Systemic Loops and Liquidity Regulation

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Banks are subject to liquidity-solvency nexus (Pierret 2015 recent evidence)

Fragility on liability side (liquidity scarcity) → early projects
- liquidation → fire sale externalities

Falls in asset returns (fire sales accounting losses) → news reach investors → run the bank

Theoretical models focus typically on one side of the nexus. Policy neglects nexus: LCR → no role for asset position

*We model endogenously contagion risk on both sides of banks’ balance sheet (including the nexus) → explore the role of LCR*
Contagion in Theoretical Models

- Only *asset price contagion*:
  2. Network interconnections (debt default): Elliot, Golub and Jackson 2012
  3. Aldasoro, Delli Gatti and Faia 2014: both

- *Only liability-side contagion* and nexus (asset side is exogenous or macro-fundamentals):
  1. Diamond and Rajan 2005 or Rochet and Vives (2004) banks’ runs triggered by exogenous shocks on assets
  3. Angeloni and Faia (2013) use a combination of the two above
Channels in our model

- Model endogenously contagion risk on both sides of banks’ balance sheet:

1. **Asset risk**
   a. Fire sale externalities (banks subject to heterogenous asset shocks)
   b. Interbank debt default (network externalities with endogenous propagation);

2. **Liquidity risk**
   a. Runs on STL (global games a’ la Morris and Shin 2003, Carlsson and van Damme 1993)
   b. Liquidity hoarding (Afonso and Shin 2010)
   c. Notice: interbank function as insurance device, but can also propagate contagion

3. **Nexus**
   news and regulatory requirements
LCR does not take into account this nexus: depends only on liability mix, not on asset positions

Common to all banks independently of their asset position

In fact, banks more exposed to non-liquid assets also leverage more→hence should be taxed differentially

Mildly leveraged banks shall not be taxed as they act as liquidity provider and help the insurance function of interbank markets
Policy in Our Model

- The role of LCR phase-in for systemic risk
- Design LCR based on systemic importance (macro-prudential policy) and re-assess the effect on systemic risk
- Measure systemically important banks according to BCBS criteria
Findings

- Systemic risk raises in the past phase of LCR introduction
- Systemic risk decreases monotonically only when asymmetric across banks
- Role of interbank markets for the trade-off between insurance motives and contagion propagation
  
a. Banks with low returns on non-liquid assets, leverage less and supply interbank liquidity
b. Taxing them equally as the highly leveraged banks impairs insurance function
  
c. Taxing highly leveraged banks more reduces contagion
The Model

- Optimizing risk averse banks: choose interbank exposure (possibility of debt default), non-liquid assets
- Funds themselves with STL → runs triggered by news arrival (global game)
- Price mechanism in both markets endogenous: Tâtonnement process
- Trading matching algorithm: insurance motives (Allen and Gale 200) → maximum entropy
Choose interbank lending and non-assets to maximize:

\[ U(\pi_i) = \frac{(\pi_i)^{1-\sigma}}{1 - \sigma} \]

where:

\[ \pi_i = r_i^a \frac{a_i}{p} + r^l \sum_{j=1}^{k} l_{ij} - (r^l + r_i^p) \sum_{j=1}^{k'} b_{ij} - r_i^d d_i \]

s.t.

\[ \frac{c_i + p a_i + l_i - d_i - b_i}{\omega a p a_i + \omega l l_i} \geq \gamma \]

\[ \frac{c_i}{\omega_d d_i + \omega_b b_i - \min\{\tilde{\omega} l_i, 0.75 (\omega_d d_i + \omega_b b_i)\}} \geq \alpha \]
Run region ($\varepsilon_i$ is a news shock):

$$\exp(-\varepsilon_i) \frac{r_i^a a_i}{p} + r^l l_i - r_i^b b_i \geq r_i^d d_i$$

Unique threshold-switching strategy in a simultaneous incomplete information game:

$$\tilde{\varepsilon}_i = \log \left( \frac{r_i^a a_i / p}{r_i^d d_i + r_i^b b_i - r^l l_i} \right)$$

Share of deposits being withdrawn will be then given by

$$\rho_i = \int_{-\infty}^{\tilde{\varepsilon}_i} \theta(\varepsilon) d\varepsilon = \Theta(\tilde{\varepsilon}_i).$$
Sequential Price Tâtonnement

