Computational Modelling of Social Systems (10)
M. Raddant – TU Graz – 2024

Epidemics and Cascades

Today

The connection of structure and function in networks

…and why networks can be really bad: about epidemics, cascades and risk.

- Percolation
- SI-R-S Model
- Epidemics
- Cascades, online and offline
- Financial contagion, systemic risk
- Multiplex networks
- Complex systems, Polycrisis

Background literature for this lecture: Chapter 17 from the book ‘Networks, An Introduction’ by M. Newman, Oxford 2010

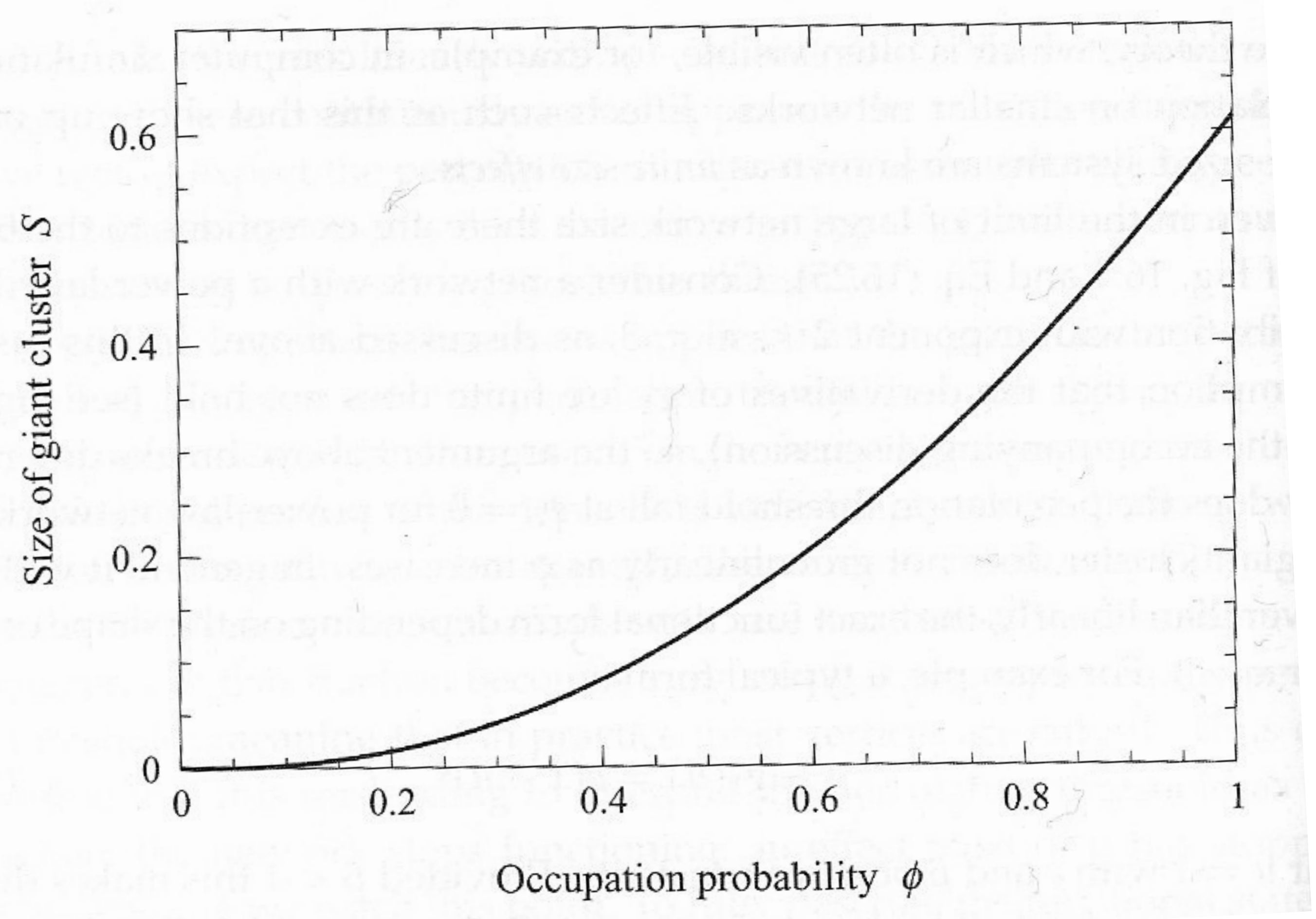
Percolation

- **Percolation** refers to a process where single parts of a network fail or are removed
- **Site percolation**: removal of vertices
- **Bond percolation**: removal of edges
- A lot of examples exist, where real world networks have an ongoing percolation process or where human action can be interpreted as a percolation effect

- **Technical infrastructure** and the failure of single components:
  - Nodes of the power grid
  - Routers in the internet
  - Junctions and crossings in transportation networks
- Animals and humans with **infections diseases**, where the **immunization** is an act of percolation

- Hence, in a percolation model vertices can be function or dysfunctional. The terminology for this is “**occupation**”
- The occupation probability $\boldsymbol{\varphi}$, can vary between ***0*** and ***1***
- For most networks one can observe a **percolation transition**, which means that at some critical level for $\boldsymbol{\varphi}$ a „disfunctional“ collection of unconnected clusters form a **giant cluster**

Figure from Newman (2010)



- We will skip the theoretical treatment of percolation models here and go straight to some application:
- Often it is possible to analyze networks by **simulating percolation**, and to get some insights into the stability of a network and critical parts.
- A straight forward approach is to generate variations of the original network with a random set of the **vertices removed** and to calculate the mean of the size of the largest component $\boldsymbol{S(\varphi)}$

- This can be achieved by repeatedly using a **breach-first based** algorithm to find the largest component and calculate its size
- The repeated calculation of the clusters and sizes however, is rather time consuming
- It **is more efficient** to work the other way around: start with an empty network and "switching on" vertices in a random order several times

- Use an algorithm like this:
- Start with an **empty network** and choose a **random order** to add vertices, give each cluster a label
- After adding a vertex, check it the **labels** of now connected vertices are the same. If not, give them the same name
- **Update** the number of different labels (# clusters) and the maximum of items with the same label (giant component size)
- Repeat until all vertices are added
- Repeat for different random orders

Epidemics

- Models of epidemics on networks are widely used to analyze the spread of diseases like HIV and the flu.
- In the basic version however, there is no network, and we only look at the interaction of the healthy and infected part of the population.
- This is called the **SI** model, short for **susceptible** and **infected**

- The basic model assumes that the transmission of a disease takes place in a kind of mass interaction, so that everybody has the same chance to be infected
- Assume a **population** where ***S(t)*** describes the expected number of people who are susceptible and ***X(t)*** the expected number of infected at time ***t***
- Assume that people **meet at random** with a rate of **β** **contacts per time unit**

- A susceptible gets infected only when he meets an infected person
- The **population** size is given by ***n*** (a constant)
- Probability to **pick** a susceptible is ***S/n***
- An infected has contact with **β*S/n*** susceptible per time unit
- Since the average number of infected is defined as ***X***, the average of **new infections** is **β*SX/n***
- We can write this as a differential equation

- The rate of change of ***X***

$$\frac{dX}{dt} = \beta \frac{SX}{n}$$

- and in the same manner for the susceptible ***S***

$$\frac{dS}{dt} = -\beta \frac{SX}{n}$$

- We can define ***s*** and ***x*** as variables to represent the fractions, such that

