Systemic risk in economic and financial networks

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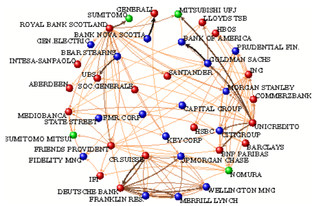
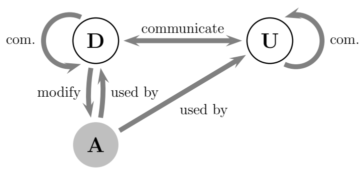
- Main Research Areas
  - **Economic Networks** & **Social Organizations**
    - e.g. ownership networks, R&D networks, financial networks, ...
    - e.g. online communities, OSS projects, animal societies, ...





- Methodological Approach: **Data Driven Modeling**
  - **economic databases**: ORBIS, Bloomberg, patent databases
  - **online data**: user interaction, communication records, blogs

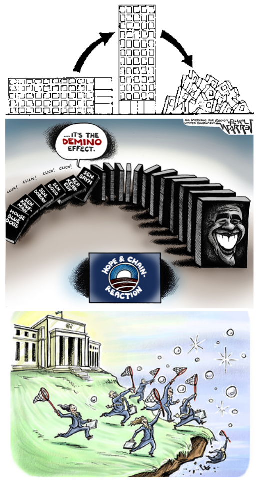
Risk: Two Perspectives

- **systemic risk**
  - risk that a whole system comprised of many agents fails
  - opposed to individual agent failure ⇒ impact on others
  - *agents, interactions* ⇔ *systemic properties*?
- **macro level approach** ⇒ **systems dynamics**
  - small number of representative agents, nonlinear feedback
  - critical conditions of control parameters ⇒ *regulation*
- **micro level approach** ⇒ **complex systems**
  - large number of heterogeneous, strongly interacting agents
  - systemic risk as *emerging property* ⇒ focus on collective effects

F. Schweitzer: *Systemic Risk*, in: M. Aoki, H. Aoyama, Y. Aruka, H. Yoshikawa (Eds.): *The 50 keywords of Economics: What is Socioeconophysics?*, Tosho Co., Tokyo 2011 (in Japanese)

Why do systems fail?

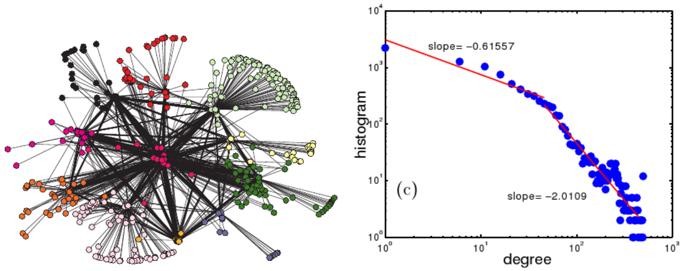
1. **external or internal pertubations**
   - supercritical shocks ⇒ increase resistance
   - **solution:** *"more of the same"*
   - **problem:** *likelyhood of extreme events*
2. **cascading effects**
   - agents affected by spreading failure
   - **solution:** *control structure*
   - **problem:** *optimal heterogeneity*
3. **contagious effects**
   - agents follow the crowd (herding)
   - **solution:** *control feedback*
   - **problem:** *acceleration, trend reinforcing*



Structural perspective: Network topology

Some Empirics: Financial Networks

- **skewed distributions**: few banks interact with many others
- **clusters**: banks with similar investment behavior



Example: Banking network of Austria (M Boss *et. al*, Quantitative Finance **4** (2004) 677-684)

(left) Clusters are grouped (colored) according to regional and sectorial organization
(right) Degree distribution of the interbank connection network

Hubs - good or bad for systemic risk?

