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Interdependent networks in Economics and Finance—A Physics approach

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H I G H L I G H T S

- Understanding mechanisms of systemic failure allows devising immunization strategies.
- Fragility in interdependent networks behaves markedly different than single networks.
- Monitoring evolution of risk concentration requires understanding of interdependence.
- Risk mitigation, optimal repair strongly depend on interdependent network structure.
- Network-based economic importance highlights surprising players in global economy.

A R T I C L E I N F O

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A B S T R A C T

Over the past few decades the world underwent several major economic and financial bubbles, such as the dot-com bubble of early 2000s and the global crisis following the collapse of the US housing market in 2008. Here we review the progress made in network theory as applied to economics and highlight some important insights complex networks allow into the highly interconnected economic system. Richness of phenomena that appears once we increase our complexity beyond a single network is explored and main results, as well as future research are discussed.

1. Progress in complex networks

It has been long understood that while fundamental Erdos–Renyi (E–R) random graphs provide a leap forward from mathematical theory to real life complexity, the leap may not suffice. Characteristics such as Small world and the scale-free degree distribution found in real-world networks strongly disagree with the E–R model and lead to phenomena not found in simple random graphs. An important example is the existence of a giant cluster (i.e. a connected subset of nodes that grows extensively with the graph) above a finite critical average degree in E–R networks, known as the percolation transition, and the lack of such transition (ubiquitous existence of a giant cluster) for scale free networks.

Models of networks exhibiting real-world link lengths and degree distributions have been constructed and studied with interesting results [1–7]. The past two decades have seen an explosion of research applying ideas from complex networks to many various fields of science, from cellular biology [8–11] through internet modeling [3,12–14] and traffic [15] to climate phenomena [16–18]. A field that started from questions of crossing bridges, traversing graphs, coloring them and splitting them into subsets saw wide applicability with the understanding that networks not only show interesting behavior (percolation transition) but can also provide reasonable description of real-world scenarios (small world phenomenon,

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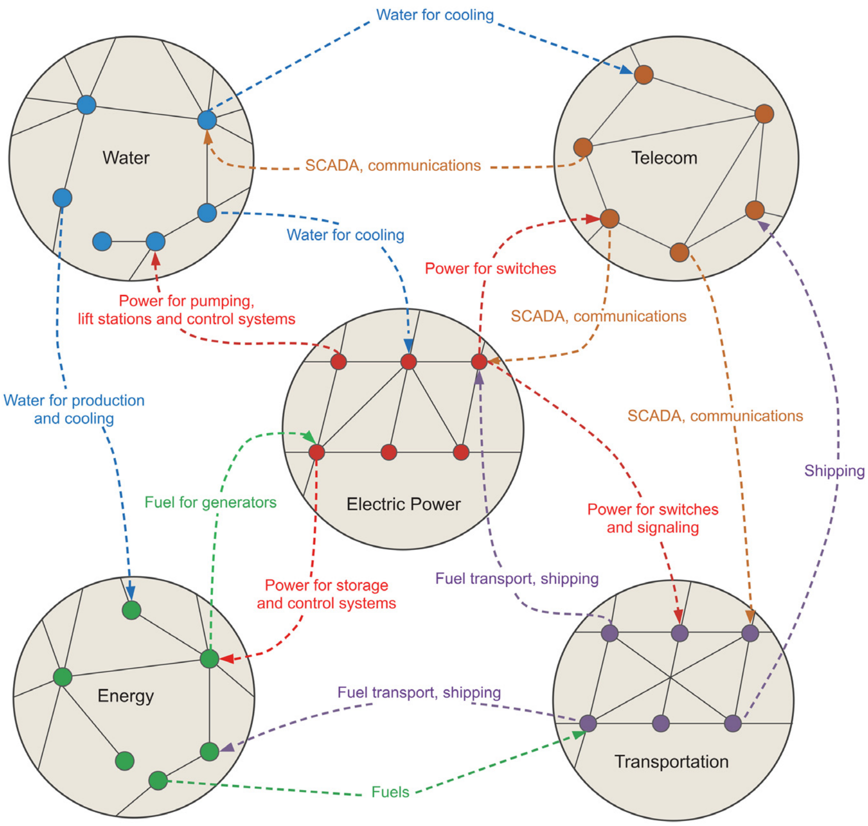

Fig. 1. An example of the non-trivial inter-network relation as it takes place in the infrastructure setting. Every network may provide every other network with resources critical for their operation. As shown in [19] a collapse of a power grid node may cause a cascading failure to spread, among others, and cause the collapse of the telecommunications network.

scale-free degree distribution). These and other findings helped make noticeable progress in our understanding of complex systems. There remain, however, layers beyond the explaining power of classical complex networks.