  s=S/n and ***x=X/n***

- We can than rewrite the equations as

$$\frac{ds}{dt} = -\beta s x$$

$$\frac{dx}{dt} = \beta s x$$

- Since ***n=S+X*** or ***1=s+x*** , we can write ***s=1-x***

- This leaves us with the **logistic growth** equation

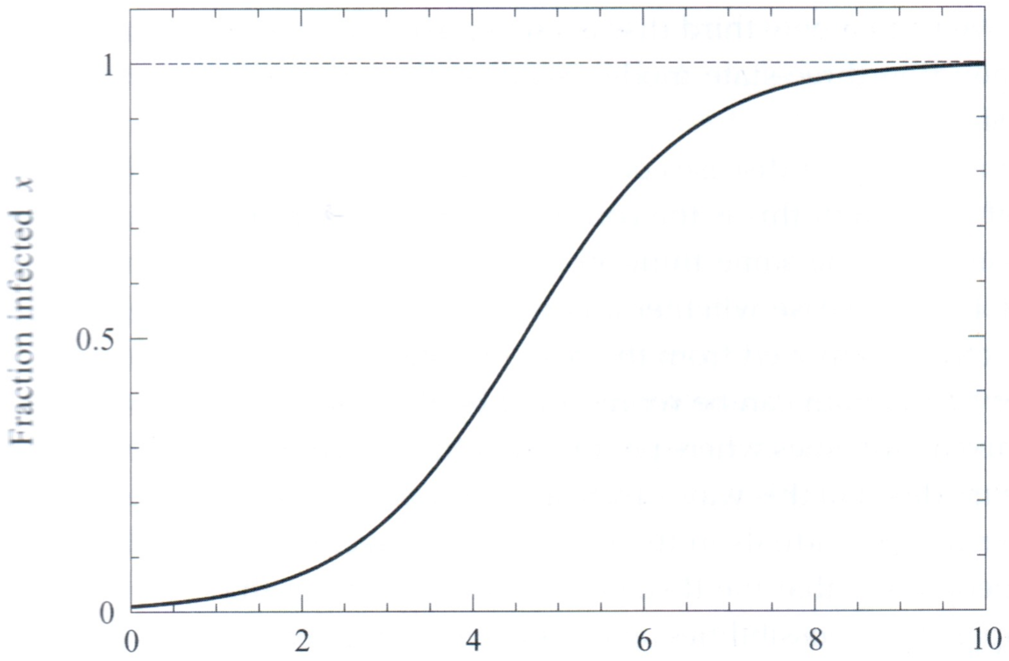
$$\frac{dx}{dt} = \beta(1 - x)x$$

- The solution to this is

$$x(t) = \frac{x_0 e^{\beta t}}{1 - x_0 + x_0 e^{\beta t}}$$

- Which will produce an S-shaped curve

Figure from Newman (2010)



- This is probably not the most realistic representation of a disease, since it mostly does not infect the entire population. Also part of the population is or may become immune. If the speed is slow also other effects will become important in these dynamics.

SIR

- One extension to the SI model is to add the feature of **recovery**. This means that some time after the infection people can recover from the disease.
- Mostly this also means that they cannot get infected again
- This leads us to the **Susceptible-Infected-Recovered model**

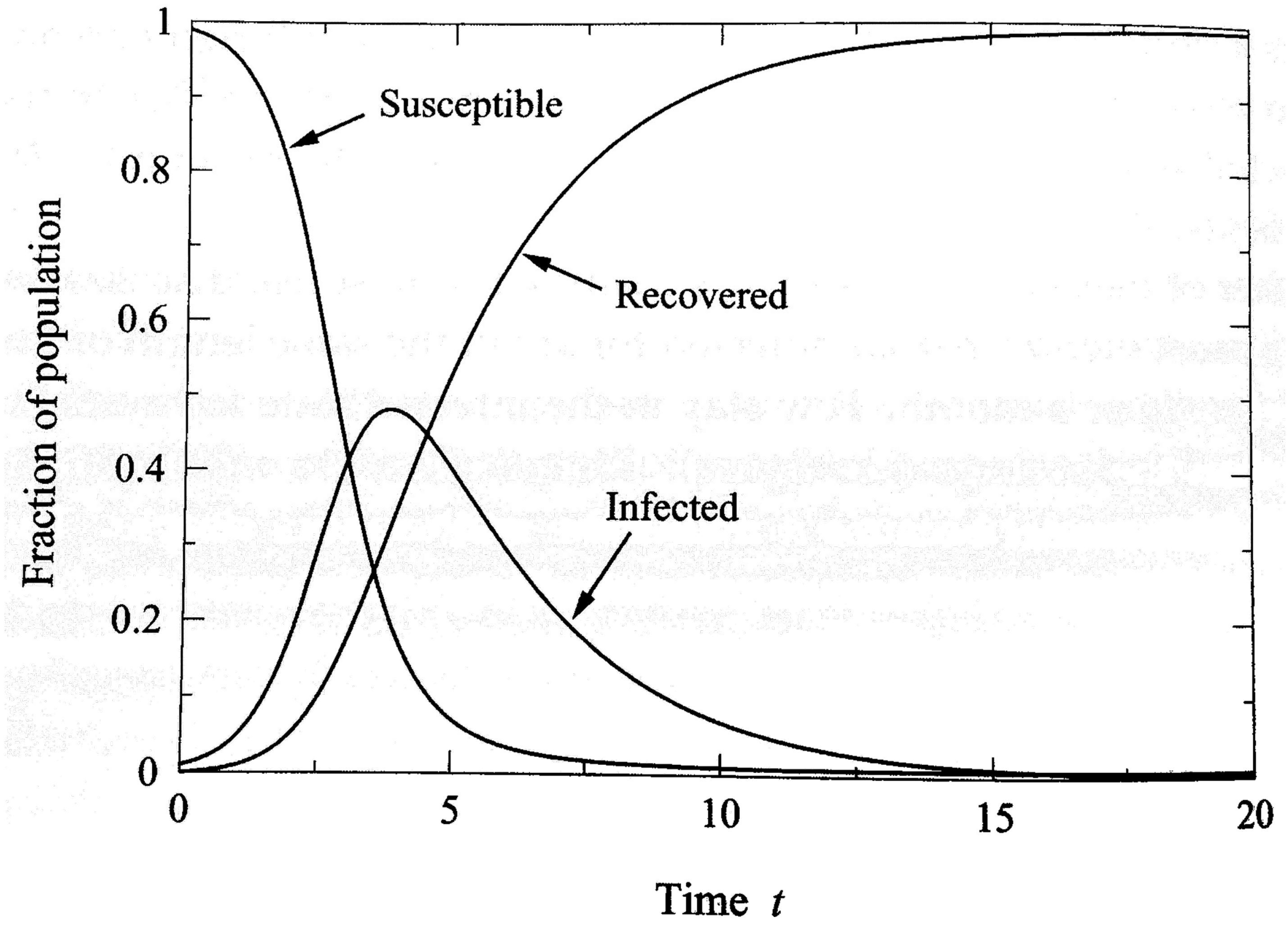
- We add a second stage to our model where infected people can **recover** (or die) at a rate **γ**
- The equations of the SIR model are

$$\frac{ds}{dt} = -\beta s x$$

$$\frac{dx}{dt} = \beta s x - \gamma x$$

$$\frac{dr}{dt} = \gamma x$$

Figure from Newman (2010)



- This modified model can be used to calculate the outbreak size of a disease (the number of people ever infected)

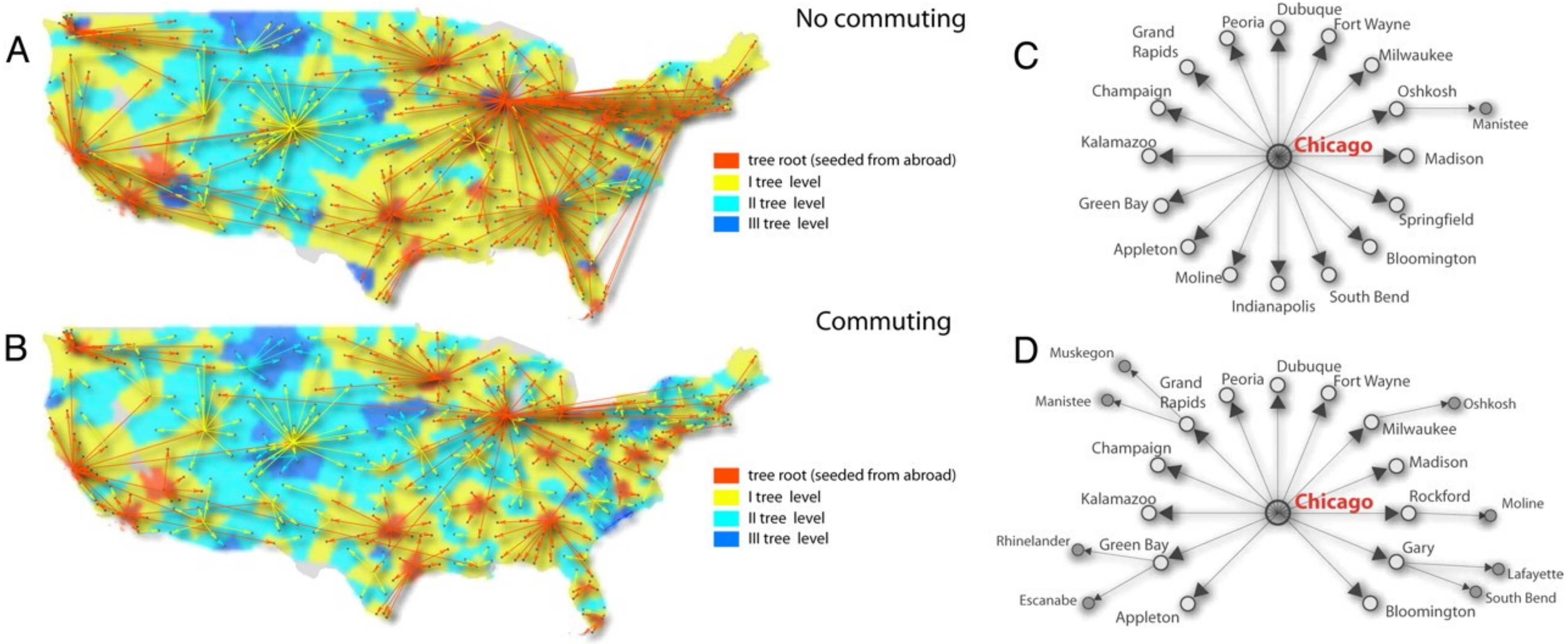
- Yet another variation is the **SIS model**, which allows for **re-infection**
- In the simplest version this means that people continuously switch between the two states

