A multi-layer network perspective on systemic risk

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Systemic risk This denotes the risk that a system consisting of many agents fails to a large extent. Hence, the *fraction of failed agents* in the system is often taken as a measure of systemic risk. In an economic or financial system these agents could be firms, banks, funds, or other institutions. While a convential view mainly focuses on the conditions of a single agent to fail, the systemic perspective emphasizes the impact of an individual failure on other agents.

In order to understand how the "failure of the few" can be amplified into large failure cascades, we need a system representation that takes the interaction between agents into account. The *network representation* is best suited for this. Here agents are represented by *nodes* in the network, and interactions between agents by *links*, which are usually *weighted* and *directed*. The recent research on *temporal networks* also takes into account that these interactions are *ordered* and *bound in time* [5]. Interestingly, temporal correlations can lead either to a *slow-down* or a *speed-up* of failure propagation [6].

A new perspective In [7, 8] we advocate a new perspective on economic networks that combines *"micro"* and *"macro"*. The former denotes the socio-economic perspective which explains the network architecture based on the strategic behaviour of single agents, to form or to delete links to other agents. The latter denotes the statistical approach from physics and computer science which focuses on the statistical regularities of the network as a whole.

Data-driven modeling is a methodological framework to merge these two perspectives. It allows to infer the *interaction rules* of agents from the data, to generate large scale networks with the same dynamical and structural properties as their empirical counterparts. This approach has been successfully applied to model e.g. R&D networks [9]. Therefore, in times of *big data*, why not using it to understand the structure and dynamics of other economic networks, to evaluate their vulnerability against economic shocks?

This involves a number of methodological problems that are usually not reflected, or simply neglected. Hence, naively applying data driven modeling will generate artefacts that prevent us from understanding real economic networks. In my talk, I will address some of these methodological problems, as follows.

(1) Networks are (re)constructed Networks shall represent the interactions between agents, but in most cases we do not have data about time-resolved individual interactions. Instead, we have *aggregated data*, mostly aggregated over time or over activities. For example, we only have data about the *total* quarterly OTC derivative exposure of a major bank, but not about its individual contracts. Hence, in order to estimate systemic risk, we need to reconstruct the *network of counterparty risk* from such aggregated data, which can be done at least approximately [4].

But even if we have (big) data from individual economic interactions, we do not have the network yet. Instead, the network has to be constructed from such data by aggregating over small time windows. Choosing this time window decides whether we get a *sparse* or a *dense* network, and this topology subsequently determines which nodes in the network we identify as *important* (using different network measures).

Aggregating over time windows already destroys an important property of interations, namely their ordering in time. Bank A can lend to bank B only after it received some funds from bank C - and not the other way round. To capture such temporal correlations, new higher-order representations of networks need to be used, and have been developed recently [5, 6].

(2) Economic networks are multi-layer networks It is important to note that the network representation, described so far, only captures *one type* of interactions. However, economic agents like banks or firms are *at the same time* involved in *different types* of interactions. This can be represented by a *multi-layer network*, where each layer contains the same nodes, but different types of links, i.e. different interactions.

One layer can be for example the *ownership network* [10], in which weighted and directed links indicate *shareholding* and, hence, *control* of the nodes. Another layer can be the *network of knowledge transfer* [3], in which weighted links indicate R&D collaborations and knowledge exchange. Obviously, the decision to join an R&D alliance and to share knowledge with partners will not be completely independent of the ownership relations. Hence, the two layers are *coupled* and influence each other, to some degree.

This multi-layer picture also extends to *financial networks.* The same set of financial institutions is tied up in a credit network, but also in a derivative network, in addition to crossholding relations. Hence, firms or banks interact in different layers at the same time. If a bank goes bankrupt, this will not only start a cascade in one layer, it will probably affect other layers as well. Only in rare cases, these layers are really decoupled. On the contrary, failure cascades in one layer most likely amplify failure cascades in other layers.