Most systems in real life, whether biological, natural or man-made, do not seem to exist in isolation but rather as a part of a wider, interacting system (e.g. see Fig. 1). The added level of complexity leads to new and important phenomena.

Networks of varying topologies and interconnectedness drew attention as a better and more realistic representation of our interconnected world and the physical phenomena they revealed showed new levels of richness.

One prominent way to bring theoretical models closer to their real-life counterparts is to define several networks, each existing in their own right, and then add interactions between those networks (Fig. 1). One example where the distinction is clear is the case of connectivity links within each network and dependency links between networks. A classic example from [19] is that of a power grid as one network and its communication controlled system as the other allowing each other to function. In the model proposed, the networks are interconnected via dependency links in such a manner that a collapse of a node in one network causes the collapse of its dependent node in the other. Nodes that find themselves disconnected from the giant component due to their neighbors' collapse also shut down causing a cascading failure to spread through the networks. When the initial impact is at or above a critical level both networks collapse.

A significant reason to explore complex systems is to assess their fragility or ability to withstand random failure or targeted attacks. The motivation is clear—collapse of infrastructures, spreading of disease or onset of financial crises all have great bearing on society and thus need to be understood and possibly mitigated. Answers to these questions may (and often do) depend on the topology of the network of networks, its dynamics and the mechanism of failure propagation. Following the new approach of interdependent networks, qualitatively new types of behavior emerged [20].

Interacting networks, networks of networks and multilayer networks became the new frontier in network science [19–27].

As with simple networks, different networks-of-networks structures (Fig. 2) lead to different phenomena [24–26] with the additional degree of freedom from the behavior of the dependency links (one may vary how many dependent layers there are and how strongly they are interdependent, for example). All these affect, among others, the propagation of cascading failure and redefine fragile networks.

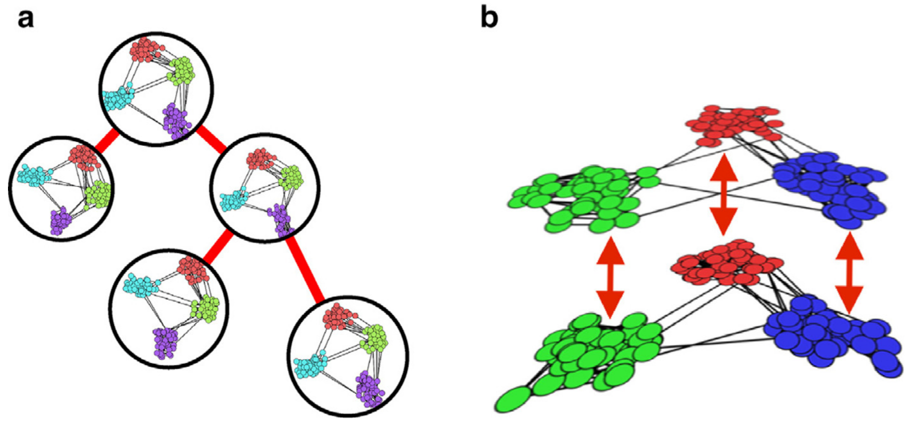

Fig. 2. (a) A treelike network of networks where each network has a modular structure. Dependency links (red) are restricted such that they only connect nodes within the same communities, i.e. a node in module m_a in network i will depend on a node also in module m_a in network j. (b) Demonstration of the dependency relations between a pair of interdependent networks. Dependency links exist between nodes of the same color in different layers. After [23] . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