- In the **SIRS model** people can recover from a disease and develop **temporary immunity**
- After some time, when immunity is lost they become susceptible again

Epidemics on networks

- Taking these models to networks means to get rid of the assumption that all people can meet with the same probability, instead we can approximate the **real contacts** by information about the **location** of people, and their regular **commuting** patterns, like going to work, meeting neighbors, and neighbors.
- Where we do not have information about individuals we can **model groups**, e.g., the behavior of children, workforce, senior citizens, together with their group specific infection risk

Epidemic invasive tree.



Epidemic invasive tree. (A and B) Geographical representation of the continental U.S. epidemic invasion tree with only airline traffic (A) and when both airline traffic and commuting are considered (B). Red represents the roots (i.e., the first cities that were seeded from abroad), and, as we move down the tree, the colors change from yellow to dark blue. The arrows representing the edges of the tree are colored as the parent node. (C and D) We also provide a schematic representation of the invasion tree rooted at Chicago when only flights are considered (C) and with both air traffic and commuting (D). As demonstrated in both examples, the spreading pathway is completely dominated by the airline hubs as the only sources of imported seeds. However, the hierarchy is broken by the introduction of commuting flows as the number of shells around the airline hubs and the branches at the secondary nodes increase.

 Balcan D et al. PNAS 2009;106:21484-21489

SCIENTIFIC REPORTS

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The Dynamics of Protest Recruitment through an Online Network

SUBJECT AREAS:
PHYSICS
APPLIED PHYSICS
STATISTICAL PHYSICS, THERMODYNAMICS AND NONLINEAR DYNAMICS
MATHEMATICS

Sandra González-Bailón[1], Javier Borge-Holthoefer[2], Alejandro Rivero[2] & Yamir Moreno[2,3]

[1]Oxford Internet Institute, University of Oxford, 1 St. Giles OX1 3JS, Oxford, UK, [2]Institute for Biocomputation and Physics of Complex Systems, University of Zaragoza, Campus Rio Ebro 50018, Zaragoza, Spain, [3]Department of Theoretical Physics, Faculty of Sciences, University of Zaragoza, Zaragoza 50009, Spain.

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The recent wave of mobilizations in the Arab world and across Western countries has generated much discussion on how digital media is connected to the diffusion of protests. We examine that connection using data from the surge of mobilizations that took place in Spain in May 2011. We study recruitment patterns in the Twitter network and find evidence of social influence and complex contagion. We identify the network position of early participants (i.e. the leaders of the recruitment process) and of the users who acted as seeds of message cascades (i.e. the spreaders of information). We find that early participants cannot be characterized by a typical topological position but spreaders tend to be more central in the network. These findings shed light on the connection between online networks, social contagion, and collective dynamics, and offer an empirical test to the recruitment mechanisms theorized in formal models of collective action.

- Nowadays the **spread of opinion** is a much discussed topic. The graph shows the twitter users which are active into discussions about protests in Spain.
- Similar studies are available for the Arab spring movement and about blog entries about an upcoming recessions in internet forums.

Figure from Scientific Reports, see slide 23.

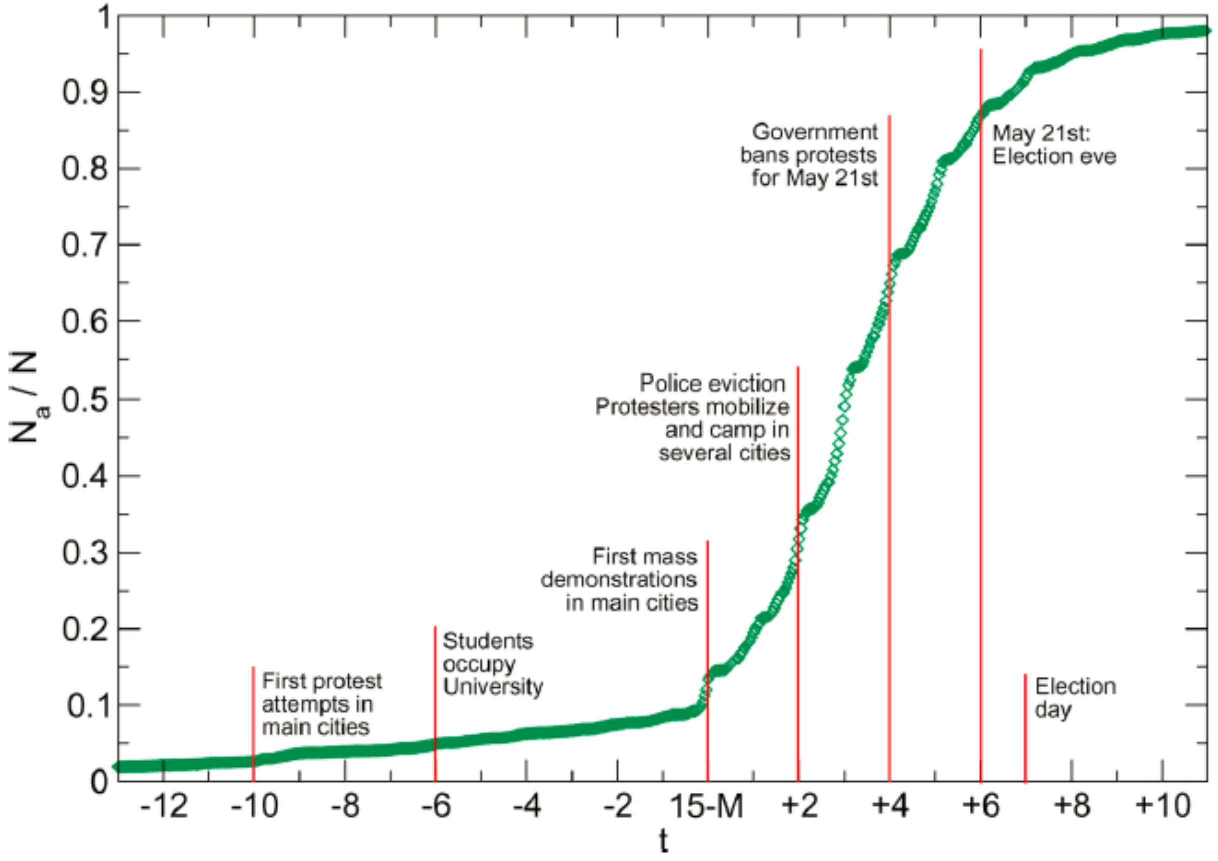


Figure 1 | Fraction of recruited users over time. The vertical axis is normalized by the total number of users (87,569), the horizontal axis tracks the number of activated users accumulated by hours. At the end of our time window the proportion of activated users is 98.03%, which means that the vast majority of users sent at least one protest message during this month. Vertical labels flag some of the events that took place during the period.

