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remedy this initial failure, the government reopened the fishery but divided the coastal area into more than 50 sectors, assigned transferable quotas, and required that all ships have neutral observers onboard to record all catches (*32*).

Furthermore, the long-term sustainability of rules devised at a focal SES level depends on monitoring and enforcement as well their not being overruled by larger government policies. The long-term effectiveness of rules has been shown in recent studies of forests in multiple countries to depend on users' willingness to monitor one another's harvesting practices (*15*, *31*, *33*, *34*). Larger-scale governance systems may either facilitate or destroy governance systems at a focal SES level. The colonial powers in Africa, Asia, and Latin America, for example, did not recognize local resource institutions that had been developed over centuries and imposed their own rules, which frequently led to overuse if not destruction (*3*, *7*, *23*).

Efforts are currently under way to revise and further develop the SES framework presented here with the goal of establishing comparable databases to enhance the gathering of research findings about processes affecting the sustainability of forests, pastures, coastal zones, and water systems around the world. Research across disciplines and questions will thus cumulate more rapidly and increase the knowledge needed to enhance the sustainability of complex SESs. Quantitative and qualitative data about the core set of SES variables across resource systems are needed to enable scholars to build and test theoretical models of heterogeneous costs and benefits between governments, communities, and individuals and to lead to improved policies.

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PERSPECTIVE

Economic Networks: The New Challenges

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The current economic crisis illustrates a critical need for new and fundamental understanding of the structure and dynamics of economic networks. Economic systems are increasingly built on interdependencies, implemented through trans-national credit and investment networks, trade relations, or supply chains that have proven difficult to predict and control. We need, therefore, an approach that stresses the systemic complexity of economic networks and that can be used to revise and extend established paradigms in economic theory. This will facilitate the design of policies that reduce conflicts between individual interests and global efficiency, as well as reduce the risk of global failure by making economic networks more robust.

The economy, as any other complex system, reflects a dynamic interaction of a large number of different agents, not just a few key players. The resulting systemic behavior, observable on the aggregate level, often shows consequences that are hard to predict, as illustrated by the current crisis, which cannot be simply explained by the failure of a few major agents. Thus, we need a more fundamental insight into the system's dynamics and how they can be traced back to the structural properties of the underlying interaction network.

Research examining economic networks has been studied from two perspectives; one view comes from economics and sociology; the other originated in research on complex systems in physics and computer science. In both, nodes represent the different individual agents, which can represent firms, banks, or even countries, and where links between the nodes represent their mutual interactions, be it trade, ownership, R&D alliances, or credit-debt relationships. Different agents may have different behaviors under the same conditions and have strategic interactions (*1*). These evolving interactions can be represented by network dynamics that are bound in space and time and can change with the environment and coevolve with the agents (*2*). Networks are formed or devolve on the basis of the addition or deletion of either agents or the links between them.

The socioeconomic perspective has emphasized understanding how the strategic behavior of the interacting agents is influenced by—and reciprocally shapes—relatively simple network architectures. One common example is that of a star-spoke network, like a very centralized or-

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ganization, in which a central "hub" channels all communication among agents. In this "micro" perspective we focus on the individual system elements and their detailed network of relations. In contrast, for large setups, one adopts a "macro" perspective that focuses on the statistical regularities of the network as a whole. Each approach has its advantages and disadvantages. Previous work on the micro perspective was strongly rooted in oversimplifying assumptions on both the structure of the network and on agents' behaviors (*3*). For example, the micro approach may have emphasized agent incentives in the development of informal links within firms and may have failed to successfully predict realistic dynamic outcomes. The macro approach better accounts for the large-scale system properties, but fails in linking these to the economic motivation of individual agents (*4*).

In recent micro approaches, economic networks were often viewed as the result of a network-formation game among competing and cooperating agents. In this regard, agents include firms that collaborate in joint R&D projects (*5*) or workers who share information on job opportunities (*6*); their links are added or deleted as the consequence of purposeful decisions attempting to maximize their payoffs. In this context, agents must rely on (and be able to) anticipate what others may do (in a generally imperfect and asymmetric manner); use information about their environment (which may be limited); frame the problem within some necessarily bounded time horizon; and learn from the past, which may create a biased experience if similar situations are encountered later.