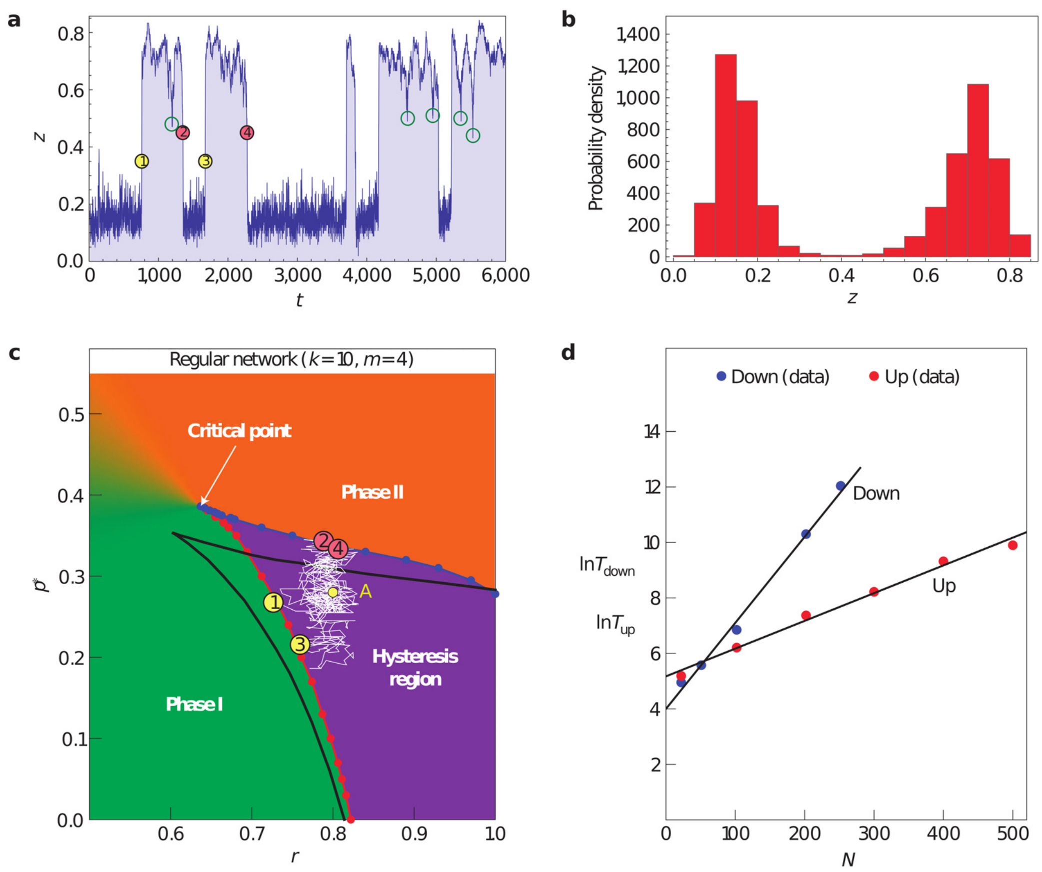

Fig. 3. a. Active and inactive phases of the network b. the bimodal probability distribution of fraction of active nodes. c. The phase space of the system with a specific realization of a path of the system in a single simulation. d. The lifetime of the system per state vs various system sizes. After [29].

2. Physics of interdependent networks

Traditional complex networks have been rigorously analyzed for almost two decades. It was shown that when a change in the state of activity of even a single node occurs, the network undergoes nontrivial phase transitions [28].