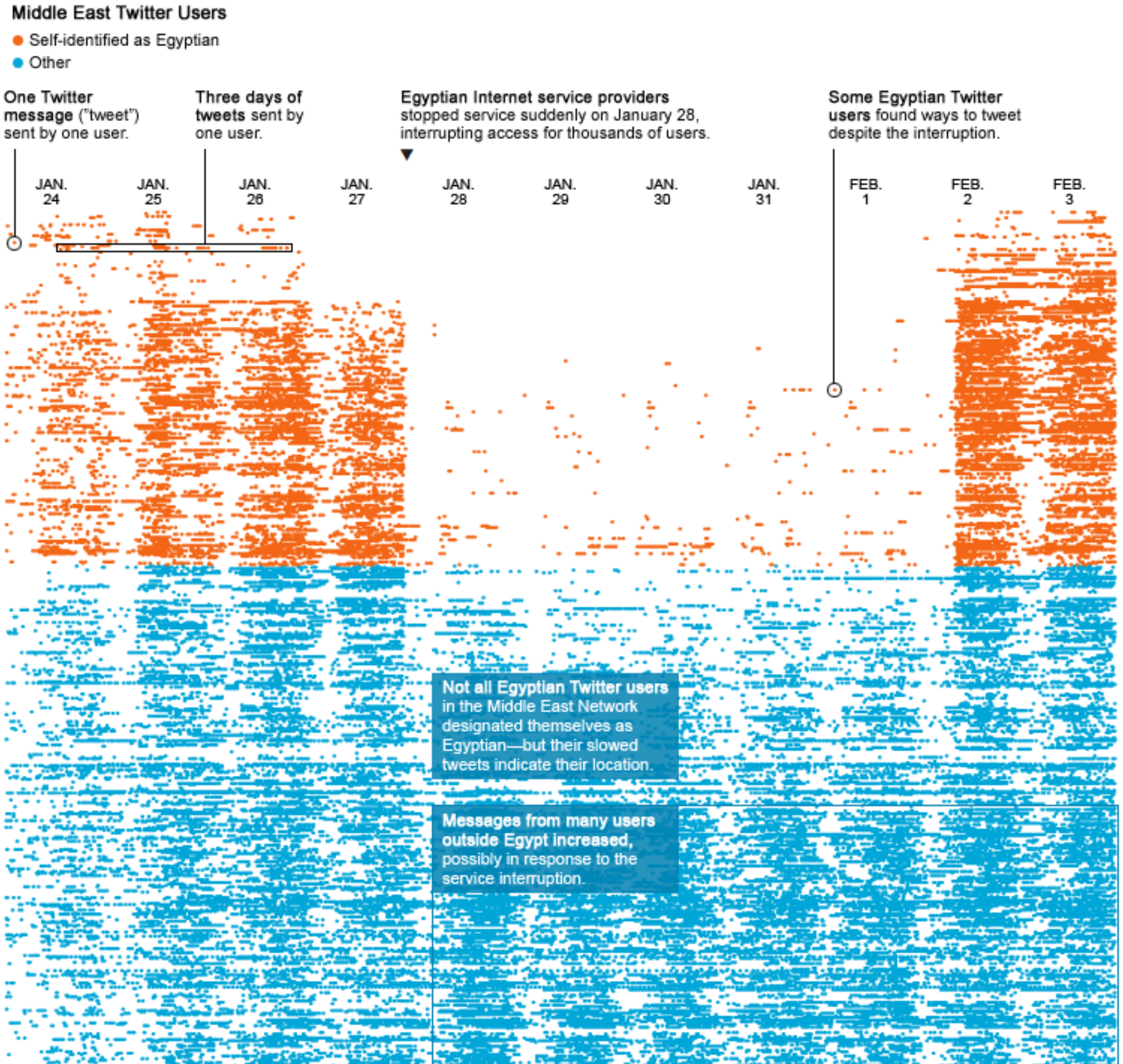


Figure from National Geographic, 07 2011

Risks in Financial Markets

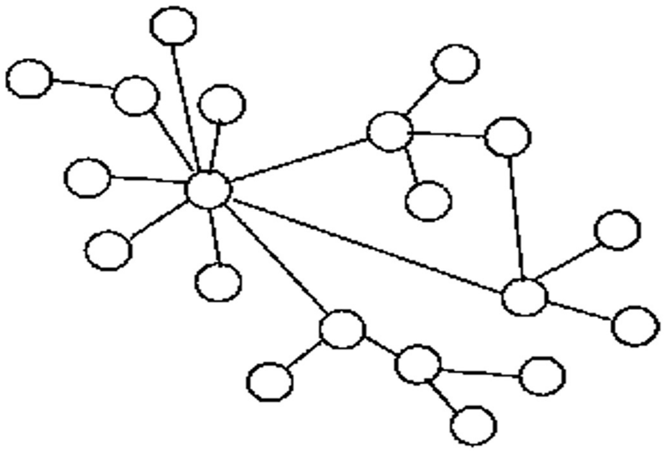
- Counterparty risk
  - default of a institution you have a deal with
- Settlement risk
  - failure to deliver a security or cash value
- Market risk
  - losses due to change of the price
- Liquidity risk
  - inability to convert assets in the short term
- Systemic risk
  - collapse of a financial system

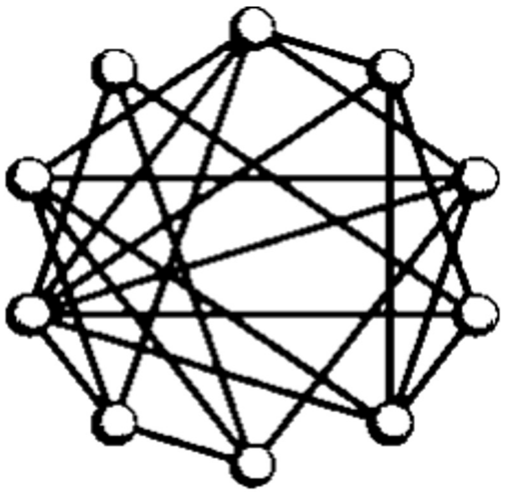
More on **Systemic Risk**

- The concept of ***systemic risk*** is rooted in the analysis of disease spreading, i.e., has is origins in Biology and Ecology
- In financial systems, a ***systemic event*** is defined to happen when information about an institution (including its default) leads to subsequent failure of one or several other institutions or markets
- Mostly, the case in which subsequent failures lead to a default are labeled ***strong systemic events***, or ***contagion***

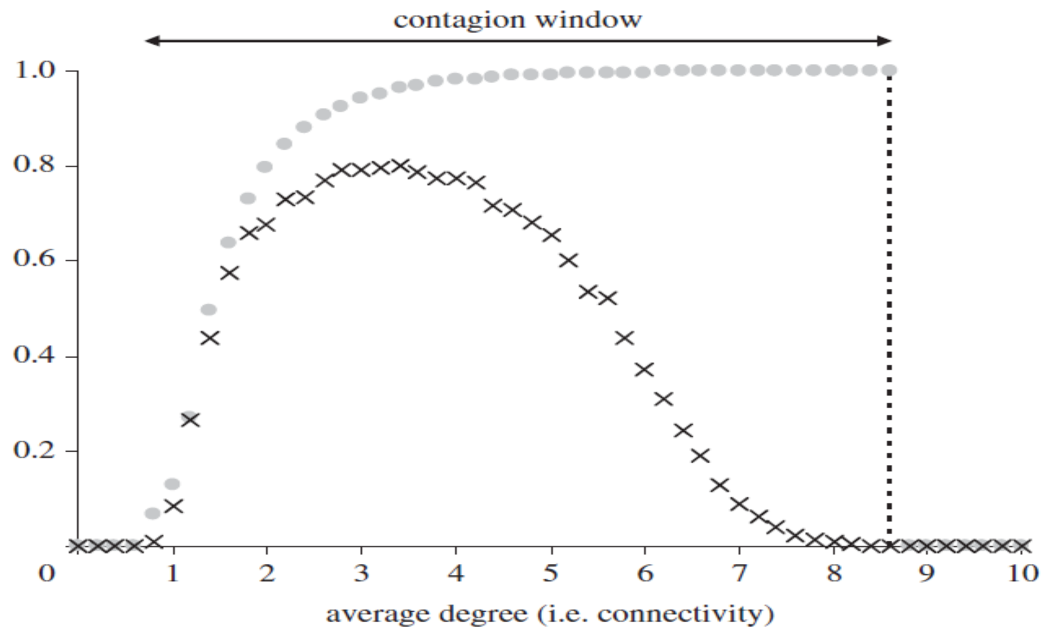
Stability of the interbank network

- An important part of interbank networks exists in the form of the interbank loan market, where banks provide liquidity to each other via overnight loans
- Interbank networks are (approximately) scale-free networks, which are less susceptible to most shocks than (Bernoulli) random graphs (where the connectivity is homogenous)
- This makes the outcome of shocks difficult to predict





