Correlation networks to measure the systemic implications of bank resolution

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Disclaimer: the paper represents the authors’ personal opinions and does not necessarily reflect the views of the institutions with which they are affiliated.
A key component of systemic risk is the **probability of default** of financial institutions.

Default probabilities can be calculated using market-based data (e.g. CDS spreads), or by looking at the balance-sheet structure of banks.

This paper: from a **micro**- to a **systemic** approach. Default probability of each financial institution $\rightarrow$ Joint default probability of the entire financial system.

FOLTF banks can be subject to different resolution decisions.

**Objective**

What would happen to each single bank, and to the entire banking system, in case an adverse scenario materialises, taking into account the regulatory BRRD/SRM context established in the Euro area.

- Market-based data + micro-data + systemic risk tools;
- Consequences of banks resolution
  - at the bank level
  - at the system level
We define a risk measure for each single bank (based on CDS spreads);
We find one or more financial institutions under distress (assumed to be FOLTF);
We derive the consequences of having FOLTF banks in the system according to two perspectives:
  - for each single financial institution,
  - for the entire banking system;
and under three alternative scenarios:
  - FOLTF banks are liquidated,
  - FOLTF banks are recapitalised through a private intervention,
  - FOLTF banks are subject to bail-in resolution;
We compare the consequences (measured in terms of expected losses) under the three scenarios and according to the two perspectives, in order to identify the ”best” resolution decision as the one that minimises losses.
1. Conditional quantiles:
   ▶ Acharya et al. (2010), Adrian & Brunnermeier (2011), Brownlees & Engle (2012)
   ▶ Identify SIFIs → Do not describe contagion transmission;

2. Regression methods:
   ▶ Koopman et al. (2012), Betz et al. (2014), Duprey et al. (2015), Hautsch et al. (2015)
   ▶ Provide predictive models → Do not describe contagion transmission;

3. Network models:
   ▶ Battiston et al. (2012), Billio et al. (2012), Minou and Reyes (2013), Diebold and Yilmaz (2014)
   ▶ Describe contagion transmission → Do not provide predictive models.

Our contribution

▶ Systemic risk measure based on CDS spreads;
▶ Contagion mechanism based on partial correlation networks.
Banks resolution in the Euro area: overview

▶ ECB (or SRB in exceptional circumstances) identifies a bank as FOLTF;
▶ SRB identifies the resolution strategy;
▶ FOLTF bank is **not systemically important** → liquidation;
▶ FOLTF bank is **systemically important** → Bail-in
  ▶ waterfall hierarchy of bail-in able resources to cover losses,
  ▶ consequences on private creditors rather than on taxpayers.
▶ IF and ONLY IF two conditions are met:
  ▶ no alternative private interventions would prevent the failure of the FOLTF bank,
  ▶ bail-in is necessary in the public interest.

Our contribution

Comparison between the expected losses (for each bank and for the entire system) in case of:
▶ liquidation,
▶ private intervention (recap),
▶ bail-in.
Measuring systemic risk

Univariate EL
From CDS spreads of financial institutions.

Contagion effect
From the partial correlation network between the CDS spreads of financial institutions.

Multivariate EL
Can be used to assess contagion between financial institutions, for example in the BRRD context.
The banks’ perspective

- Let $A$ be a vector of (net) asset values: $A = \{A_1, \ldots, A_N\}$.

\[
EL_n = A_n \cdot (PD_n) \cdot (1 - RR_n).
\]

- Let $S_n$ be the CDS spread: in the simplified case of a one-year contract

\[
EL_n = A_n \cdot S_n,
\]

- We extend $EL_n$ into a multivariate expected loss ($TEL$) that takes contagion between CDS spreads into account:

\[
TEL_n = EL_n + \sum_{m \neq n} c_{mn|\text{rest}} EL_m,
\]

where $\text{rest} = V \setminus \{m, n\}$.