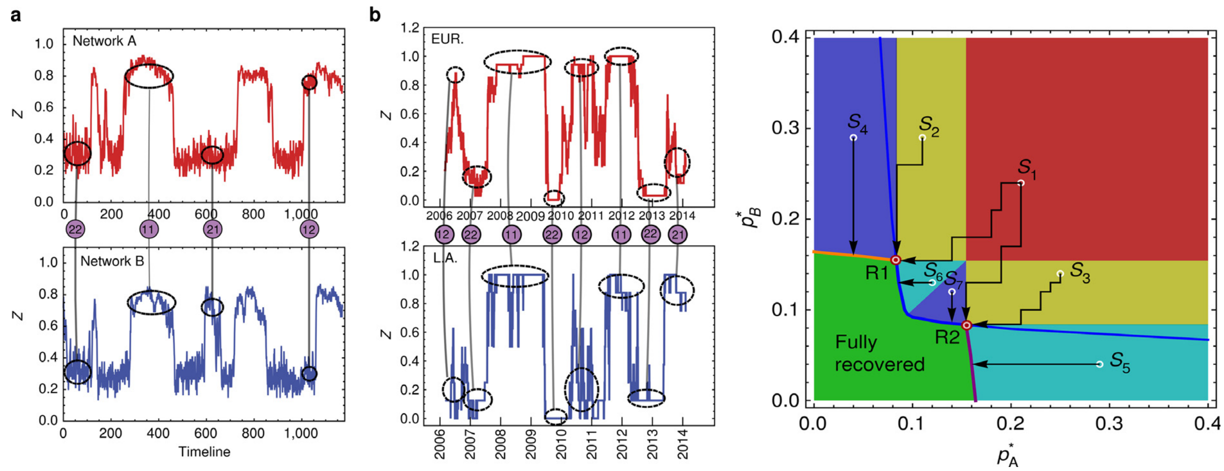

Fig. 4. Left: Simulated (a) and real (b) coupled networks, showing transitions between phases as described in [30]. Knowing what state the coupled system is in can help devise an optimal restoration strategy (Right). Right: Phase space for two interdependent networks. After [30].

Majdandzic et al. [29] introduced the concept of recovery in percolation where nodes are allowed to recover, i.e. return after failure from an inactive state (0) to an active state (1). In this case, a richer phase space is discovered showing a hysteresis region that allows active and inactive phases to occur spontaneously. Additionally, it permits large moves (called "flash crashes") that do not result in global phase transitions (Fig. 3, a, c).

Another story altogether emerges when recovery exists and networks are interdependent [30]. Assuming two networks with two states each, there are now 10 different possible phase transitions. Importantly, the dependence here is probabilistic rather than deterministic—in the models described above a failure of a node on one end of a dependency link led to a failure of the node on the other side. Here, however, a failure of a node in one network increases the probability of failure for the connected node in the adjacent network but not to unity.

We began with complex networks with a single possible transition (active → inactive) that demonstrated cascading failures. Next, we saw single networks with recovery dynamics (active → inactive → active) leading to bimodal activity dynamics and allowing phenomena reminiscent of the flash crash (whereby an asset or financial index dip strongly and recover fast), see Fig. 3a. Finally, we get to coupled systems with complicated phase transitions. For example, in Fig. 3a we observe four possible states compared to two states found for a single network (Fig. 3a). Fig. 4b shows that Fig. 4a behavior is similar to coupling between markets in financial systems where, as shown below, different markets (Credit Default Swaps in the example below) may be found in opposite or identical states at various points in time (Fig. 4, right).

3. Networks in economics and finance—an introduction

The global financial crisis of 2008 led by the burst of the housing bubble in the US and exacerbated by complicated financial instruments spread throughout financial institutions worldwide and is still felt today. Central banks only now, a decade later, are starting to raise interest rates and slow down purchases of government issued bonds. The direct result is at best a decade during which conservative investments were almost worthless in terms of yield which led many money managers to invest in riskier assets seeking returns. A noteworthy event was the credit crunch at the very beginning of the 2008 crisis following the collapse of Lehman Bros. It was noted that the tight relationships between various bank significantly contributed to the scale and spread of the impact. This presented itself as an ideal candidate for development of network methodologies in order to better understand the origins of the crisis. It was of interest to show whether or not a cascading failure process may take place in a financial network and if so how it may be explained. Like much of network science, initial progress in the application of complex networks to economics and finance was made using the single layer framework.

More specifically, in the case of bipartite graphs, it was shown with a fairly parsimonious model of shared holdings [31], where multiple banks hold the same set of assets (Fig. 5). A surprising result of this model is that the classical financial approach of diversification as a method of risk reduction may not achieve the desired results as it in fact leads to stronger coupling between institutions and increases the likelihood of systemic failure.