- Centralized price mechanism: Duffie and Zhu 2011 (bilateral Afonso and Lagos 2012)
- First, Price Tâtonnement in interbank: $r^l$ adjusts step-wise to within a bid-ask band and to equilibrate $\sum_{j=1}^{k} l_{ij}$ and $\sum_{j=1}^{k} b_{ij}$
- Second, Price Tâtonnement in non-liquid asset markets (Cifuentes et. al 2005): total excess supply (aggregate of individual optimizations) equilibrate aggregate demand $p = \exp(-\beta \sum s_i)$
- Matching trading partners: maximum entropy → banks distribute trading evenly to maximize insurance (Allen and Gale 2000)
Contagion channels

- Asset side:
  1. Asset commonality, regulatory constraints and endogenous price mechanisms → pecuniary externalities
  2. Endogenous interbank debt default

- Liability side:
  1. STL runs: coordination problem due to news arrival
  2. Risk averse banks hoard liquidity in face of large shocks
     - Insurance motives: evenly spread matching partners. Shall be balanced with contagion

- Nexus:
  a. Accounting losses → news → runs and liquidity hoarding
  b. Liquidity shortage → unfulfilled regulatory requirements → fire sales
Simulation of shocks: assign default losses sequentially via clearing algorithm (Eisenberg and Noe 2001)

Calibration:

1. Policy parameters are taken from regulation
2. Banks are heterogenous: asset shock distribution and STL returns distributions calibrated on European banks (Alves et. al 2013)
2. Other parameters estimated, method of moments (empirical targets: max level of assets, skewness asset distribution, average leverage and interbank assets)

Systemic risk:

\[ \Phi = \frac{\sum_{\Omega} \text{assets}_\Omega}{\sum_i \text{assets}_i} \]
liquid assets) and also leverage more (external funding is needed to cover the intense investment activity). Those banks are the ones that contribute the most to systemic risk. In fact the more leveraged they are on the interbank market the higher is the loss that they would transmit to the system in case of debt default. Second, as they invest heavily in non-liquid assets they are obliged to hold a high level of bank capital: upon an adverse shock those banks are forced into massive fire sales thereby prompting severe asset price declines and transmitting large accounting losses to other banks. Hence, not surprisingly those banks are assigned a high index of systemic importance (red colored ball in the snapshot).

5.2 Interbank Matrix and Network Properties

The second and last part of the process of matching the network of large European banks consists in obtaining the interbank matrix from the optimal balance sheet structure obtained above. The optimization problem of banks delivers the row sum and column sum of the interbank matrix (i.e. total lending and total borrowing by bank respectively). Given the optimal balance sheet quantities chosen by banks, we reconstruct the interbank matrix using the RAS algorithm, as noted in subsection 3.6. This algorithm efficiently delivers the maximum entropy solution and can incorporate any additional information besides the marginals of the target matrix. In particular, we use the matrix of exposures between large European banks as a prior. This allows us to generate an interbank matrix which respects the optimal quantities chosen by banks in our model while at
Given our baseline network representation we can compute a number of traditional network metrics and compare them to the data equivalent. Table 2 presents this comparison for a number of network metrics.\textsuperscript{36} The table immediately shows that the matching is almost perfect.

Alves et al. (2013) note that the European banking system features a network with some “national champions” which are heavily connected between themselves, therefore exhibiting a relatively high density of 63%\textsuperscript{37}. Our model replicates the density metric very well. The average number of connections per bank is 30 in the data\textsuperscript{38}, implying an average path length close to 1. Both numbers are matched well by the model. We compute centrality metrics and clustering coefficients as averages for all nodes in the network. For the former we consider eigenvector and betweenness centrality and in both cases the model is very close to the data. For the latter, which represents the tendency of neighbors of a given bank to be connected between themselves, the model is also notably close to the data. Interbank networks typically present clustering coefficients which are larger than in random networks with the same degree distribution, but smaller than other economic networks such as input-output or trade networks. The network of large European banks presents a particularly

\textsuperscript{36}Note that the two networks present the same number of nodes, namely 49. An online appendix presents a more formal treatment of the network measures shown in Table 2, which are standard in the literature.

\textsuperscript{37}This is somehow in contrast with the observations of other banking systems that are characterized by low density with graphs featuring a small core of highly connected banks and a large, loosely connected periphery.