- The geometric average between the coefficients is equal to the partial correlation between $EL_m$ and $EL_n$:

\[
|\rho_{mn|\text{rest}}| = |\rho_{nm|\text{rest}}| = \sqrt{c_{mn|\text{rest}} c_{nm|\text{rest}}}.
\]
**The system’s perspective**

\[
TEL_{\text{system}} = \left[ \sum_{i=1}^{N} A^i \right] \cdot \left[ Pr \left( \bigcap_{i=1}^{N} D^i \right) \right] = \\
\left[ \sum_{i=1}^{N} A^i \right] \cdot \left[ Pr(D^1) \cdot Pr(D^2|D^1) \cdot \ldots \cdot Pr(D^N|D^1, D^2, \ldots, D^{(N-1)}) \right].
\]
**The effects of banks resolution**

- **ASSUMPTION**: one bank ($B^m$) is identified as FOLTF.
- **QUESTION**: does another bank ($B^n$) in the system prefer $B^m$ to be liquidated, recapitalised (private intervention) or subject to bail-in?
- Each bank should evaluate the consequences of the three alternative scenarios in a long-run perspective.
- We aggregate the expected losses over time (survival analysis).
- The preferred scenario is the one that minimises the expected losses of:
  - each single bank (banks’ perspective),
  - the entire banking system (system’s perspective).
- Discrete time-line

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**Example: three banks**

\[ A_1 = 40 \text{ bn} \ \varepsilon, \ A_2 = 20 \text{ bn} \ \varepsilon, \ A_3 = 4 \text{ bn} \ \varepsilon \]

\[ S_n \sim \mathcal{N}(\mu_{S_n}, \sigma_{S_n}^2) \text{ with } \mu_{S_1}, \mu_{S_2} = 0.01, 0.03, 0.05, 0.07 \text{ and unit variances} \]

\[ \rho_{mn} \sim \mathcal{N}(\mu_{\rho_{mn}}, \sigma_{\rho_{mn}}^2) \text{ with } \mu_{\rho_{12}}, \mu_{\rho_{13}}, \mu_{\rho_{23}} \sim \mathcal{U}([-0.5, 0.5]) \]

\[
\begin{cases}
S_{3,t_j} \sim \mathcal{N}(\mu_{S_3,t_j}, \sigma_{S_3}^2), \\
\mu_{S_3,\{t_0,t_1\}} = 0.10, \\
\mu_{S_3,t_2} \sim \mathcal{U}([0, 0.30]),
\end{cases}
\tag{1}
\]
The private intervention always minimises losses in case of positive correlations;

This effect is even stronger for smaller and safer (lower PD) banks.
Simulation results 2

Bank 1

-1.0 -0.5 0.0 0.5 1.0
-0.10 -0.05 0.00 0.05 0.10
rho13

Bank 2

-1.0 -0.5 0.0 0.5 1.0
0.010 0.020 0.030 0.040
rho23

Bank 1

-1.0 -0.5 0.0 0.5 1.0
0.010 0.020 0.030 0.040
rho12

Bank 2

-1.0 -0.5 0.0 0.5 1.0
0.010 0.020 0.030 0.040
rho12

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Correlation networks to measure the systemic implications of bank resolution
### Data: CDS Spreads and Size of Italian Banks