These considerations tended to result in a dramatically large number of options that agents must choose from on the basis of limited information. The micro analysis of economic networks relies on game theory, which aims at identifying Nash equilibria (i.e., situations that are strategically stable in the sense that no agent has an incentive to deviate). It can also rely on operations research, where algorithms for searching and optimizing have been developed. As the number of nodes and possible links scales up, however, such problems become very difficult to solve, and classical approaches are unsatisfactory.

The game-theoretic literature has highlighted the crucial role of incentives in the endogenous and induced behavior of socioeconomic networks (*3*, *7*, *8*). However, this micro approach has not typically been integrated with macro approaches that can identify the complex systemic forces at work. Without this information, we cannot fully understand important issues, such as the conflict between individual incentives and aggregate welfare, or their impact on the overall efficiency in the performance of the network at large. Furthermore, this problem is exacerbated if the underlying environment is subject to persistent volatility, which may, for example, be due to the intrinsic ephemerality of innovation (*9*), and if agents are out of equilibrium, as in most real-world situations. If this is the case, it is reasonable to posit that agents follow simple bounded-rational rules that are modified in light of their experiences. However, under such conditions, agents are unable to attain efficient configurations, despite their continuous efforts to adapt to an ever-changing situation. Additionally, even small changes in environmental volatility can have drastic consequences in the overall configuration of the system [e.g., (Fig. 1)].

The inability of previous approaches to reproduce statistical regularities that have been observed empirically in network structures justifies our pursuit of a complex-systems approach that may provide predictions for large-scale networks. These predictions are made from the testing of stochastic rules that affect link formation and that take into account, in addition to some sort of randomness, the characteristic features of the agents, such as their degree of connectivity (number of links) or their centrality, as measured on the basis of the importance of a node—which, in turn, can be affected by its links to other nodes.

However, the complex-systems approach postulates rules exogenously and does not explicitly examine how these rules might be grounded on the basis of the economic incentives of the agents. Thus, instead of focusing on understanding the endogenous behavior of individual agents, the complex-systems approach centers on understanding how the network-formation rules systematically affect the emerging link structure (*4*).

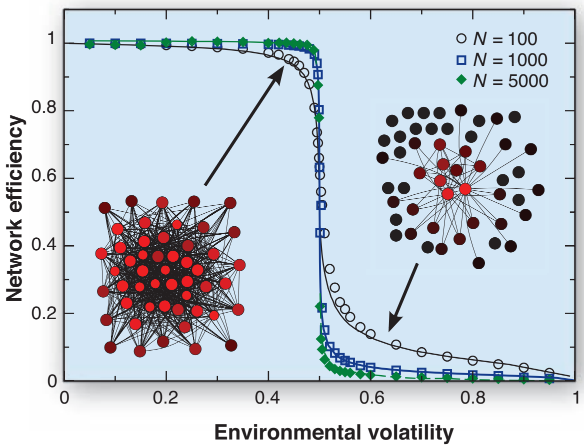

Fig. 1. The structure and efficiency of an equilibrium network strongly depend on the conditions under which myopic agents can form links. We show computer simulations that assume that agents prefer to connect to the neighbors of their neighbors that have a higher centrality, which creates local shortcuts. Network efficiency is measured on the basis of the aggregate centrality of agents. Environmental volatility measures the risk that if any single agent is exposed to an exogeneous shock, it will force the deletion of one link. If the loss of links pushes the network efficiency down and environmental volatility up past some critical level, the strongly homogeneous network structure will break down into a sparse, hierarchical structure, similar to a core-periphery structure and is accompanied with a breakdown in network efficiency.