\textsuperscript{38}This is actually a large number relative to country-specific studies.
### Table 2: Network indicators of model and data

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density (%)</td>
<td>63.14</td>
<td>63.14</td>
</tr>
<tr>
<td>Average Degree</td>
<td>30.31</td>
<td>30.31</td>
</tr>
<tr>
<td>Average Path Length</td>
<td>1.17</td>
<td>1.17</td>
</tr>
<tr>
<td>Betweenness Centrality (Av.)</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Eigenvector Centrality (Av.)</td>
<td>0.08</td>
<td>0.10</td>
</tr>
<tr>
<td>Clustering Coefficient (Av.)</td>
<td>0.41</td>
<td>0.40</td>
</tr>
<tr>
<td>Assortativity</td>
<td></td>
<td></td>
</tr>
<tr>
<td>out-in degree</td>
<td>-0.25</td>
<td>-0.25</td>
</tr>
<tr>
<td>in-out degree</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
<tr>
<td>out-out degree</td>
<td>-0.06</td>
<td>-0.06</td>
</tr>
<tr>
<td>in-in degree</td>
<td>-0.11</td>
<td>-0.11</td>
</tr>
<tr>
<td>Modularity (Maximum)</td>
<td>0.22</td>
<td>0.22</td>
</tr>
<tr>
<td>Reciprocity</td>
<td>0.72</td>
<td>0.72</td>
</tr>
<tr>
<td>Reciprocity (normalized)</td>
<td>0.25</td>
<td>0.25</td>
</tr>
</tbody>
</table>

The large average clustering coefficient.

The assortativity coefficient measures the tendency of high (low) degree nodes to be connected to other high (low) degree nodes. The empirical evidence suggests that interbank networks are dis-assortative (i.e. present negative assortativity), a feature closely associated to the existence of a core-periphery structure and which implies that high degree nodes tend to be connected with low degree nodes. The network of large European banks is no exception and our simulated network mimics this feature very well. The modularity of a network measures the extent to which the network presents communities or modules within which the connections are maximized. Both the data and the model show positive modularity, indicating that there are more connections between nodes of the same type (i.e. nodes belonging to the same community) than one can expect by chance. Finally, the reciprocity index quantifies how many connections in one direction are reciprocated by another connection going in the opposite direction. Again, the indicator for both model and data coincide: if bank A lends to bank B there is a 72% probability that bank B also lends to A.\(^{39}\)

The last statistic that we consider is the degree distribution (the distribution of the number of connections). This informs about the underlying microstructure of the market. Degree distributions which resemble Poisson processes are typical of random networks with atomistic/competitive agents. Skewed distributions (like power laws) are indicative of networks with few "hubs" with high degrees.

\(^{39}\)The unnormalized reciprocity indicator ranges from 0 to 1. We also present a normalized version of reciprocity which allows for better comparability between different networks and also provides a measure of the reciprocity present in the network relative to a random network with the same number of nodes and links. The value of normalized reciprocity of 0.25 indicates that more links are reciprocated than could be expected based on a random network that preserves nodes’ degrees. For more details on network methods and the relevant references see the online appendix.
and a large majority of nodes with low degrees. For the sake of completeness, Figure 3 presents the
distribution of in- and out-degrees in both the model and the data in log-log scale as is standard in
the literature. The model-based and the data-based distributions are very close to each other and
they are both very much skewed.

![In-degree distribution](image1)

![Out-degree distribution](image2)

**Figure 3:** Degree distribution for model and data in log-log scale.

Finally, Figure 4 presents the network configuration (graphs) for both model and data. In
order to have better visibility, only the largest 150 links in value are shown for each chart.\(^{40}\) For
both networks this represents close to 10\% of all non-zero links (in number), whereas in terms of
exposures, the top 150 links account for roughly half of all exposures in the data and about 60\% in
the model. In both data and model the big players in terms of size account for a big share of the
market and transact the largest amounts, in particular between themselves. The last observation is
another manifestation of the non-random nature, but rather the hub-based characterization of our
banking network.

Three elements are responsible for the model ability in matching data. The first is that our model
is fairly rich as it includes several realistic channels of contagion. Second, relevant model parameters
have been calibrated by a method of simulated moments: this allows the model-based distribution
of variables to stay close to the true data generating process. Finally, the interbank matrix obtained
from the model mimics very well the structural features of the real world counterpart.