- agent dynamics: $s_i(t+1) = \Theta[\phi_i(t, \mathbf{s}, \mathbf{A}) - \theta_i]$
- fragility ϕ_i of agent i depends on failure of neigbors, $s_j \in \{0, 1\}$
- **(i) 'inward' variant**: increase of fragility depends on *in-degree*

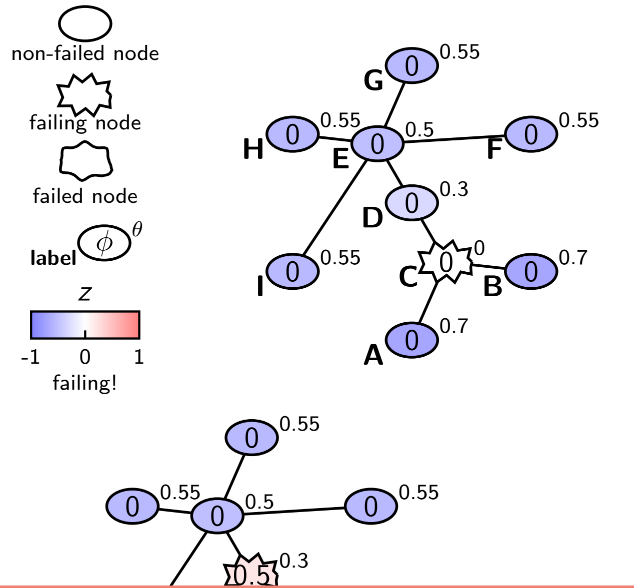
$$\phi_i(t) = \frac{1}{k_i^{\mathrm{in}}} \sum_{j \in \mathrm{nb_{in}}(i,A)} s_j(t)$$

- **(ii) 'outward variant'**: increase of fragility depends on *out-degree*
  - load of failing node (i.e. 1) is shared equally among neighbors

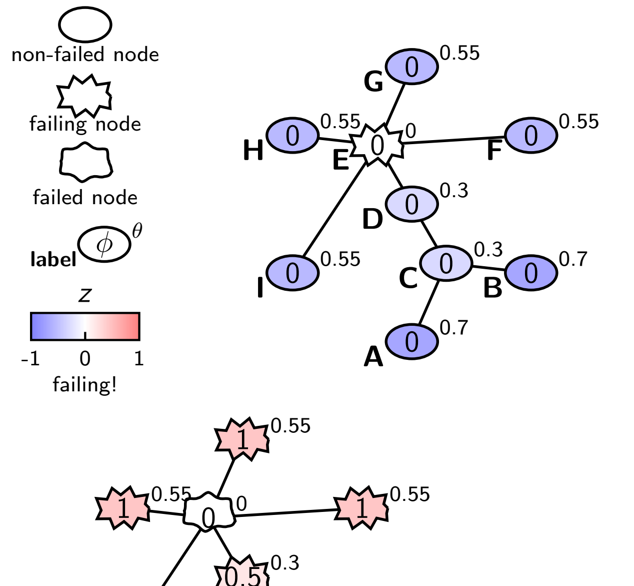
$$\phi_i(t) = \sum_{j \in \mathrm{nb_{in}}(i,A)} \frac{s_j(t)}{k_j^{\mathrm{out}}}$$

J. Lorenz, S. Battiston, F. Schweitzer: Systemic Risk in a Unifying Framework for Cascading Processes on Networks, *European Physical Journal B* vol 71, no 4 (2009) pp. 441-460, http://arxiv.org/abs/0907.5325

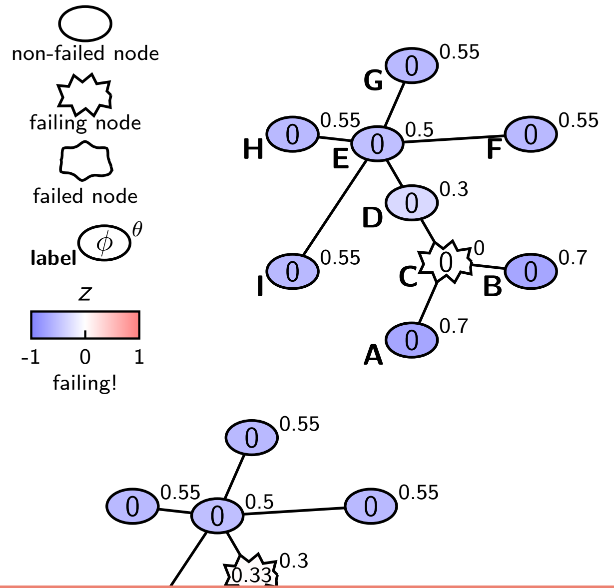
Example: Inward variant - node *C* fails