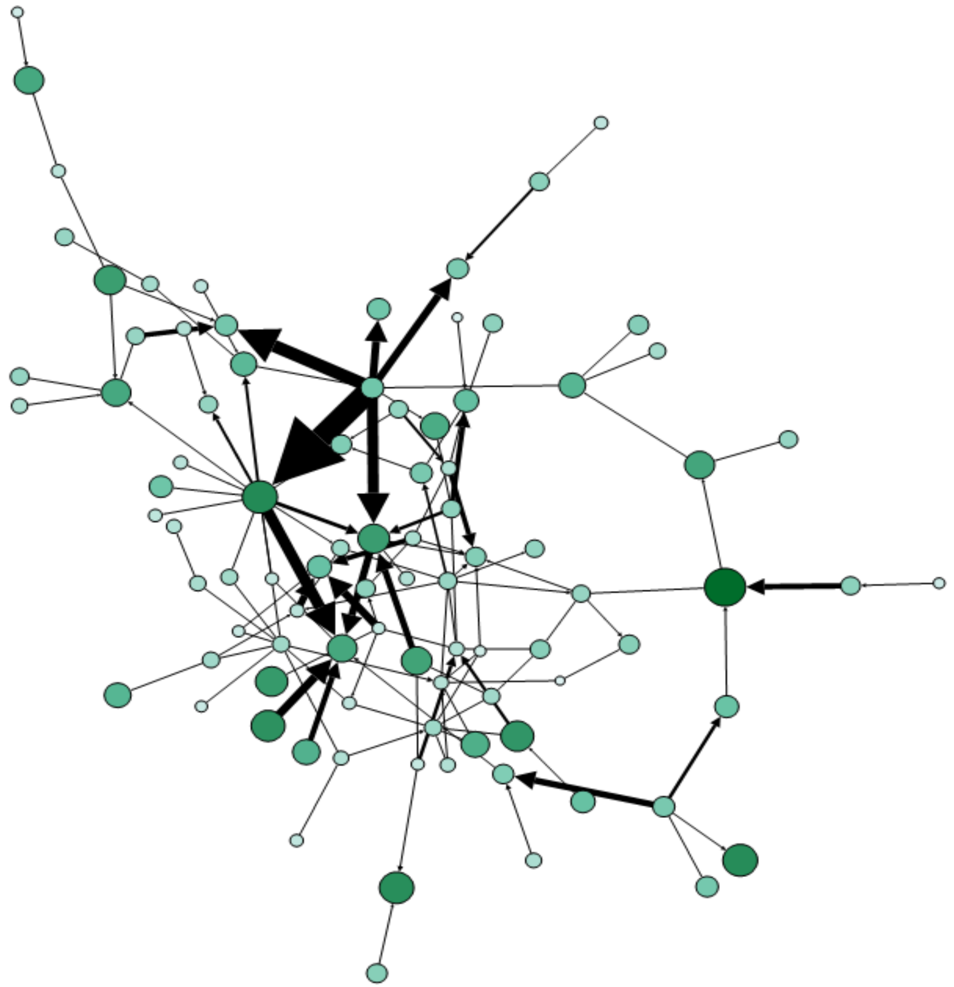
- Question: Is connectivity stabilizing?
- Answer: Mostly
  - once we reach a certain threshold
  - and if shocks are not excessive



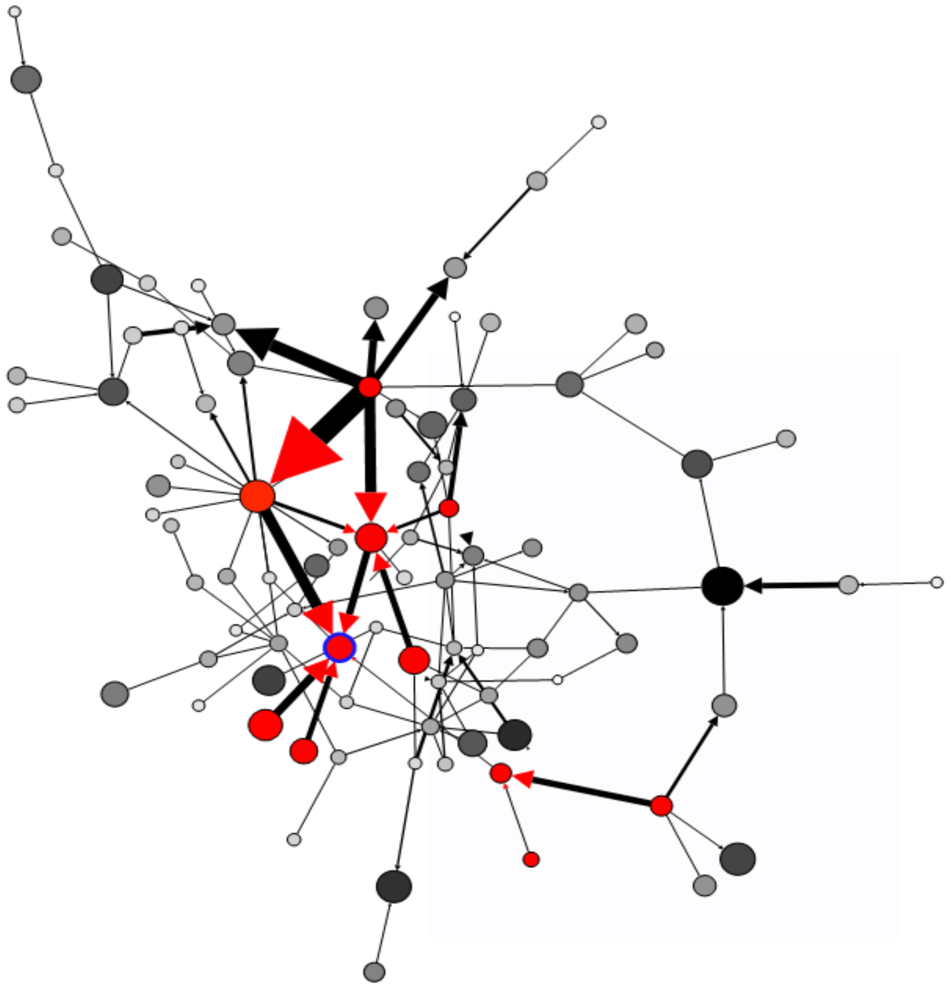
source: Gai and Kapadia, Proc R Soc A, 2010

Cascade simulations with empirical data

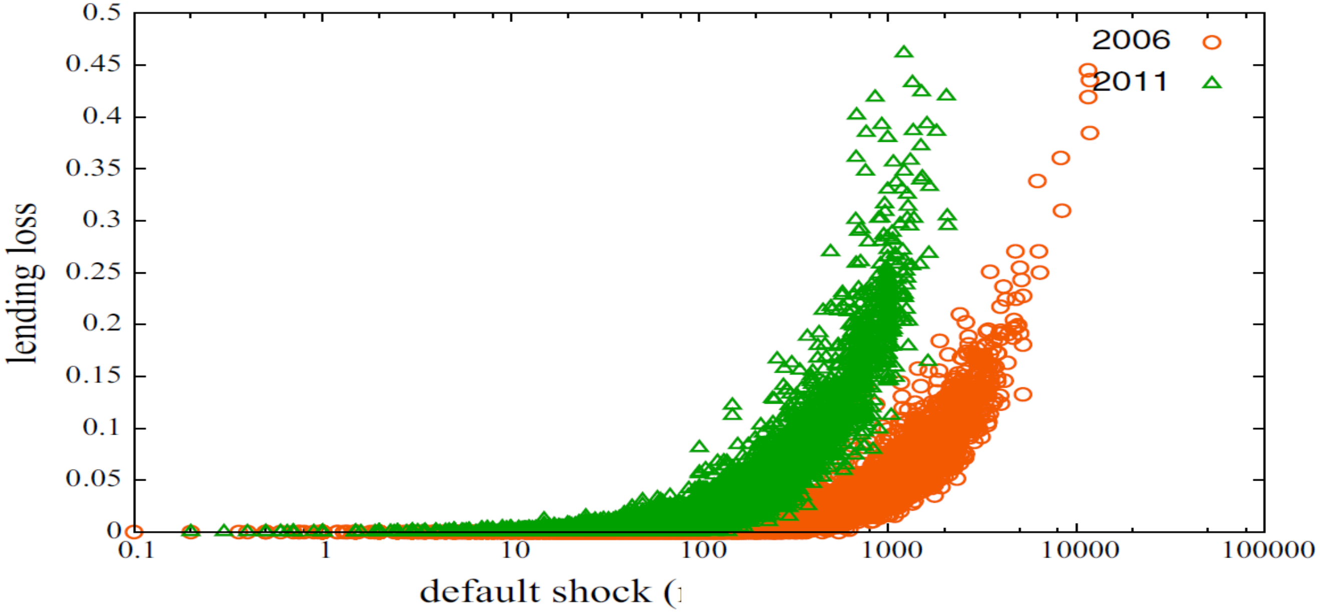
One week snapshot of the network of Italian overnight loan market E-mid. Nodes are banks and links are loans. Node size is according to their degree and link size is according to the loan.