But can systemic risk also *decrease* by means of multi-layer couplings? In order to better understand such dynamics, we need to develop a framework for systemic risk in multi-layer networks, which focuses particularly on the *role of inter-layer links.* In the talk, I will present a recent example that helped us to understand under what conditions systemic risk can be *mitigated* rather than exacerbated [2].

Toward a modeling framework of systemic risk So, let us assume that we have now what is requested: time-resolved data about different types of individual interactions between agents, which will allow us to reconstruct the temporal multi-layer network of e.g. financial institutions. Will we be able to calculate systemic risk scenarios from this? Obviously not, because we did not specify under what conditions these agents will fail and how this will impact neighboring agents. I.e., what is needed in addition to all of the *link* data is data/information about the vulnerability of *agents* (e.g. assets/liabilities of banks) and about the specific mechanisms by which they impact their counterparties.

For the latter, we can already build on existing theoretical work by financial economists and mathematicians, see e.g. [1] and references therein. Specifically, there are already models and analytical results to calculate the systemic risk (measured as the fraction of failed agents) for different network topologies and broad assumptions about the failure conditions of agents.

These insights have already helped us to understand that *risk diversification* with more counterparties can increase, rather than decrease, chances of individual failure, because of the systemic coupling. We could also verify that an *optimal heterogeneity* among agents can mitigate the risk of large cascades, i.e. regulations should not enforce sameness. Eventually, the *big hubs* with the largest number of counterparties in the network are not always the most dangerous spreaders of failure, and not always the best choice to control the dynamics on a (multi-layer) network.

Conclusion: We can build on this theoretical work, but need to extend it with the temporal and multi-layer perspective, to get a bigger, and better picture of how systemic risk spreads. And we need access to the right data, to make use of these theoretical efforts.

References

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[1] Burkholz, R.; Garas, A.; Schweitzer, F. (2015). How Damage Diversification Can Reduce Systemic Risk. *ETH Risk Center WP series.*

[2] Burkholz, R.; Leduc, M.; Garas, A.; Schweitzer, F. (2015). Systemic risk in multiplex networks with asymmetric coupling and threshold feedback. *Physica D* .

[3] Koenig, M. D.; Battiston, S.; Napoletano, M.; Schweitzer, F. (2012). The efficiency and stability of R&D networks. *Games and Economic Behavior* **75(2)**, 694–713.

[4] Nanumyan, V.; Garas, A.; Schweitzer, F. (2015). The Network of Counterparty Risk: Analysing Correlations in OTC Derivatives. *PLOS ONE* **10**, e0136638.

[5] Pfitzner, R.; Scholtes, I.; Garas, A.; Tessone, C. J.; Schweitzer, F. (2013). Betweenness Preference: Quantifying Correlations in the Topological Dynamics of Temporal Networks. *Phys. Rev. Lett.* **110**, 198701.

[6] Scholtes, I.; Wider, N.; Pfitzner, R.; Garas, A.; Tessone, C. J.; Schweitzer, F. (2014). Causality-driven slowdown and speed-up of diffusion in non-Markovian temporal networks. *Nature Communications* **5**, 5024.

[7] Schweitzer, F.; Fagiolo, G.; Sornette, D.; Vega-Redondo, F.; Vespignani, A.; White, D. R. (2009). Economic networks: the new challenges. *Science (New York, N.Y.)* **325(5939)**, 422–425.

[8] Schweitzer, F.; Fagiolo, G.; Sornette, D.; Vega-Redondo, F.; White, D. R. (2009). Economic Networks: What do we know and What do we need to know? *Advances in Complex Systems* **12(04)**, 407–422.

[9] Tomasello, M. V.; Perra, N.; Tessone, C. J.; Karsai, M.; Schweitzer, F. (2014). The Role of Endogenous and Exogenous Mechanisms in the Formation of R&D Networks. *Scientific Reports* **4**, 5679.

[10] Vitali, S.; Glattfelder, J. B.; Battiston, S. (2011). The network of global corporate control. *PLoS-ONE* **6(10)**, 1– 6.