Example: Inward variant - node *E* fails



Example: Outward variant - node C fails



Macroscopic reformulation

- **global fraction of failed nodes** $\Rightarrow$ *prediction*

$$X(t) = \frac{1}{n}\sum_{i=1}^{n} s_i(t)$$

  - **systemic risk:** $X(t \to \infty) = X^\star \to 1$
    - **aim:** compare different model classes $\to$ set $p_{z(0)}$
    - **assumptions:** fully connected network
- **macroscopic dynamics**

$$X(t+1) = \int_0^\infty p_{\langle\phi(t)\rangle-\theta}(z)dz = P_\theta(\langle\phi(t)\rangle)$$

$$P_\theta(x) = \int_{-\infty}^{x} p_\theta(\theta)d\theta$$

- **procedure:** express $\langle\phi(t)\rangle$ in terms of $X(t)$ $\Rightarrow$ recursive equation

Realistic scenario: Load redistribution

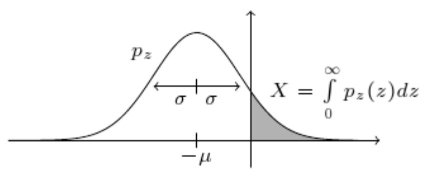
- major challenge in real networks: failure causes *redistribution*
  - neighboring nodes have to compensate $\Rightarrow$ increases risk of failure
  - examples: financial networks, supply networks (power grid)
- **redistribution** (given network **A**, states $\mathbf{s}(0)$)
  - if node fails, load is distributed to active neighbors (if links exist)

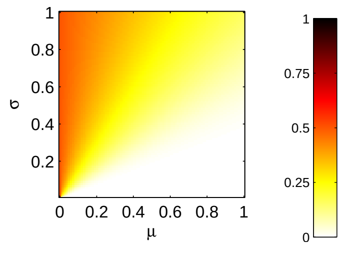
$$\phi_i(t) = \begin{cases} \phi_i(t-1) + \sum\limits_{j\in\mathrm{fail_{in}}(i)} \frac{\phi_j(t-1)}{\#\mathrm{sus_{out}}(j)} & \text{if } s_i(t)=0 \\ 0 & \text{otherwise} \end{cases}$$

  - $\mathrm{fail_{in}}(i)$: set of in-neighbors of i which failed at $t-1$
  - $\mathrm{sus_{out}}(j)$: set of out-neighbors of j which remain alive after $t-1$
- **twofold reinforcement:** $\mathrm{fail_{in}}(i)$ *increases*, $\mathrm{sus_{out}}(j)$ *decreases*

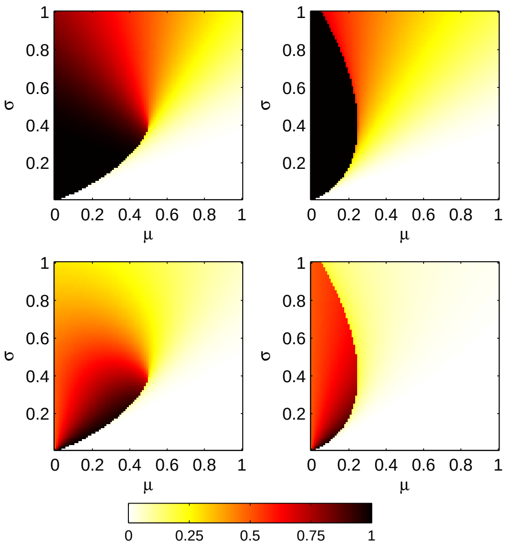
Comparison of Macrodynamics

- initial conditions normally distributed: $z(0) \sim \mathcal{N}(-\mu, \sigma)$
  - case (i): $\theta \sim \mathcal{N}(\mu, \sigma)$, case (ii): $\theta \sim \mathcal{N}(\mu + \phi^0, \sigma)$
  - σ: measure of *initial heterogeneity* in θ across nodes
- initial failure: $X(0) = \Phi_{\mu,\sigma}(0)$
  - cumulative normal distribution function