<table>
<thead>
<tr>
<th>Bank</th>
<th><strong>μ (%)</strong></th>
<th>Max (%)</th>
<th>Min (%)</th>
<th><strong>σ (·10^{-2})</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>MPS</td>
<td>7.321</td>
<td>8.836</td>
<td>3.714</td>
<td>1.429</td>
</tr>
<tr>
<td>BPM</td>
<td>3.318</td>
<td>4.043</td>
<td>2.168</td>
<td>0.456</td>
</tr>
<tr>
<td>BAPO</td>
<td>3.771</td>
<td>4.871</td>
<td>2.608</td>
<td>0.484</td>
</tr>
<tr>
<td>MB</td>
<td>2.250</td>
<td>3.081</td>
<td>1.601</td>
<td>0.351</td>
</tr>
<tr>
<td>UCG</td>
<td>1.430</td>
<td>1.584</td>
<td>1.292</td>
<td>0.097</td>
</tr>
<tr>
<td>UBI</td>
<td>2.915</td>
<td>3.417</td>
<td>2.067</td>
<td>0.354</td>
</tr>
<tr>
<td>ISP</td>
<td>1.693</td>
<td>2.395</td>
<td>1.168</td>
<td>0.291</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Bank</th>
<th>Asset</th>
</tr>
</thead>
<tbody>
<tr>
<td>MPS</td>
<td>9.58</td>
</tr>
<tr>
<td>BPM</td>
<td>4.44</td>
</tr>
<tr>
<td>BAPO</td>
<td>6.92</td>
</tr>
<tr>
<td>MB</td>
<td>8.08</td>
</tr>
<tr>
<td>UCG</td>
<td>48.00</td>
</tr>
<tr>
<td>UBI</td>
<td>7.63</td>
</tr>
<tr>
<td>ISP</td>
<td>41.06</td>
</tr>
</tbody>
</table>
Partial correlation network

Node dimension = Assets

Node dimension = CDS spreads

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Correlation networks to measure the systemic implications of bank resolution
System’s view on MPS distress (1/3)

- Within the sample considered, MPS has the highest riskiness indicator according to our measure of distress;
- MPS thus assumed to be the FOLTTF bank in our system.
System’s view on MPS distress (2/3)

![Graphs showing expected losses in scenarios b and c.](image)

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System’s view on MPS distress (3/3)

Scatter plot showing expected losses for Scenario b compared to Scenario c, with density distributions for different values of S, including S=S_t1, S=0.035, and S=0.14.

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**Conclusions**

- **Banks’ perspective:**
  - The smaller or the safer a bank is, the bigger the reduction of EL in case of private intervention,
  - Liquidation reduces EL only in case of strong negative partial correlations,
  - The reduction of EL in case of private intervention is
    - a decreasing function of the PDs of the safe banks,
    - an increasing function of the correlations between safe banks and the FOLTF one.

- **System’s perspective:**
  - Private intervention and bail-in minimise losses,
  - Bail-in resolution slightly reduces contagion effects with respect to private intervention,
  - An increase in the PD of the FOLTF bank after bail-in/private intervention increases EL of the entire system,
  - Such increase is stronger for the private intervention scenario.
Caveats

- Proxies for bail-inable liabilities and interbank exposures (no confidential data);
- Not considered alternatives such as bridge banks, extraordinary public bail-out/precautionary recap, ...;
- No macroeconomic impact of the three scenarios → no effects on taxpayers, or sovereigns-banks loop;
- Static approach (time dimension introduced only in the form of three steady states).
Thank you for your attention!
## Liquidation

<table>
<thead>
<tr>
<th></th>
<th>$t_0$</th>
<th>$t_1$</th>
<th>$t_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>$B^1$</td>
<td>$A_1$</td>
<td>$A_1 - f_1 \cdot k[A_3 - Eq_3]$</td>
</tr>
<tr>
<td></td>
<td>$B^2$</td>
<td>$A_2$</td>
<td>$A_2 - f_2 \cdot k[A_3 - Eq_3]$</td>
</tr>
<tr>
<td></td>
<td>$B^3$</td>
<td>$A_3$</td>
<td>$A_3$</td>
</tr>
<tr>
<td>$S$</td>
<td>$B^1$</td>
<td>$S_1$</td>
<td>$S_1$</td>
</tr>
<tr>
<td></td>
<td>$B^2$</td>
<td>$S_2$</td>
<td>$S_2$</td>
</tr>
<tr>
<td></td>
<td>$B^3$</td>
<td>$S_{3,t_0}$</td>
<td>$S_{3,t_1} = 1$</td>
</tr>
<tr>
<td>Marg. Corr.</td>
<td>$B^1$</td>
<td>$R_{t_0} (3 \times 3)$</td>
<td>$R_{t_0} (3 \times 3)$</td>
</tr>
<tr>
<td></td>
<td>$B^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$B^3$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part. Corr.</td>
<td>$B^1$</td>
<td>$[(R_{t_0})^{-1}]<em>{mn} = \rho</em>{mn}|s$</td>
<td>$[(R_{t_0})^{-1}]<em>{mn} = \rho</em>{mn}|s$</td>
</tr>
<tr>
<td></td>
<td>$B^2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$B^3$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$A_i = $ Net asset values  
$Eq._i = $ Equity  
$f_i, k \in [0, 1]$
### Private Intervention

