; such problems are the most difficult to solve in the context of complex network structures. These problems have been addressed with a mathematical framework or with simulations built on strong simplifications. The game theoretical approach usually limits the network context to the simplest topologies (such as a star or a complete network, where everyone interacts with all others). The game-theoretic literature highlights the crucial role of incentives in the endogenous and induced behavior of socio-economic networks such as those of collaboration, innovation and R&D (6;7;8). If we are to combine the micro and macro approaches the competition of interests between individual incentives and aggregate welfare need to be captured, along with their impact on the overall efficiency in the network performance.

The problem of equilibrium changes substantially if the underlying environment is subject to persistent volatility, such as rapid innovation, sociopolitical instability, or environmental change (9) and agents can not be posited to be at equilibrium. Models of
optimization do not work when agents follow simple satisficing rules (decision-making strategies that attempt to meet criteria for adequacy, rather than to identify an optimal solution) that may change in light of their experiences [31]. In such cases the ability of agents to attain (jointly) efficient configurations may be curtailed, as they are often sensitive to small changes in environmental volatility. The satisficing rule exemplified in Fig. 1 is one where agents lose ties randomly (creating tie volatility) and connect to the most connected neighbor’s most connected neighbor. Here there is a threshold probability at .5 that a node will lose a tie, below which clusters are maximally dense and above which they form core-periphery structures. This partner-selection rule is an example of local search processes in networks that have complex bifurcations of network structure as volatility changes [9].

In the complex systems approach, stochastic rules for link formation are tested to find the simplest assumptions that can reproduce statistical regularities in the observed empirical network structure. These rules take into account the characteristic features of the agents, such as their connectivity degree (number of links) or centrality (measuring the importance of a node either through the number of shortest or random paths that pass through it or the recursive weighting of the importance of its neighbors), and no longer focus purely on understanding the endogenous behavior of individual agents as strictly economically motivated agents. These models, therefore, supplement classical Walrasian (supply-and-demand driven) agents to identify as well the systemic implications of the network-formation rules on the emerging link structure (10;11) and of that link structure as a constraint on the options for agents.

In general, 'links' are not just binary (they either exist or not), but are weighted according to the economic interaction under consideration and represent traded volumes, invested capital, etc. and their weight can change over time. Distinguishing networks at different levels of abstraction, e.g., considering directed or undirected, weighted or unweighted links, may illuminate the evolution of their topological properties. We have seen how this works for the overnight money market example [15]. The worldwide network of major financial institutions has also been studied empirically (see Fig. 2).
Findings from study of the International Trade Network (21) emphasize how integrative weighting of ties due to the structure of the network (measuring betweenness as the proportion of times random walks between all pairs of countries pass through each other country, weighted by directed trading intensity) give a better sense of how strength of integration in the network differentiates the patterns of economic growth in different regions. Comparison of high-performing Asian economies (HPAE) with Latin American economies (LATAM) shows very similar in growth pattern over the eight 5-year periods from 1970 to 2005 when measured by amount of trade or trade relative to GDP, that is, by the trade attributes of the countries. The profile of growth in trade betweenness, however, shows the Asian Tigers to be very different as they become much more integrated into the world economy. Thus, network-based approaches provide a means by which to monitor complex economics systems, and may provide better control in managing and governing these systems. [[A slight qualm: Other studies show that GDP/capita is a good predictor of position as between core - IP or SP - P - O. Does it differentiate the Asian Tigers from the Latin American group as well as betweenness centrality? If not, score two for the network approach. Separate issue: [30] shows the network to be weakly assortative but that doesn’t add to the overall argument]]

We anticipate that a new wave of research should begin to merge the description of individual agent’s strategies with their co-evolving networks of interactions, enriched by theorems of micro-macro linkage that include those discovered in the process of simulation [8]. There is much more to discover from approaches combining the economic emphasis of individual strategic decisions with a network approach of interactions and adaptive feedbacks. Sometimes, such methods may lead to single equilibria, but more often they result in multiple coexisting equilibria, regime shifts and out-of-equilibrium transients, as well as sudden bifurcations to new regimes which more accurately characterize real-world systems. Below, we briefly describe problems that need to be tackled in this endeavor.