Final fraction of failed nodes $X^\star$

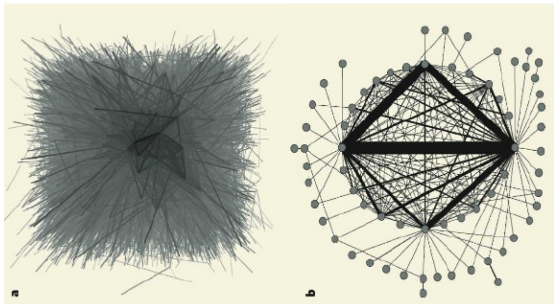


- **First-order phase transition:** small variations in initial conditions lead to complete failure
- non-monotonous behavior for case (ii): intermediate σ most dangerous

Top left: class (i) constant load. Top right: class (ii) load redistribution with initial load $\phi^0 = 0.25$. Bottom line: Net fraction of failed nodes $X^\star - X(0)$ $\Rightarrow$ Systemic risk resulting from *cascades* only

Topology: Financial Networks

- **weighted network**: links represent transaction volumes
- **existence of a backbone**: involves small number of nodes



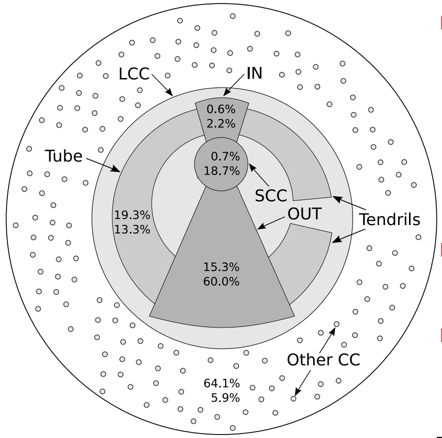
Example: Fedwire interbank payment network (K. Soramäki *et al.* Physica A **379** (2007) 317-333)

(left) Thousands of banks and tens of thousands of links representing USD 1.2 $\times 10^{12}$ in daily transactions

(right) Core of the network: 66 banks accounting for 75 % of transfers, 25 banks being completely connected.

Topology: The highly connected core

Ownership Network of Transnational Companies (TNCs)

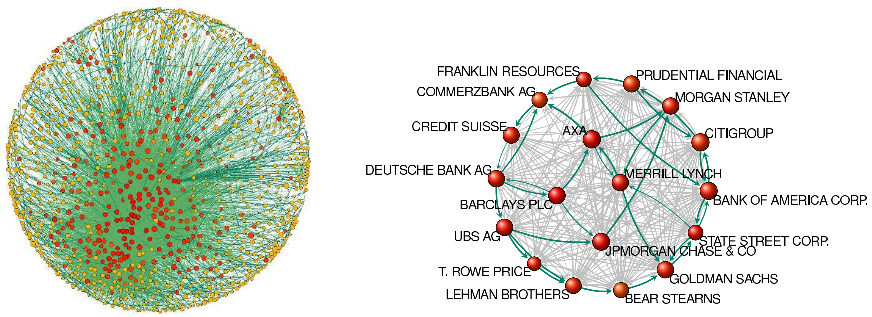


Size of components scaled by (log) number of TNC.

- Largest connected component (LCC) contains giant bow-tie:
  - IN-section, strongly connected component (SCC) core, OUT-section,
  - tubes and tendrils.
- Remaining small connected components (CC).
- Numbers refer to
  - percentage of contained TNC,
  - total TNC operating revenue.