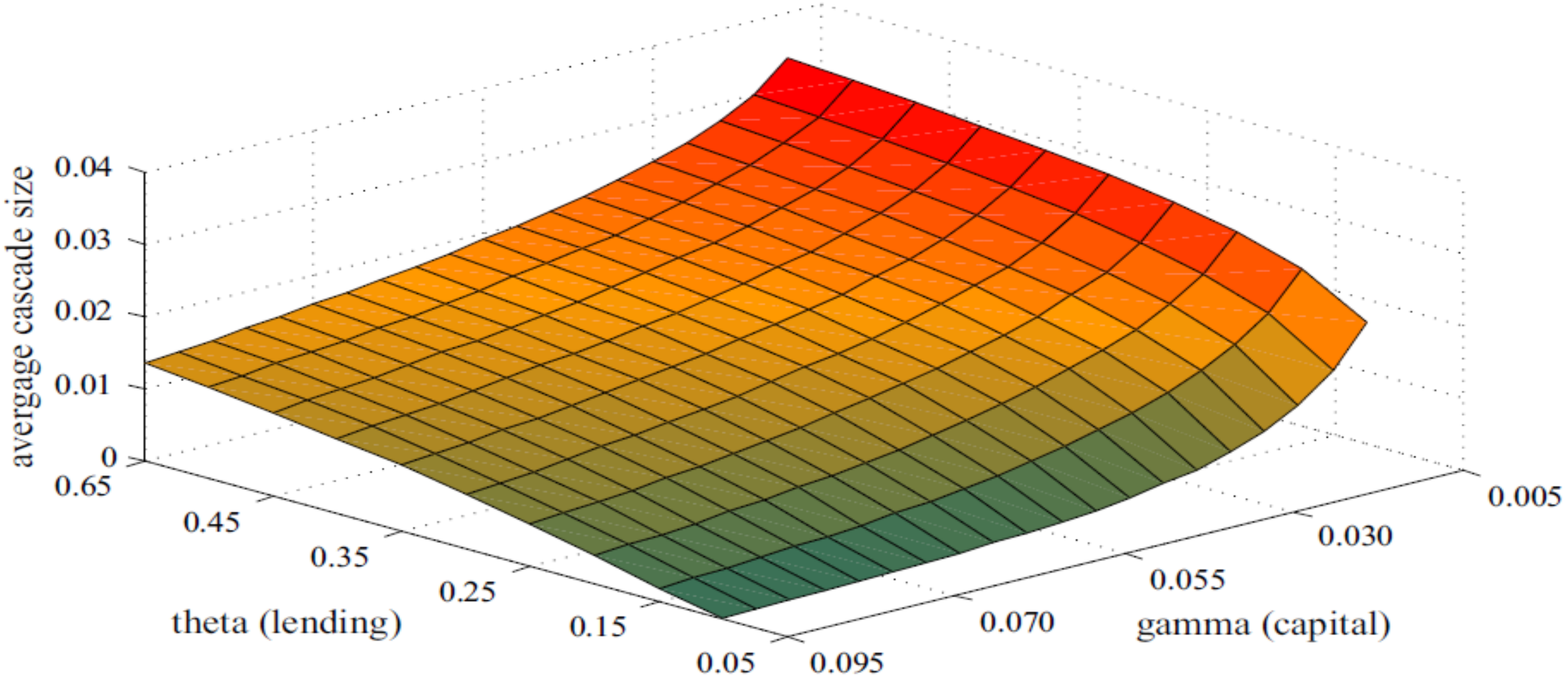
Interbank network under default shock. The bank with the blue circle defaults and it gives shock to its lenders.



Karimi/Raddant (2016), Cascades in Real Financial Markets, CompEcon .



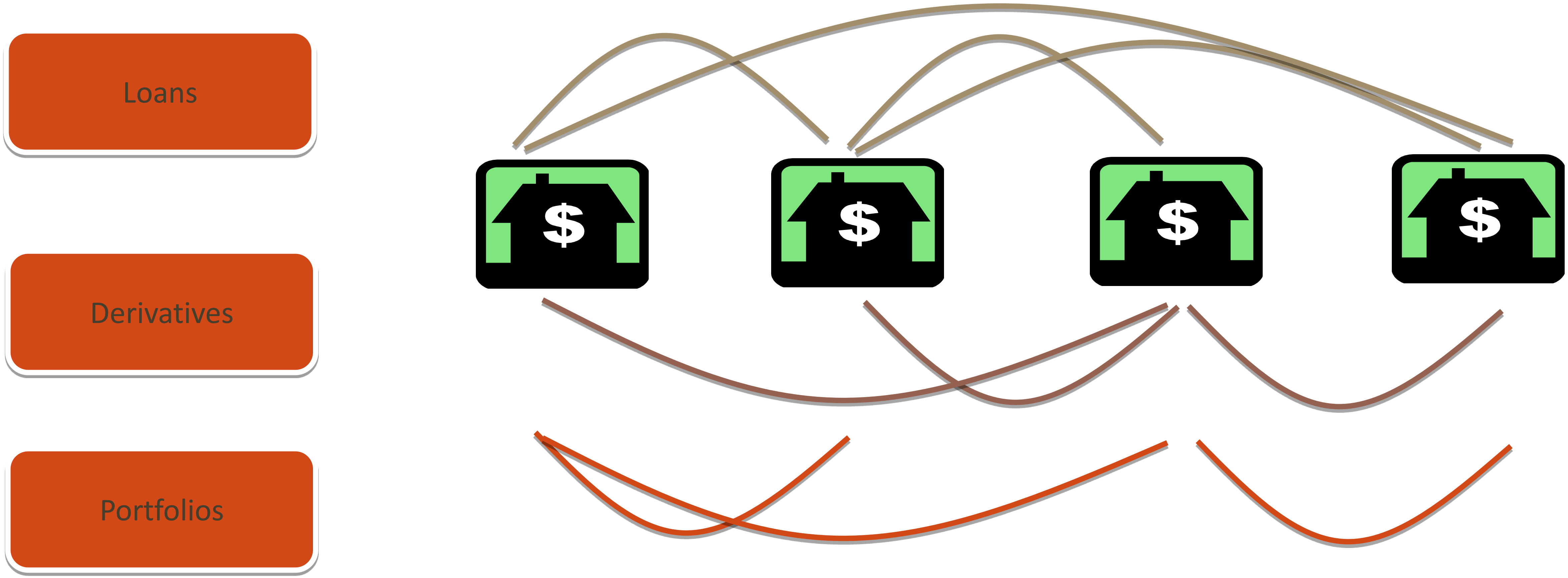
Only very few shocks lead to default cascades, smaller shocks are mostly negligible



The level of defaults depends heavily on the parameterization of the model

The Financial Multiplex

Long chains of defaults can mostly not be reproduced by cascade simulations in loan networks. Also the dispersion of shocks to different regions demands more complex structures. Including the holdings of securities and assuming some dynamics for their price seems like a useful way to reproduce the effect of macro shocks.