A rich research agenda in economic networks is being built upon the foundation of self-organization resulting from the interplay between a single agent’s action and the dynamic interactions among agents. However to maximize the information from such studies three lines of research must be pursued: (a) empirical studies providing insights
into economic networks from massive data analysis, (b) theory encompassing the appropriate description of economic agents (heterogeneity, strategic interaction) and their interactions (network dynamics, time boundedness, coevolution of agents and interactions), and (c) a systemic perspective bestowing a new understanding of systemic effects as coming from varying network interactions.

The network approach brings a whole new series of theorems [8,B], many of which are used in very specific applied contexts in simulations, that bring new understandings to the interdependencies of multilevel economic network phenomena that have seemed intractable. This greatly strengthens the early view of network economy [32] that “Such analysis can give rise to interesting behaviour on the aggregate level which is very different from that which might have been predicted by looking at the individuals in isolation.” Even this modest claim, however, belies the methodological individualism that was axiomatic to classical economic theory.

Our supplementary materials provide additional discussions of more specific problems in economic network science and some additional references:

- Massive Data Analysis
- Time and Space
- Structure Identification
- Beyond Simplicity
- Experimental Network Economics
References


22 (Supplementary)
23 (Supplementary)
26 (Supplementary)
27 (Supplementary)
28 (Supplementary)
29 (Supplementary)
30 (Supplementary) could be cited in the text along with 15 but could be dropped … right
now it’s in Supplementary
31 (Supplementary)
2003.
[34] F. Allen and D. Gale. Financial contagion. Journal of political economy,
chains and bankruptcy propagation in production networks. Journal of Economic
[37] Jan Lorenz and Stefano Battiston. Systemic risk in a network fragility model
analyzed with probability density evolution of persistent random walks. Networks and
Heterogeneous Media, 3(2):185{200, 2008.

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Figures
Fig. 1: The structure and efficiency of an equilibrium network strongly depend on the
conditions under which myopic selfish agents can form links. The underlying model
assumes that agents prefer to connect to the neighbors of their neighbors that have a
higher centrality, creating local shortcuts. Network efficiency is measured on the basis of
the aggregate centrality. Environmental volatility results from the risk that any single
agent is exposed to an exogeneous shock, forcing the deletion of one link. Beyond a
critical volatility, the strongly homogeneous network structure will break down into a
sparse, hierarchical structure, similar to a core-periphery structure, found e.g., in interbank payment networks and is accompanied with a breakdown in network efficiency.

Fig. 2: A sample of the international financial network, where the nodes represent major financial institutions and the links (directed and weighted) represent the strongest existing relations among them. Node colors express different geographical areas: European Union members (red), North America (blue), other countries (green). Even with the reduced number of links, the network shows a high connectivity among the financial institutions that have mutual shareholdings as well as longer cycles indicating a strong interdependency within the financial sector that may affect market competition and systemic risk. [Data- please move to the references and ref to the number Orbis Database (End of 2007), Bureau Van Dijk. The figure illustrates that the density of the network (together with the cycles) for real networks is indeed quite high, which makes it vulnerable to instability.

**Supplementary material**

**Massive Data Analysis:** Knowledge of how systems of connections work will rely on our ability to obtain more and better data, fostering the transition of the field of economics networks from a qualitative to a quantitative and evidence-based science. As computational power increases it allows large scale network data on different levels of the economy (e.g., firms, industries, countries) to be gathered as well as the testing of models reflecting the generation of large synthetic data sets. In fact, new means by which business data and internet communication are processed [FRANK, MICHAEL: ??], allows for analysis of data soon to be or already available This includes detailed panel data (longitudinal or cross-sectional time series data) on specific firm interactions (employee flows, R&D collaborations, etc.) or firm-bank credit market interactions. The ability to process large data streams will require new tools to squeeze out every last drop of available information reflecting agent interactions and network properties (instead of deriving them from theoretical approaches). Such databases therefore, may complement
both economic network experiments (22*;23*) and empirical economic network studies (24;25*;26*) by allowing large-scale observations in real-time (27*).