The model managed to capture the phenomenology of cascading failure and correctly score the riskiest type of loans, as well as identify failed banks. The idea that banks' interconnectedness may contribute to *systemic* risk existed for a while ([32,33] to name a few) however network theory required for thorough analysis had not yet been developed so other than making qualitative claims there was little contribution to understanding the nature of that risk. The model described above, along with several others [34,35] led to a quantitative theory where actual holdings and relationships could be used to run simulations, perform calculations, eliminate systemic risk and reach concrete conclusions to determine vulnerabilities and

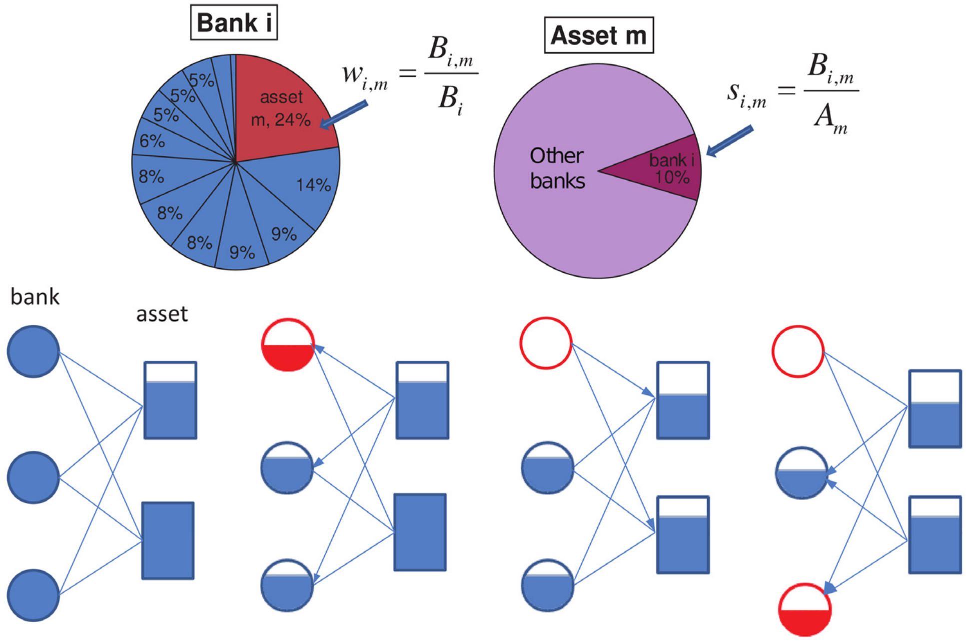

Fig. 5. Bank-asset bipartite network model with banks as one node type and assets as the other node type. After [31].

offer preventive measures. Interestingly, a complicated process such as the cascading failure of banks due to mutual holdings is explained successfully in this model via a very simple set of interactions and behaviors, without bringing into play high-level economic models of risk and capital. These models, however enlightening, still remained simplistic and needed further development.

4. Networks in economics and finance—applications and current research

Ongoing research makes the effort to incorporate various types of relationships between financial institutions, firms, commodities and more. Fig. 6 shows an example of the various financial activities and services offered by banks and the situation in which the same bank offers several types of services to their clients. Thus, a corporation may receive loans from a financial institution that also holds share of the company and holds its cash deposits. Thus, the interaction between the actors is no longer simple but rather complex.

Furthermore, in addition to the multi-level relation between corporations and financial institutions, corporations are related to *each other* in several types of links, such as supply chain, Merger and Acquisition processes, sharing or competing for resources and more. These relations may lead to another set of questions. For instance, assuming a flow of goods and products for cash between to companies, a failure in one of them may lead to failures in others. This is potentially bi-directional because a failure of a critical supplier may leave a company without essential elements of production while a failure of a major client may compromise a company's cash flow and impede with its ongoing operations up to bankruptcy, see Fig. 7. Researchers in [37] asked whether or not different nodes affect the network differently in terms of the cascading failure taking place following their removal (complete failure). They have shown (Fig. 8) that grouping industries by countries, the global network is becoming more susceptible to failures of Chinese companies after many years of American companies' dominance. The researchers analyzed a data set quantifying inter-sector activities for several countries. They assumed a tolerance model where a sector fails when a fraction of its trade partners ceases to exist (quantified as reduction of revenue). The cascading failure process is described in Fig. 7.