G-SIBs as of November 2023[10] allocated to buckets corresponding to required levels of additional capital buffers

Bucket[11]	G-SIBs in alphabetical order within each bucket
5 (3.5%)	(Empty)
4 (2.5%)	JP Morgan Chase
3 (2.0%)	Bank of America Citigroup HSBC
2 (1.5%)	Agricultural Bank of China Bank of China Barclays BNP Paribas China Construction Bank Deutsche Bank Goldman Sachs Industrial and Commercial Bank of China Mitsubishi UFJ FG UBS
1 (1.0%)	Bank of Communications (BoCom) Bank of New York Mellon Groupe BPCE Groupe Crédit Agricole ING Mizuho FG Morgan Stanley Royal Bank of Canada Santander Société Générale Standard Chartered State Street Sumitomo Mitsui FG Toronto Dominion Wells Fargo

Financial market regulation after 2008

Some regulation based on the centrality of banks: Additional capital requirements of “SIFIS”

G-SIBs as of November 2023, allocated to buckets corresponding to required level of additional loss absorbency

FSB, Nov 2023

Interconnected networks

- An extension of single network cascade effects are networks that are interconnected either as **multiplex systems** – or – **networks of networks**
- Assume (for now) two networks of similar size, where the health of a node in network A depends also on the health of a corresponding node in network B

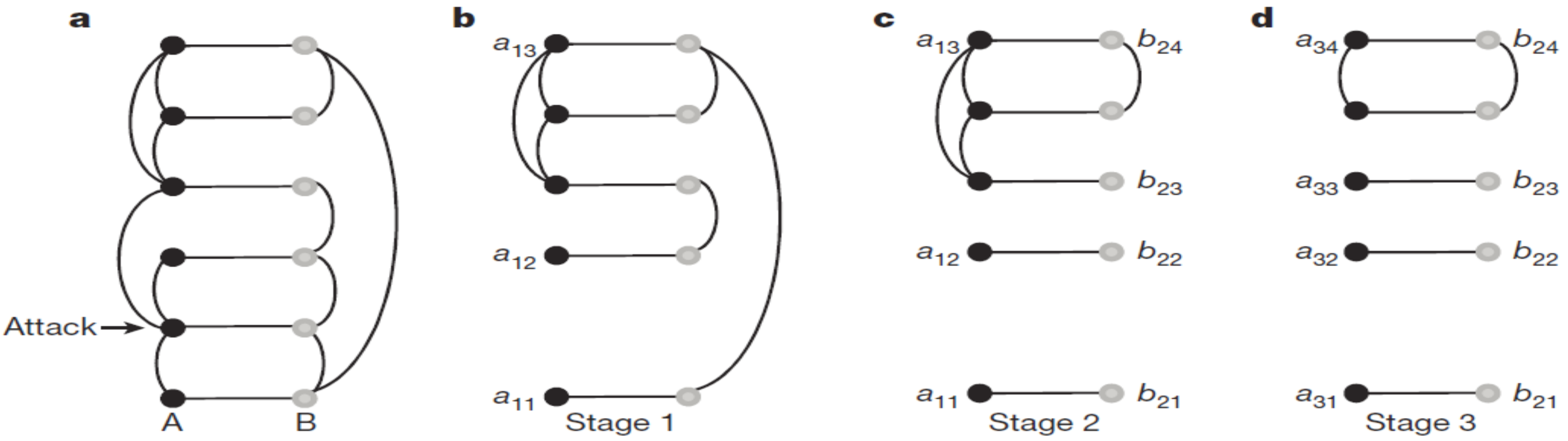


Figure 2 | Modelling an iterative process of a cascade of failures. Each node in network A depends on one and only one node in network B, and vice versa. Links between the networks are shown as horizontal straight lines, and A-links and B-links are shown as arcs. **a**, One node from network A is removed ('attack'). **b**, Stage 1: a dependent node in network B is also eliminated and network A breaks into three a_1-clusters, namely a_{11}, a_{12} and a_{13}. **c**, Stage 2: B-links that link sets of B-nodes connected to separate a_1-clusters are eliminated and network B breaks into four b_2-clusters, namely b_{21}, b_{22}, b_{23} and b_{24}. **d**, Stage 3: A-links that link sets of A-nodes connected to separate b_2-clusters are eliminated and network A breaks into four a_3-clusters, namely a_{31}, a_{32}, a_{33} and a_{34}. These coincide with the clusters b_{21}, b_{22}, b_{23} and b_{24}, and no further link elimination and network breaking occurs. Therefore, each connected b_2-cluster/a_3-cluster pair is a mutually connected cluster and the clusters b_{24} and a_{34}, which are the largest among them, constitute the giant mutually connected component.

Buldyrev et al. (2010), Catastrophic cascades of failures in interdependent networks, Nature (Letters), Vol 464

- The simulations show that at a certain point the **giant component** of one of the networks breaks down, which would resemble a system wide failure
- Interestingly in this case a broader degree distribution increases the vulnerability of the coupled system
- The system stays functional as long as the giant components are intact
- A real life example is the **power blackout** in Italy in September 2003, shown on the next slide

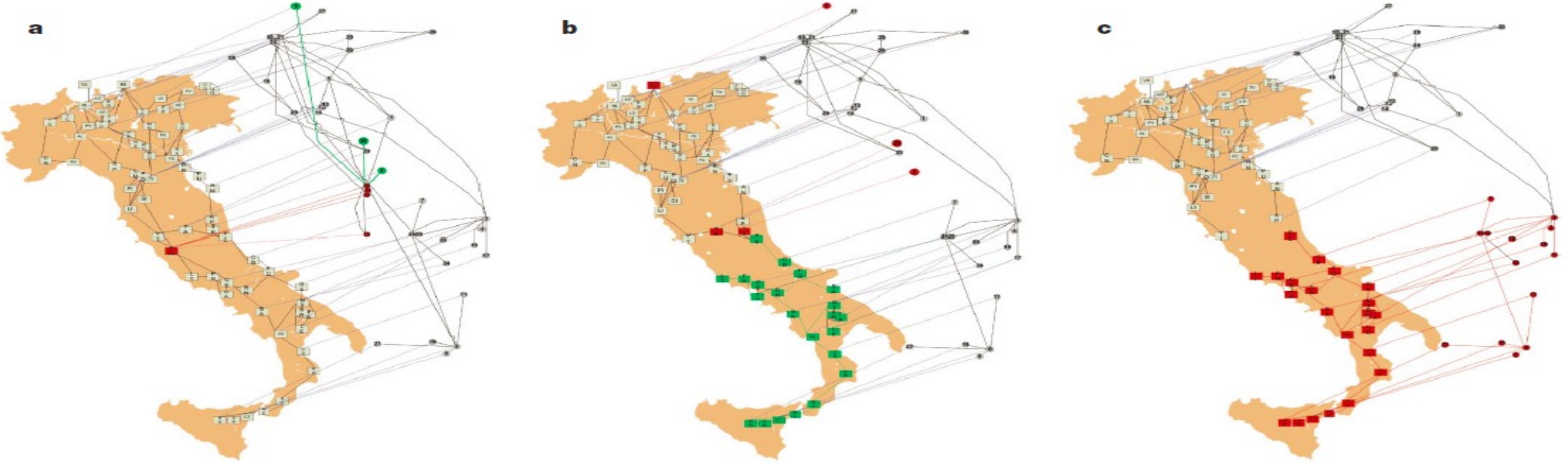
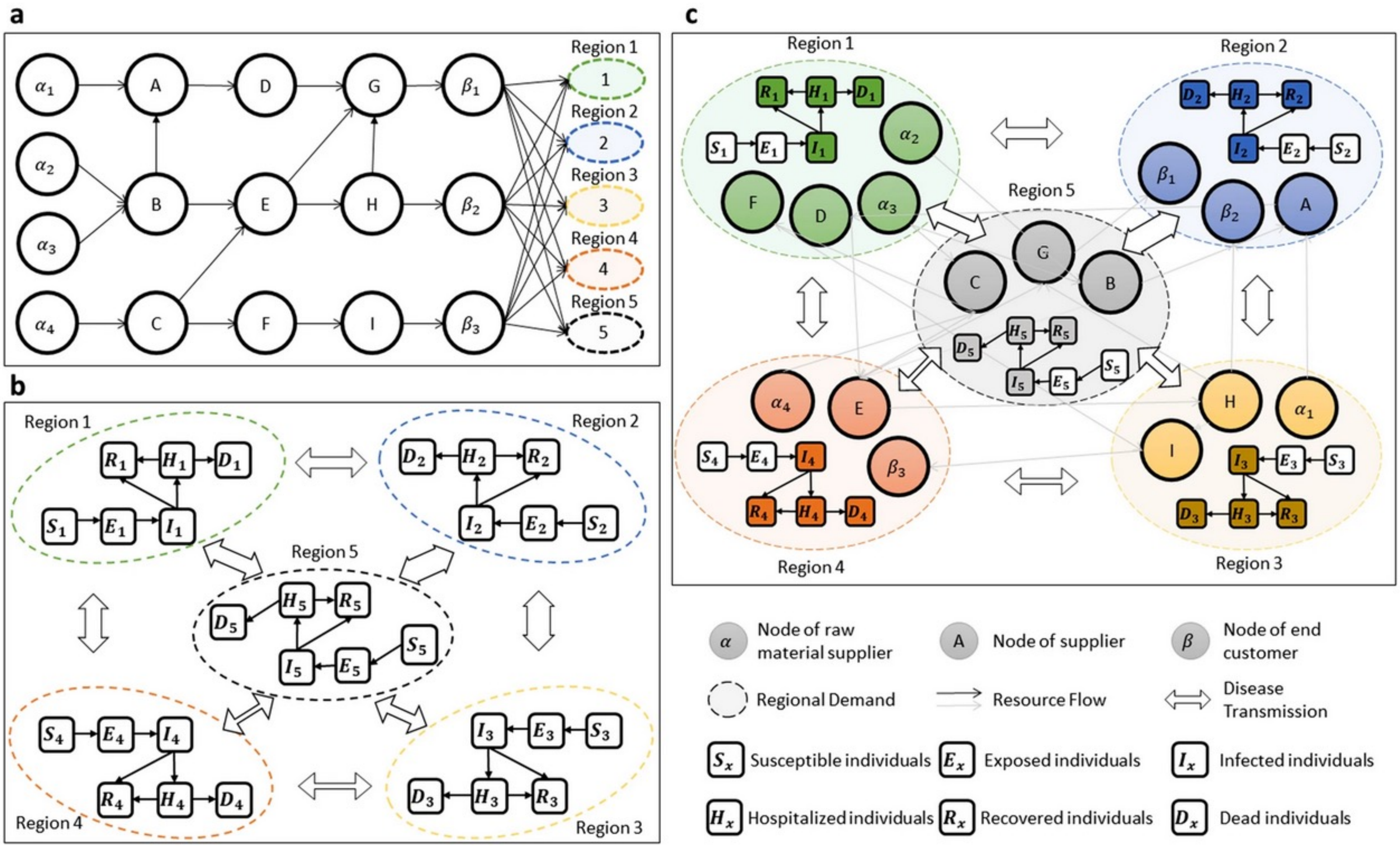


