Agent-based dynamics of credit and liquidity shocks propagation on reconstructed financial networks

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Systemic Risk analysis: 
assess robustness of the financial network to shocks

- Build synthetic (reconstructed) financial networks
- Model network dynamics of shocks propagation
- Design an Agent-Based Model of bank behavior
- Employ this framework in regulatory stress tests
The financial system: a network of interconnected balance sheets

Battiston et al. (2016) *The price of complexity in financial networks*

\[ E_i = \left\{ A_i^E + \sum_j A_{ij} \right\} - \left\{ L_i^E + \sum_j L_{ij} \right\} \]

Battiston et al. (2016) *Leveraging the network* [...]

Gai & Kapadia (2010) *Contagion in financial networks*
Reconstructing the network

Network effects are important for Systemic Risk analysis, but:

✓ data on aggregated exposures (assets / liabilities) public
✗ data on individual exposures often not available (privacy!)

⇒ RECONSTRUCT THE NETWORK exploiting only aggregated balance sheet information

M. Montagna, T. Lux (2017) Quantitative Finance 17 (1) 101–120.
Fitness-Induced MaxEnt Reconstruction

Reconstructed network: 
*maximally random graph compatible with constraints* \( D, \{A, L\} \)

Two-step inference:
1. Infer **link probability** using *Fitness + Configuration model*  
   (ansatz: *total exposure = fitness induced by degree*)

   \[
   D = \sum_{i \neq j} p_{i \rightarrow j} \equiv \sum_{i \neq j} \frac{zA_i L_j}{1 + zA_i L_j} \Rightarrow \text{find } z \text{ to obtain } \{p_{i \rightarrow j}\}_{i,j}
   \]

2. Infer **link weights** by *degree-corrected Gravity Model*  
   (obeys network topology + preserves marginals)

   \[
   w_{i \rightarrow j} = \frac{A_i L_j}{Wp_{i \rightarrow j}} \tilde{a}_{i \rightarrow j} = \frac{z^{-1} + A_i L_j}{W} a_{i \rightarrow j}
   \]
Reconstructed?

eMID (electronic market for interbank deposits)
Reconstructed vs Reconstructed

⇒ info on topology is crucial (if properly employed)


Dynamics of Credit & Liquidity Shocks

\[ i \xrightarrow{A_{ij}} j \xrightarrow{A_{jk}} k \]

- **Credit shock** (*counterparty risk*)
  - If \( k \) fails, it won’t meet obligations and \( j \) suffers a loss \( A_{jk} \)
  - If \( A_{jk} > E_j \), also \( j \) fails and \( i \) suffers a loss \( A_{ij} \)

- **Liquidity shock** (*rollover risk*)
  - If \( j \) fails, \( k \) cannot roll its debt again over \( A_{jk} \)
  - To replace the lost liquidity, \( k \) must sell its illiquid assets
  - During fire sales, illiquid assets trade at a discount: \( k \) must sell assets worth \((1 + \gamma)A_{jk}\), with overall loss \( \gamma A_{jk} \) \((\gamma \text{ : assets depricing factor})\)

\( \Rightarrow \) contagion and amplification through bilateral exposures!
A Debt-Solvency Rank

[IMF GFS report 2009]:

\[ j \text{ defaults } \rightarrow -\Delta E_i = \lambda A_{ij} + \gamma \rho A_{ji} \rightarrow i \text{ defaults? } \rightarrow \text{ domino effect} \]

Even with no default, equity losses for a bank do imply:

- a decreasing value of its obligations (credit shock) – Debt Rank!
- a decreasing ability to lend money (funding shock)

\[ \Rightarrow \text{ potential relative equity loss by iteratively spreading individual distress levels weighted by the potential wealth affected} \]

Distress of bank \( i \) at round \( n \):

\[ h_i(n) = 1 - \frac{E_i(n)}{E_i(0)} \]