Networks generated with different stochastic algorithms, such as random, scale-free or small-world networks, have been compared with real complex networks including those in biology, i.e., metabolic and genetic networks; infrastructure, i.e., road networks and power grids; communication, i.e., internet and mobile phone; and social interaction, i.e., collaborations (*1*, *2*, *10*). Comparing network structures across these different disciplines suggests that economic networks may also reflect a similar universality (*11*). Indeed, the connections of banks in an interbank network (*12*, *13*), show the fat tail, characteristic of a scale-free system, that indicates that only a few banks interact with many others. In this example, banks with similar investment behavior will cluster in the network. Similar regularities also can be traced for many examples including the international trade network (ITN) (*14*, *15*) and regional investment or ownership networks (*16*).

In the complex-network context, "links" are not binary (existing or not existing), but are weighted according to the economic interaction under consideration [for example, in a network of major financial institutions worldwide shown in (Fig. 2)]. Furthermore, links represent traded volumes, invested capital, and so on, and their weight can change over time. Distinguishing networks at different levels where we consider directed or undirected and weighted or unweighted links helps illuminate the evolution of their topological properties.

When the foreign direct investments (FDI) among European firms are presented as a directed network, power-law scaling is observed. This scaling depends on the number of employees in both the investing and the firm invested in, and on the number of incoming and outgoing investments of both firms (*16*) This allows single time-point predictions about the investments that regions will receive or make, on the basis of the activity and connectivity of their firms.

Similar structural transitions can also be detected in the ITN. By weighting a country's centrality in terms of the likelihood that any given additional dollar traded in the world reaches that country by following existing links with a probability proportional to its weight, the relative changes in centrality over time show trends for different countries that predict divergence in

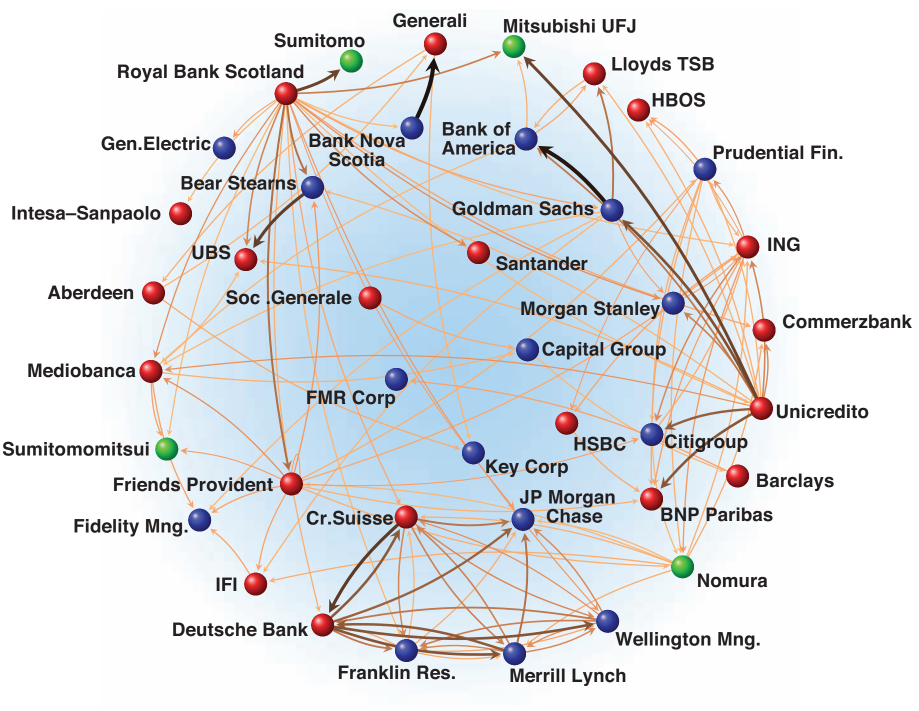

Fig. 2. A sample of the international financial network, where the nodes represent major financial institutions and the links are both directed and weighted and represent the strongest existing relations among them. Node colors express different geographical areas: European Union members (red), North America (blue), other countries (green). Even with the reduced number of links displayed in the figure, relative to the true world economy, the network shows a high connectivity among the financial institutions that have mutual share-holdings and closed loops involving several nodes. This indicates that the financial sector is strongly interdependent, which may affect market competition and systemic risk and make the network vulnerable to instability.

