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

Why do systems fail?
1. external or internal perturbations
   - supercritical shocks ⇒ increase resistance
   - solution: “more of the same”
   - problem: likelihood 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


(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: \( s_i(t+1) = \Theta[\phi_i(t,s,A) - \theta_i] \)
- fragility \( \phi_i \) of agent \( i \) depends on failure of neighbors, \( s_j \in \{0,1\} \)
- (i) 'inward' variant: increase of fragility depends on in-degree
  \[ \phi_i(t) = \frac{1}{k_i} \sum_{j \in \text{nb}_i(i,A)} s_j(t) \]
- (ii) 'outward variant': increase of fragility depends on out-degree
  - load of failing node (i.e. 1) is shared equally among neighbors
  \[ \phi_i(t) = \sum_{j \in \text{nb}_i(i,A)} \frac{s_j(t)}{k_j} \]

Example: Outward variant - node C fails

Realistic scenario: Load redistribution

- major challenge in real networks: failure causes redistribution
- neighboring nodes have to compensate ⇒ increases risk of failure
- examples: financial networks, supply networks (power grid)

redistribution (given network A, states s(0))
- if node fails, load is distributed to active neighbors (if links exist)

\[ \phi_i(t) = \begin{cases} \phi_i(t-1) + \sum_{j \in \text{fail}_{\text{in}}(i)} \frac{\phi_j(t-1)}{\text{sus}_{\text{out}}(j)} & \text{if } s_i(t) = 0 \\ 0 & \text{otherwise} \end{cases} \]

- \text{fail}_{\text{in}}(i): set of in-neighbors of i which failed at \( t-1 \)
- \text{sus}_{\text{out}}(j): set of out-neighbors of j which remain alive after \( t-1 \)
- twofold reinforcement: \( \text{fail}_{\text{in}}(i) \) increases, \( \text{sus}_{\text{out}}(j) \) decreases

Macroscopic reformulation

- global fraction of failed nodes ⇒ prediction

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

- systemic risk: \( X(t \to \infty) = X^* \to 1 \)
  - aim: compare different model classes → set \( p_\phi(0) \)
  - assumptions: fully connected network

macropscopic dynamics

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

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

procedure: express \( \langle \phi(t) \rangle \) in terms of \( X(t) \) ⇒ recursive equation

Comparison of Macrodynamics

- initial conditions normally distributed: \( z(0) \sim N(-\mu, \sigma) \)
  - case (i): \( \theta \sim N(\mu, \sigma) \), case (ii): \( \theta \sim N(\mu + \phi^\theta, \sigma) \)
  - \( \sigma^2 \): measure of initial heterogeneity in \( \theta \) across nodes
- initial failure: \( X(0) = \Phi_{\mu, \sigma}(0) \)
  - cumulative normal distribution function

\[ X = \int_{-\infty}^{\infty} p_\mu(z) dz \]
Final fraction of failed nodes $X^*$

- **First-order phase transition:** Small variations in initial conditions lead to complete failure
- **Non-monotonic behavior** for case (ii): intermediate $\sigma$ 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 $X^* - X(0) \Rightarrow$ Systemic risk resulting from cascades only

**Problem: Self-Ownership**

- **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

**Topological: The highly connected core**

- **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.

**Ownership Network of Transnational Companies (TNCs)**

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<th>Ownership Network of Transnational Companies (TNCs)</th>
<th>Topological: The highly connected core</th>
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**Topology: Financial Networks**

- **Weighted network:** Links represent transaction volumes
- **Existence of a backbone:** Involves a small number of nodes


(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.
Acceleration due to trend reinforcement

1. Load redistribution
   - Topological effect: fewer agents have to carry the load
   - Increasing load \( \Rightarrow \) increasing risk of failure

2. Individual history matters
   - CDS spreads: failure today \( \Rightarrow \) worse conditions tomorrow
   - Bad trend \( \Rightarrow \) increasing risk of failure

3. Global coupling matters
   - US housing bubble: banking crisis due to macroeconomic feedback
   - Erosion of value and worse economy \( \Rightarrow \) increasing risk of failure

Bad Trends: Macroeconomic Feedback

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

- 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

Trend Reinforcement Model

Fragility of \( n \) agents evolves as

\[
\phi(t + 1) = \phi(t) + \sigma \xi(t) + \alpha \text{sign}(\Delta \phi(t))
\]

- Fragility\( \phi(t) \)
- Stochastic shocks\( \sigma \xi(t) \)
- Trend reinforcing\( \alpha \text{sign}(\Delta \phi(t)) \)

- Trend reinforcing\( \uparrow \rightarrow \uparrow \uparrow \rightarrow \uparrow \uparrow \)
- Reducing volatility\( \sigma \)
  - Decreases stochastic shocks\( \rightarrow \) less bankruptcies, BUT
  - Reduces possibility to break bad trends \( \rightarrow \) more bankruptcies!

Conclusion: We are safest with intermediate volatility


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 peripheral regions \( \Rightarrow \) crowds become less reliable
  3. "Confidence effect" (psychological)
     - Convergence leads to overconfidence, despite lack of improved accuracy

Laboratory Experiments

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

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

EPJ Data Science starts Jan 2012 ... stay tuned