The assumption is straight forward: a failure of industry i leads to a reduction of revenue in industry j the magnitude of their interaction. If the fraction of reduced income is below the tolerance, the impacted industry absorbs the impact and lives on. If it is above—the industry topples, reducing, in turn, its share of revenue from its neighbors. Obviously, when the tolerance is low, almost every reduction causes the network to collapse and the network is very brittle. As the tolerance increases, only significant impacts i.e., failure of significant industries, cause failures. We can now say that the node whose removal causes the network to fail at higher levels of tolerance have a stronger significance in the network. The top panel of Fig. 8 shows the evolution over time of the largest cascade-inducing industry tolerance per country. It can be observed that since the mid-2000s the industry with the highest impact (i.e. capable of bringing down the network at the highest tolerance) is Chinese rather than American, as was the case in the years before. Not only that, but even when taking several most significant industries, by 2010 China's impact surpasses that of the US. While in terms of size the US remains the

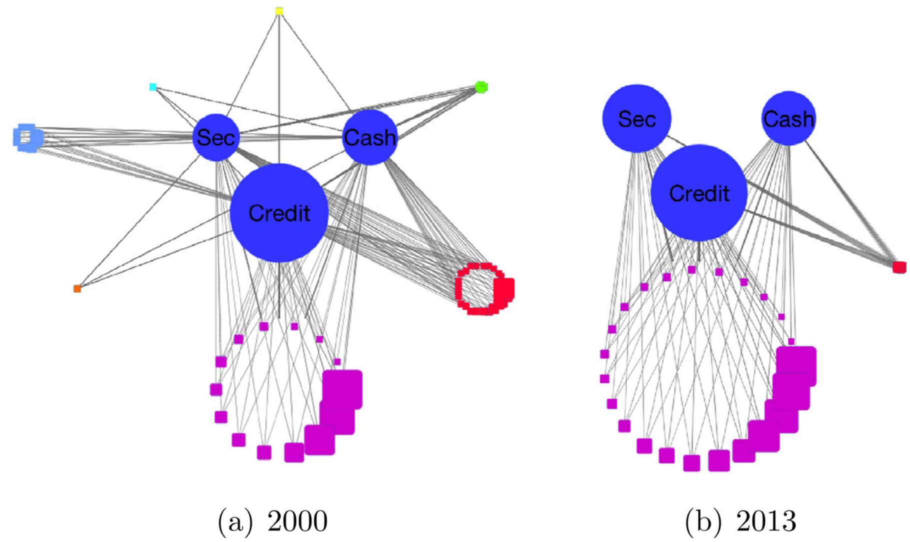

Fig. 6. Banking network structure for December 2000 (left) and December 2013 (right) with aggregate assets showing the transition from banks specializing in certain financial activities to larger banks doing everything. After [36].