regional integration within the global economy and do so better than traditional international trade and macroeconomic statistics (*17*). This is also because the latter do not account for the entire network topology but only consider bilateral direct trade links. For example, between 1980 and 2005 East Asian countries experienced huge increases in their centrality scores, but the centrality ranking of most Latin American countries fell. The trade statistics of these regions, however, displayed similar patterns. In other words, these astonishingly different development records were not well tracked by international trade and macroeconomics statistics. Thus, network-based approaches may provide a more powerful way to manage, monitor, and govern complex economics systems.

However, a focus on centrality or other such properties of networks can only provide a first-order classification that emphasizes the role of fluctuations and randomness and cannot predict the underlying dynamics of the agents, whether they are firms or countries. We anticipate that the next generation of research will be able to measure any deviations from universality and will allow us to identify the idiosyncrasies associated with individual agent dynamics and their decision-making processes. This new wave of research should begin to merge the description of individual agents strategies with their coevolving networks of interactions. We should then be able to predict and propose economic policies that favor networks structures that are more robust to economic shocks and that can facilitate integration or trade. Below, we briefly describe what is needed to tackle this endeavor.

Massive data analysis. Our ability to obtain more and better quality data will foster the transition from a qualitative to a quantitative and evidence-based science. As computational power increases, large-scale network data can be gathered for different levels of the economy (e.g., firms, industries, and countries), and models can be tested through the generation of large, synthetic, data sets. New processing methods should open a wide range of business data and internet communication that can be exploited. It will then be possible to gather individualized data on specific interactions over time such as employee flows, R&D collaborations, and so on within a business or firm-bank credit market interactions. These large data streams require more powerful tools to digest and manipulate the huge scale of available information reflecting agent interactions and network properties. Databases containing this information may therefore complement both theoretical economic network experiments (*18*, *19*) and empirical economic network studies (*20*, *21*) and provide large-scale observations in real-time (*22*).

Time and space. By allowing a time-dependent resolution of the properties of economic networks, we will be able to move beyond a single-snapshot approach. This will allow the researcher to identify the evolutionary path of networks through the combination of complementary information sources. A good illustration of this is provided by the R&D networks in the field of human biotechnology (*20*), which follow a predictable life cycle related to the timing of the exchange and integration of knowledge.

Structure identification. Extracting network topology from reported data, in particular for aggregated economic data, is very difficult. This is particularly true for the banking sector, where detailed accounts of debt-credit relations are not publicly available, although theoretical decompositions of aggregated data have been studied (*13*). Even then, analyses may resemble reading tea leaves and reveal only previously known or predicted information. Statistical regularities in economic networks can be identified through large-scale data sets, but difficulties in assessing the relevance of the various measures remain. In an evolving economic network, we require information about agents' roles, their function and their influence (*23*). New methods are needed to identify patterns, and new concepts are needed to quantify both direct and indirect influence (e.g., through ownership). The identification in the ITN of such roles based on similar positions in the network suggests that promising steps have begun to identify functional roles played by interactive agents that relate to specific patterns in the link structure of their multirelational interaction network (*24*). Mapping a large network as a homologous small one, with statistically optimal sets of distinctive roles, gives a statistical correspondence in the case of the ITN world alignments for New World–Afro–East Asian versus North and Central Eurasia alignments by cross-cutting each of their interconnected cores, semiperipheries, and peripheries, as in world system models, but with much greater precision.

Beyond simplicity. All economic networks are heterogeneous with respect to both their agents and interaction strength and can also strongly vary in time (*25*). Previous studies of efficient (i.e., not wasteful) and equilibrium (or strategically stable) networks assumed homogeneity. However, as the differences between weighted and unweighted network properties indicate for the ITN case (*14*), any prediction of phase transitions may fail under these simplified assumptions. In fact, heterogeneities of agents can turn out to prevent phase transitions, i.e., become a source of stability.