**Time and Space:** Time-dependent resolution of the properties of economic networks moves beyond a single-snapshot approach, and allows the researcher to identify conditions for dynamical or path dependent evolution of networks by combining findings with complementary information, i.e. the correlations between economic network evolution and other macroeconomic dynamics. For example, the longitudinal analysis of human biotechnology (24*) suggests that there is a life cycle of research and development networks related to the timing of the exchange of knowledge. ORDER REVERSED Economic networks, as other real-world systems, also evolve in physical space as well as time. The transmission of information or the adoption of a new states and physical distances for interaction, such as trade, occurs over natural time scales. This challenges both theoretical concepts and how raw data are mapped into data models for testing against theory in ways that may be advantageous to scientific advances because of the real-world constraints of time and space that are already well modeled and provide an opening for combining physics approaches with social theory and models.

**Structure Identification:** Extracting network structure from reported data, in particular for aggregated economic data, is very difficult. For example, the banking sector does not make all debt/credit relationships publicly available although theoretical decompositions of aggregated data have been studied (16). Even then, analyses may resemble reading tea leaves: only what was previously known or predicted is revealed. Statistical regularities in economic networks have been identified through sheer data processing, but challenges the importance of the various measures that are input in large scale network characterization. Thus, the utility of each term needs to be critically examined. Specifically,

- How can we extract information about the role of agents about their function or their influence in an evolving economic network? (28*,29*)
- What is the best use and interpretation of different aspects and measures of the distance between nodes?
- Similarity for the different aspects and measures of centrality?
Given that measures such as multiconnective cohesion are useful indicators (24*) related to causal processes, can we handle their computational complexity through cloud computing and use of supercomputers?

New methods are needed to identify patterns, new concepts to quantify control (direct and indirect) need to be developed—a task beyond economic applications. Promising steps have already been taken, as demonstrated by the identification of the backbone of control in ownership networks (20). roles defined by structural position (29*) or centrality rankings (21) in the ITN.

**Beyond Simplicity:** It is natural for theoretical investigations to treat the constituents of economic networks as basically homogeneous (accounting of course for their different size, etc.). Many analytical results, such as those on efficient and equilibrium networks outcomes or suing expressions for some macroscopic network properties, are dependant on this assumption. However, any prediction of phase transitions, i.e. abrupt changes beyond a critical value of some control variable, may fail under these simplified assumptions, as with the differences between weighted and unweighted network properties studied for the ITN case ([21],30*).

All economic networks are heterogeneous with respect to both their agents and interaction strength, which can vary in time. Agents may have different preferences, access to resources, failure thresholds, and will not respond to the same influence in the same (predictable) way. Although such variation might be thought to destabilize a system, heterogeneity can also be a source of stability (31*). Moreover, agent features are not constant in time, as they are co-evolving in concert with the network structure and are able to adapt to their environment (32).

Further, network interactions may be multilevel, elements of a given type may be multiscale, and the types of elements may be multiple, i.e., multi-mode, as with 2-mode memberships of agents in organizations. Most models, both in the field of strategic interaction and complex network approaches, ignore these variations.
Experimental Network Economics: In addition to empirical analysis of network structure and dynamical analysis of structural change in networks or the node and link attributes of networks, the field of experimental economics [22*,23*] provides a source of cross-validation of results to the economic network sciences, and while this cross-fertilization has already begun (24*), we predict that these intersections will provide a rich source of stimulation for the next generation of researchers.

* 10 References found only in Supplementary Bibliography

Supplementary Bibliography