<table>
<thead>
<tr>
<th>Assets</th>
<th>$t_0$</th>
<th>$t_1$</th>
<th>$t_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B^1$</td>
<td>$A_1$</td>
<td>$A_1(1 - \frac{X}{A_1 + A_2})$</td>
<td>$A_1(1 - \frac{X}{A_1 + A_2})$</td>
</tr>
<tr>
<td>$B^2$</td>
<td>$A_2$</td>
<td>$A_2(1 - \frac{X}{A_1 + A_2})$</td>
<td>$A_2(1 - \frac{X}{A_1 + A_2})$</td>
</tr>
<tr>
<td>$B^3$</td>
<td>$A_3$</td>
<td>$A_3 + X$</td>
<td>$A_3 + X$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_1$</td>
<td>$S_1$</td>
<td>$S_1$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_2$</td>
<td>$S_2$</td>
<td>$S_2$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_{3,t_0}$</td>
<td>$S_{3,t_0}$</td>
<td>$S_{3,t_2}$</td>
</tr>
</tbody>
</table>

### Marginal Correlation

$$R_{t_0} \ (3 \times 3)$$

### Particular Correlation

$$[(R_{t_0})^{-1}]_{mn} = \rho_{mn|S} \quad [(R_{t_0})^{-1}]_{mn} = \rho_{mn|S} \quad [(R_{t_0})^{-1}]_{mn} = \rho_{mn|S}$$

$X =$ amount needed by $B^3$ in order to absorb losses still meeting regulatory requirements (Pillar 1)
# Bail-in

<table>
<thead>
<tr>
<th>Assets</th>
<th>$t_0$</th>
<th>$t_1$</th>
<th>$t_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B^1$</td>
<td>$A_1$</td>
<td>$A_1 - f_1 \cdot k \cdot \text{Bail-in}_3$</td>
<td>$A_1 - f_1 \cdot k \cdot \text{Bail-in}_3$</td>
</tr>
<tr>
<td>$B^2$</td>
<td>$A_2$</td>
<td>$A_2 - f_2 \cdot k \cdot \text{Bail-in}_3$</td>
<td>$A_2 - f_2 \cdot k \cdot \text{Bail-in}_3$</td>
</tr>
<tr>
<td>$B^3$</td>
<td>$A_3$</td>
<td>$A_3 - \text{Bail-in}_3$</td>
<td>$A_3 - \text{Bail-in}_3$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_1$</td>
<td>$S_1$</td>
<td>$S_1$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_2$</td>
<td>$S_2$</td>
<td>$S_2$</td>
</tr>
<tr>
<td>$S$</td>
<td>$S_3$</td>
<td>$S_3$</td>
<td>$S_3$</td>
</tr>
<tr>
<td>Marg. Corr.</td>
<td>$R_{t_0}$ ($3 \times 3$)</td>
<td>$R_{t_0}$ ($3 \times 3$)</td>
<td>$R_{t_0}$ ($3 \times 3$)</td>
</tr>
<tr>
<td>Part. Corr.</td>
<td>[\left((R_{t_0})^{-1}\right)<em>{mn} = \rho</em>{mn</td>
<td>s}]</td>
<td>[\left((R_{t_0})^{-1}\right)<em>{mn} = \rho</em>{mn</td>
</tr>
</tbody>
</table>

Bail-in$_3$ = amount of bail-able liabilities that have to be written down/converted to allow $B^3$ to absorb losses still meeting regulatory requirements (Pillar 1)

$f_i$, $k \in [0, 1]$