\(^{40}\)Both networks are quite dense (see Table 2), so if one plots all the links present in the system it is hard to
visually appreciate where the bulk of the action is. Appendix B presents both network charts without a cap on the
number of links shown.
6 Policy Experiments

We have constructed a fairly rich banking system featuring several contagion channels. We have even ensured that the model is realistic and delivers properties which are very close to those observed in the data. Equipped with this model we are now in the position to conduct policy experiments. Our main goal is to assess to which extent the new liquidity regulations are able to contain contagion and systemic risk. There is pretty much agreement in the academic literature that liquidity crises tend to precede and lead to widespread bank insolvency (see Diamond and Rajan (2005) among others). Banks operate largely by relying on short term liabilities: when those become scarce (either because of investor runs or because of interbank market freezes) banks are forced into liquidation of productive projects and/or fire sales. The latter quickly turn a liquidity crisis into an insolvency one. As explained earlier our model captures this link and also the feedback loops between liquidity and insolvency. The mechanism just described also provided the main motivation for the Basel regulators to convincingly introduce the additional liquidity requirement.

We therefore simulate our model to assess the impact of liquidity coverage ratios on the network in general and on systemic risk. In reality new regulations are introduced gradually (through a phase-in): we take this aspect into account in our simulations below.

Figure 4: Network charts. Node size indicates total assets. Arrows go from lender to borrower and their width indicates size of exposures. Only the top 150 links in terms of value are shown.
6.1 Phase-in of the Liquidity Coverage Ratio

In the first policy experiment we evaluate the model and its response to shocks as the liquidity coverage ratio (LCR) is taken from its initial state to its full implementation as devised in the law. This translates into evaluating the model and submitting it to shocks for $\alpha \in \{60\%, 70\%, 80\%, 90\%, 100\%\}$. For each value of the parameter $\alpha$ the model is simulated from scratch and shocked 1000 times in order to evaluate the distribution of systemic risk across all realizations of the shock vector. Note that for every model (i.e. for every value of $\alpha$), the $1000 \times 1$ shock vector remains the same, allowing for better comparability.

Figure 5 presents the path of systemic risk for each phase of the LCR implementation. One would expect that a continuous increase in the coverage ratio brings about a monotonic decrease in the systemic risk profile. The figure shows that this is not the case. There is a mild reduction in the first steps, but the final move to 100% undoes the initial risk reduction. Furthermore, as the fully phased-in level of $\alpha$ is reached, there is a substantial increase in the number of high systemic risk outliers (i.e. the number of shock realizations in which a high share of the system is wiped out by the initial shocks).

![Figure 5: Systemic risk for different stages of the phase-in of LCR.](image)

The rationale for our results is as follows. An increase in LCR has both beneficial as well as
7 Concluding Remarks

Understanding the unfolding of cascades and the interaction between contagion and amplification mechanisms is key for effective regulation and crisis prevention. We build a banking network model which provides a unified framework to study these systemic loops. The model features distress and contagion stemming from both the asset and liability sides of banks’ balance sheets. Contagion can arise due to network, pecuniary (fire sale) externalities and liquidity hoarding on the asset side, and bank runs on short liabilities on the funding side. Banks can enter interbank markets for insurance motives. However, the beneficial effects of insurance have to be balanced with the above-mentioned contagion channels. Taken together, all those channels explain the emergence and fluctuations in systemic risk.

The model is calibrated to match certain aspects of the network of large European banks using a method of moments procedure. Given the empirical validity of our model we use it to assess prudential regulation. We focus in particular on the recently adopted liquidity regulation. Given that in our model liquidity freezes, due to bank runs or interbank defaults, ignite solvency crises, the environment we analyze is particularly well suited to answer those questions. We study the effects of a phase-in of the liquidity coverage ratio (LCR). We find surprisingly that LCR, while
Conclusions

- Banking network model with contagion risk on both sides of banks’ balance sheet
- Assess the role of LCR phase-in
- Bank-based policy instruments reduce systemic risk
- Future theoretical advances:
  1. Bilateral bargaining
  2. Dynamic banks’ optimization
- Optimal prudential policy: min risk/max welfare, account for policy/banks strategic interactions
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