S. Vitali, J. Glattfelder, S. Battiston: *The network of global corporate control*, PLoS ONE (2011)
http://arxiv.org/abs/1107.5728

Problem: Self-Ownership



(left) SCC (1318 nodes, 12191 links). Node size scales logarithmically with operation revenue, node color with network control (from yellow to red). Link color scales with weight.
(right) Zoom on some major TNCs in the financial sector. Some cycles are highlighted.

- 75% of the ownership of the SCC firms stays within the SCC
  - propagation of financial distress increases systemic risk
  - cross-ownership decreases competition $\Rightarrow$ market failure

S. Vitali, J. Glattfelder, S. Battiston: *The network of global corporate control*, PLoS ONE (2011)
http://arxiv.org/abs/1107.5728

Acceleration due to trend reinforcement

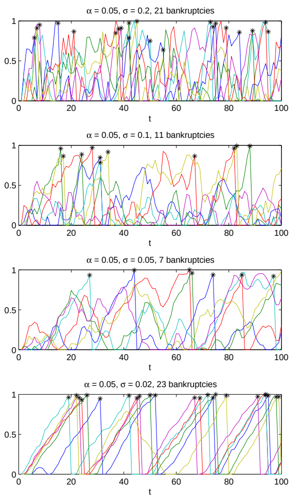
1. **Load redistribution**
   - topological effect: fewer agents have to carry the load
   - increasing load ⇒ *increasing risk of failure*
2. **Individual history matters**
   - CDS spreads: failure today ⇒ worse conditions tomorrow
   - bad trend ⇒ *increasing risk of failure*
3. **Global coupling matters**
   - US housing bubble: banking crisis due to macroeconomic feedback
   - erosion of value and worse economy ⇒ *increasing risk of failure*

Trend Reinforcement Model

- Fragility of n agents evolves as

$$\underbrace{\phi(t+1) = \phi(t)}_{\text{fragility}} + \underbrace{\sigma\xi(t)}_{\text{stochastic shocks}} + \underbrace{\alpha\ \mathrm{sign}(\Delta\phi(t))}_{\text{trend reinforcing}}$$

- trend reinforcing ↗ ⇝ ↗↗, ↘ ⇝ ↘↘
- reducing volatility σ
  - decreases stochastic shocks → less bankruptcies, BUT
  - reduces possibility to break bad trends → more bankrupcies!
- Conclusion: We are safest with intermediate volatility



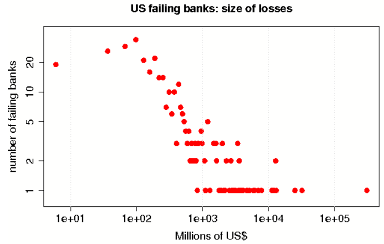
Lorenz, Jan, Battiston, Stefano: Systemic risk in a network fragility model analyzed with probability density evolution of persistent random walks , Networks and Heterogeneous Media, vol. 3, no. 2, June (2008), pp. 185-200

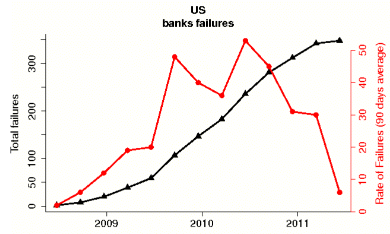
Bad Trends: Macroeconomic Feedback

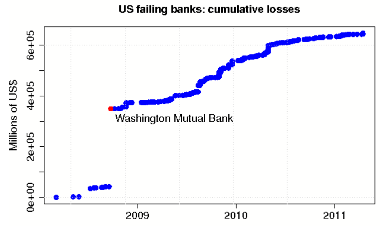
"... we had it wrong ... it was more popcorn than domino"

Edward Lazear (Stanford U)
Chairman of George Bush's Council of Economic Advisors

- **US Bank Failures** (2008-2011)
  - Data: FDIC (Federal Deposit Insurance Corporation), 2011
  - highly skewed distribution: 0.1 – 300.0 bn USD
  - *indirect interaction*: coupling due to macro economy, *no direct cascades*