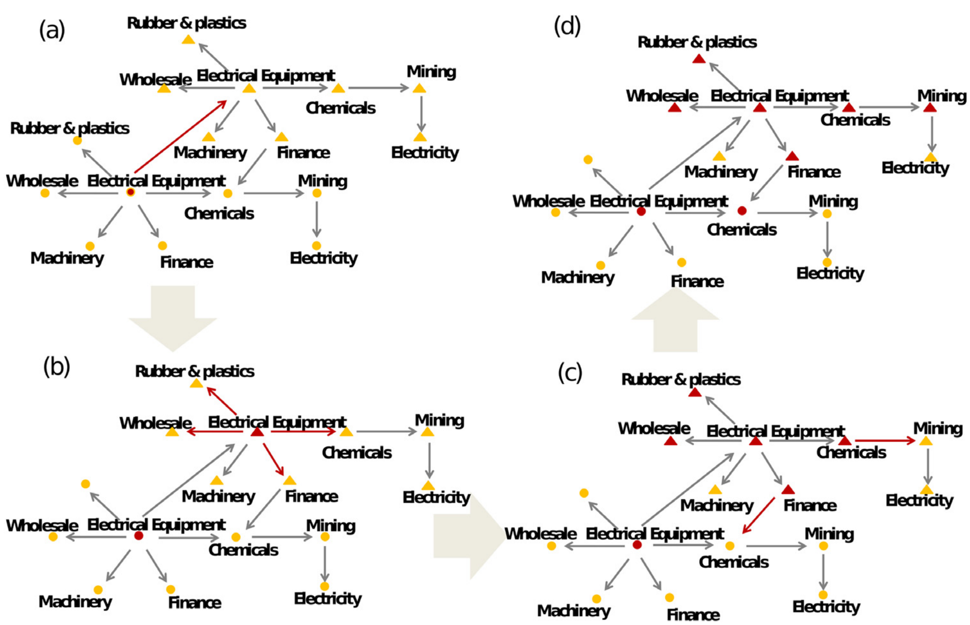

Fig. 7. Schematic representation of each step in the cascading failure propagation in the world economic network. A single industry failure in one country's sector impacts a trade partner in another country that in turn topples its partners. After [36].

world's largest economy, in terms of effect on its peers, China has taken the lead. This model takes a step forward in terms of richness in that it allows several networks to exist and interact, and from that interaction emerges the relative importance of participating nodes (industries) in the stability and fragility of the network. From the regulator's perspective, it shines a light toward possible originators of risk. From a corporate risk management point of view, it highlights the various paths leading to instability.

Next steps to take in approaching real-world complexity would include allowing various interactions, addition of realistic dynamics of network nodes [38], and explicit multilayer\multiplex behavior where each node may participate in more than one type of interaction with other nodes. While these models are sure to be less intuitive and translucent than the ones above, they will, hopefully, provide a more realistic world view and allow for better risk management on levels from corporate to government and a better quantitative understanding of our economy.

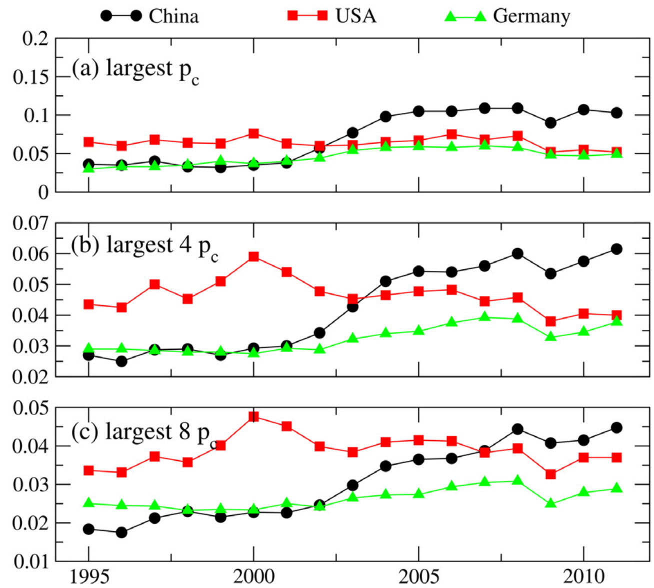

Fig. 8. Tolerance p_c changes of China, the USA and Germany for 17 years. The change in places over the past decade or two conforms to the general perception that China is increasing in economic power and while it has not yet overtaken the US in size, analysis shows it has surpassed it in its ability to affect the global interconnected economy. After [36].

5. Summary

As opposed to many physical systems, experimentation is not possible in economics. And yet, the effect of economical processes on our lives is ubiquitous. Events caused by economic malfunctions and failures permeate everyday lives profoundly. It is because of this that the understanding of inner workings of the intricate and complex economic system is critical. Complex networks have emerged as one of the most useful tools in modeling and understanding of such systems. We have reviewed the progress of network science as applied to economic research from math-free ideas [32,33] through fundamental discoveries [34] to state-of-the-art tools for risk assessment and system analysis [36–38]. A complimentary view, building upon economical and financial insights and data to reach complexity and networks is also actively researched [39–42]. These researchers [34,35,38–42] provide, among others, methodologies for constructing a model grounded in the financial inner workings of the institutions. The unifying theme, regardless the approach, is that existence of various types of interactions and entities leads to systemic behavior that really is greater than the aggregation of its constituents. The journey to understand economics using network tools is far from over, but evidence supports network science as the proper vehicle to move forward.

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