Systemic feedbacks. Simple amplification mechanisms (such as herding) can dominate the network dynamics at large, despite the best intentions of the agents. Economic networks are subject to amplifications that may result from the redistribution of the load if one node fails (e.g., electricity in a power grid or credit debt in a banking network). If a single node fails, it may force other nodes to fail as well, which may eventually lead to failure cascades and the breakdown of the system, denoted as systemic risk. This applies in particular to financial networks where links represent standing debts and claims between connected financial institutions. However, it is not well understood how the structure of a financial network affects the probability of a systemic failure. Although a topical subject, most theoretical and empirical methods are not suited to predicting cascading network effects. The mainstream view assumes that a denser network allows for a better diversification of the individual failure risk (*26*). However, systemic risk has been shown to increase, depending on the coupling strength between nodes (*27*). Furthermore, most stable dynamic network models account for only the addition or removal of a single agent to or from the network at each instance of time. However, the addition or removal of whole groups of agents to or from the network (e.g., as part of a systemic failure) may result in a larger, less predictable, and less stable system.

In summary, we anticipate a challenging research agenda in economic networks, built upon a methodology that strives to capture the rich process resulting from the interplay between agents' behavior and the dynamic interactions among them. To be effective, however, empirical studies providing insights into economic networks from massive data analysis, theory encompassing the appropriate description of economic agents and their interactions, and a systemic perspective bestowing a new understanding of global effects as coming from varying network interactions are needed. We predict that such studies will create a more unified field of economic networks that advances our understanding and leads to further insight. We are still far from a satisfactory identification and integration of the many components, but the recent advances outlined suggest a promising start.

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PERSPECTIVE

Predicting the Behavior of Techno-Social Systems

Alessandro Vespignani

We live in an increasingly interconnected world of techno-social systems, in which infrastructures composed of different technological layers are interoperating within the social component that drives their use and development. Examples are provided by the Internet, the World Wide Web, WiFi communication technologies, and transportation and mobility infrastructures. The multiscale nature and complexity of these networks are crucial features in understanding and managing the networks. The accessibility of new data and the advances in the theory and modeling of complex networks are providing an integrated framework that brings us closer to achieving true predictive power of the behavior of techno-social systems.

Modern techno-social systems consist of large-scale physical infrastructures (such as transportation systems and power distribution grids) embedded in a dense web of communication and computing infrastructures whose dynamics and evolution are defined and driven by human behavior. To predict the behavior of such systems, it is necessary to start with the mathematical description of patterns found in real-world data. These descriptions form the basis of models that can be used to anticipate trends, evaluate risks, and eventually manage future events. If fed with the right data, computational modeling approaches can provide the requested level of predictability in very complex settings. The most successful example is weather forecasting, in which sophisticated supercomputer infrastructures are used to integrate current data and huge libraries of historical meteorological patterns into large-scale computational simulations. Although we often complain about the accuracy of daily weather forecasts, we must remember that numerical weather models and predictions allow us to project the path and intensity of hurricanes, storms, and other severe meteorological occurrences and, in many cases, to save thousand of lives by anticipating and preparing for these events.

Given the success that has been achieved in weather forecasting for decades, why haven't we achieved the same success in the quantitative prediction of the next pandemic spatio-temporal pattern or the effects over the next decade of connecting billions of people from China and India on Internet growth and stability? The basic difference is that forecasting phenomena in techno-social systems starts with our limited knowledge of society and human behavior rather than with the physical laws governing fluid and gas masses. In other words, though it is possible to produce satellite images of atmospheric turbulence, we do not yet have large-scale worldwide, quantitative knowledge of human mobility, the progression of risk perception in a population, or the tendency to adopt certain social behaviors. In recent years, however, tremendous progress has been made in data gathering, the development of new informatics tools, and increases in computational power. A huge flow of quantitative data that combine the demographic and behavioral

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