Figure 1 | Modelling a blackout in Italy. Illustration of an iterative process of a cascade of failures using real-world data from a power network (located on the map of Italy) and an Internet network (shifted above the map) that were implicated in an electrical blackout that occurred in Italy in September 2003[20]. The networks are drawn using the real geographical locations and every Internet server is connected to the geographically nearest power station. **a**, One power station is removed (red node on map) from the power network and as a result the Internet nodes depending on it are removed from the Internet network (red nodes above the map). The nodes that will be disconnected from the giant cluster (a cluster that spans the entire network) at the next step are marked in green. **b**, Additional nodes that were disconnected from the Internet communication network giant component are removed (red nodes above map). As a result the power stations depending on them are removed from the power network (red nodes on map). Again, the nodes that will be disconnected from the giant cluster at the next step are marked in green. **c**, Additional nodes that were disconnected from the giant component of the power network are removed (red nodes on map) as well as the nodes in the Internet network that depend on them (red nodes above map).

Buldyrev et al. (2010), Catastrophic cascades of failures in interdependent networks, Nature (Letters), Vol 464

More recent examples

- Supply chain disruption caused by Covid'19
- Energy and food security and the war in Ukraine



System Model of supply chain and disease dynamics: **(a)** a classic supply chain network with three types of products; **(b)** a classic multi-patch disease network for COVID-19; **(c)** the model of multi-patch disease and the production and supply chain.

Li, X., Ghadami, A., Drake, J.M. et al. Mathematical model of the feedback between global supply chain disruption and COVID-19 dynamics. Sci Rep 11, 15450 (2021)

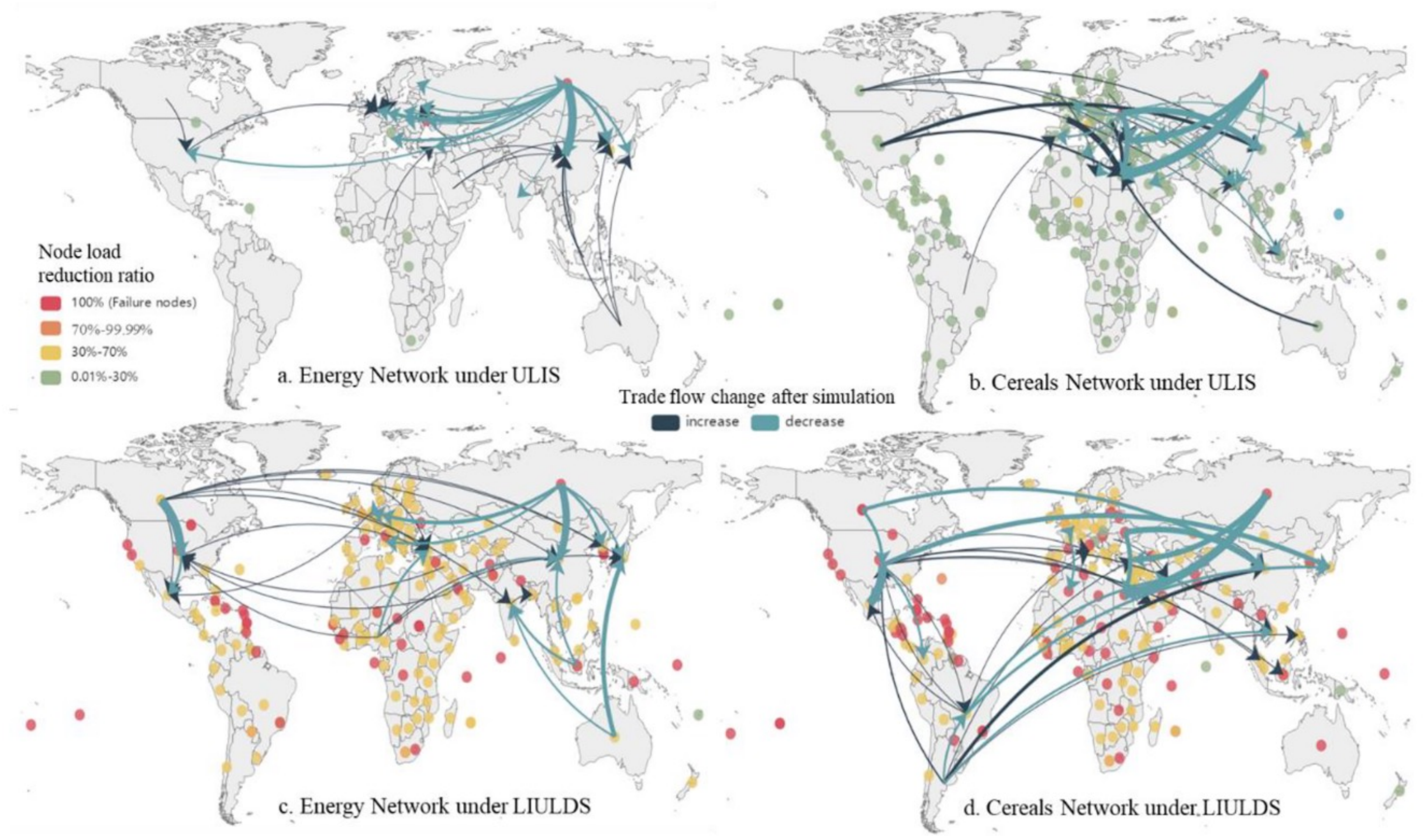


Fig. 7. Typical influence process of RUW under ULIS and LIULDS. Note: the trade flow change with the top 15 change amounts is presented including the increase amount and decrease amount respectively.

Zhou et al. Influence of Russia-Ukraine War on the Global Energy and Food Security, Resources, Conservation and Recycling,Volume 188, 2023,

Complex Systems – Polycrisis: How to deal with “multiple problems“

“A problem becomes a crisis when it challenges our ability to cope and thus threatens our identity. In the polycrisis the shocks are disparate, but they interact so that the whole is even more overwhelming than the sum of the parts.”

“What makes the crises of the past 15 years so disorientating is that it no longer seems plausible to point to a single cause and, by implication, a single fix. Whereas in the 1980s you might still have believed that “the market” would efficiently steer the economy, deliver growth, defuse contentious political issues and win the cold war, who would make the same claim today? It turns out that democracy is fragile. Sustainable development will require contentious industrial policy. And the new cold war between Beijing and Washington is only just getting going.”

Adam Tooze, Financial Times, 18 Oct 2022