Distress of bank \( i \) at \( n + 1 \):

\[ h_i(n+1) = \min \left\{ 1, h_i(n) + \sum_{j: h_j(n-1) < 1} \frac{\lambda A_{ij} + \gamma(n) \rho A_{ji}}{E_i(0)} [h_j(n) - h_j(n-1)] e^{-(n-n_j)/\tau} \right\} \]

Group DS Rank on synthetic EU interbank network

Equity potentially at risk in the system $DS(n^*) = \sum_i [h_i(n^*) - h_i(1)] \nu_i$

- Liquidity shocks increase overall losses by up to 50%
- Distance from full-fail scenario after 2008 dramatically reduced

missing: target leverage, liquidity hoarding, contagion through overlapping portfolios
ABM of the interbank market during crises

Stylized facts of GFC:

▶ If hit by a shock, a bank sells assets following a leverage targeting policy in order to reinforce its reputation and expectation of the stakeholders.

▶ After the shock and during the realignment, worries about creditworthiness may cause a “flight to quality”, for which banks withdraw liquidity from the market.

▶ Liquidity hoarding coupled with a constant liquidity demand triggers an increase of interbank interest rates, and the consequent revaluation of interbank assets and liabilities.

▶ If a bank defaults, credit and funding shocks propagate through its bilateral exposures like a bank-run contagion on financial interbank contracts.

▶ Interbank network connections and fire sales spillovers may lead to default cascades, with a consequent increasing of liquidity hoarding and interest rate.

▶ In extreme conditions, the market freezes triggering exacerbated fire sales.
ABM of the interbank market during crises

exogenous shock on external assets

bank tries to realign to target leverage by hoarding liquidity from assets sales

interbank interest rate grows as market shrinks, and balance sheets revaluate

has a bank defaulted?

no

exogenous shock on interbank assets

wave of credit and liquidity network losses from defaulted bank, until no more defaults

yes

market freeze condition

total liquidation of interbank assets triggering fire sales
Looking at out-of-equilibrium dynamics

Market equity after a crisis

Time to half-equity (how far the system can go without regulatory intervention)

Model at work: stress-test for CCPs

how to determine resources to set aside?

CCP: contract intermediary between CMs by collecting guarantees

EMIR Regulation: Default Fund to cover at least losses stemming from the default of the two CMs to which the CCP is more exposed [cover 2 rule]

Current steps to compute DF:

▶ Identify historical/hypothetical stressed scenarios
▶ Revalue CMs portfolio positions to those scenarios
▶ Recompute CMs margins and compare them with no-stressed margins
▶ DF = two (four) largest differences

Improve stress-test by a network characterization of CMs
⇒ assess second-round losses and better calibrate DF


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Stress-test work-flow

1. Assess CMs daily balance sheets with a Merton-like model
2. Reconstruct the network of inter-CMs bilateral exposures
3. Simulate an initial shock (macroeconomic, idiosyncratic, \( \sim \Delta \) margins)
4. Reverberate initial shock on the network via credit & liquidity contagion

\[ \lambda = \rho = 0.6, \text{ initial loss } 2.6\% - 3.0\%, \text{ similar stationary configurations} \]
\[ n = n^*: \text{ total uncovered exposure of defaulted CM} = €3.0 - €3.2 \text{ billions} \]
\[ \text{DF} = €3.5 \text{ billions BUT cover 4! (cover 2 not enough?)} \]
Stability analysis

\( R_{DF} \): fraction of DF after subtracting the exposures of defaulted CMs

\[ \lambda = \rho = 0.6 \]

5 \( \cdot \) \( 10^{-4} \) \( < x \) \( < 10^{-3} \): plausible initial shock (from NPLs data):

\* DF heavily deteriorated!

worst case: \( \sim 18\% \) uncovered exposures (cover 4)

\* cover 2 insufficient!

this is what happens for “severe yet plausible” market conditions
Questions?