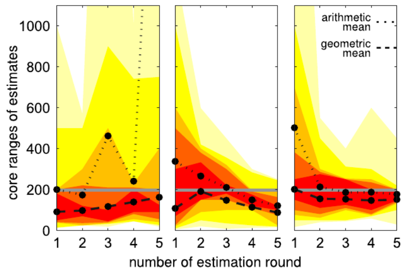


Herding into the wrong direction

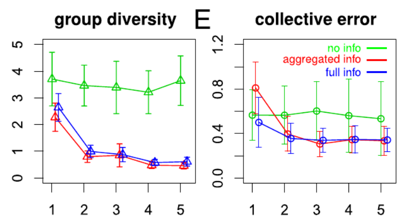
- **wisdom of crowds**
  - median estimate of groups better than estimate of experts
  - important condition: no correlations
- **crowds under "mild" information coupling**
  1. *"social influence effect"* (statistical)
     - reduces opinion diversity *without* improving collective error
  2. *"range reduction effect"* (statistical)
     - moves truth to peripherial regions ⇒ crowds become *less reliable*
  3. *"confidence effect"* (psychological)
     - convergence leads to overconfidence, despite lack of improved accuracy

J. Lorenz, H. Rauhut, F. Schweitzer, D. Helbing: How social influence can undermine the wisdom of crowd effect, *PNAS* vol 108 no 22 (2011) pp. 9020-9025

Laboratory Experiments

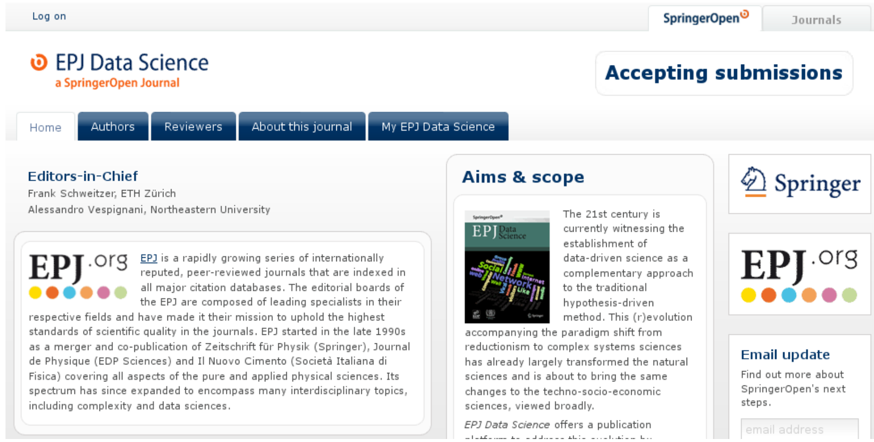


col. err.	0.6	0.5	0.3	0.1	0.0	0.4	0.0	0.1	0.3	0.7	0.0	0.1	0.1	0.1	0.1
gr. div.	1.8	1.3	2.5	1.0	3.8	3.4	1.0	1.3	0.9	1.0	2.0	0.8	0.5	0.5	0.4



- social influence triggers convergence of estimates
- wisdom of crowds, i.e. group diversity, diminishes over time
- true value moves to peripherial regions
- individuals gain confidence in their own estimates

EPJ Data Science starts Jan 2012 ... stay tuned



Conclusions: The Risk to Fail

1. **systemic risk**
   - failure of few agents is amplified (micro and macro feedback)
   - need of endogenous rather than exogeneous explanations
   - focus on *backbone*: small core of strongly connected important nodes
2. **control structure**
   - *hubs:* role of degree depends on redistribution mechanism
   - optimal agent *heterogeneity* can reduce systemic risk
   - *ownership:* highly connected core increases systemic risk
   - *phase transition:* small changes lead to big impact on systemic risk
3. **control feedback**
   - *load redistribution* amplifies agent's failure
   - *trend reinforcement:* intermediate volatility reduces failure
   - systemic risk without cascades: *macroeconomic feedback*
   - *herding into the wrong direction:* overconfidence, lack of improvement