Pandemic crises in financial systems and liquidity emergency

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Introduction

So far stress-testing exercises imperfectly take into account contagion effects when assessing banks solvency. Neglecting contagion especially tends to underestimate the probability of default of the system as its effects often cause cascading defaults. We consider a model of banks balance sheet contagion considering several channels of transmission and amplification (interbank contagion, market contagion, solvency contagion). Our main findings show that small shocks may lead to cascading failures and the rise of a so called bad equilibrium (Fig. 1).

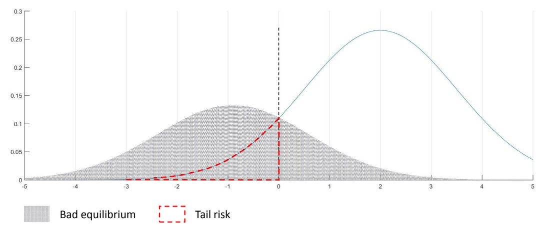

Figure 1: Bad equilibrium definition

Model

We follow [1] and [2] representation of balance sheet for a network made by n banks. Each bank owns a set of k assets, where the k^{th} asset is cash and cash equivalent items.

	Assets i	Liabilities i	
Banking equity cross-holding $\rightarrow$	$\Pi_i Y$	L_i^I	$\leftarrow$ Inter-bank liability
Inter-bank loans $\rightarrow$	$\Gamma_i L^I$	L_i^*	$\leftarrow$ Nominal liability
Exposure to exogenous assets $\rightarrow$	$X_{i,t} P_t$		
	$A_{i,t}$	L_i	

Table 4: Bank i balance sheet

Contagion is modeled through three channels:

- Banks equity cross-holdings $\Pi * Y$
- Asset markets $X * P_t$.
  Exposure matrix X encompasses elements from the banking book, trading book and cash equivalents. Assets sales and liquidations have an impact on asset prices as in [3]. $\Delta P = Traded\,Volume * (Am * R_s)$ where Am is the Amihud price impact matrix and R_s is the market correlation.
- Collateralized interbank loans market ΓL^I.
  All interbank loans are secured and collateral guarantees the loans. Collateral's value changes imply margin calls as in [4].

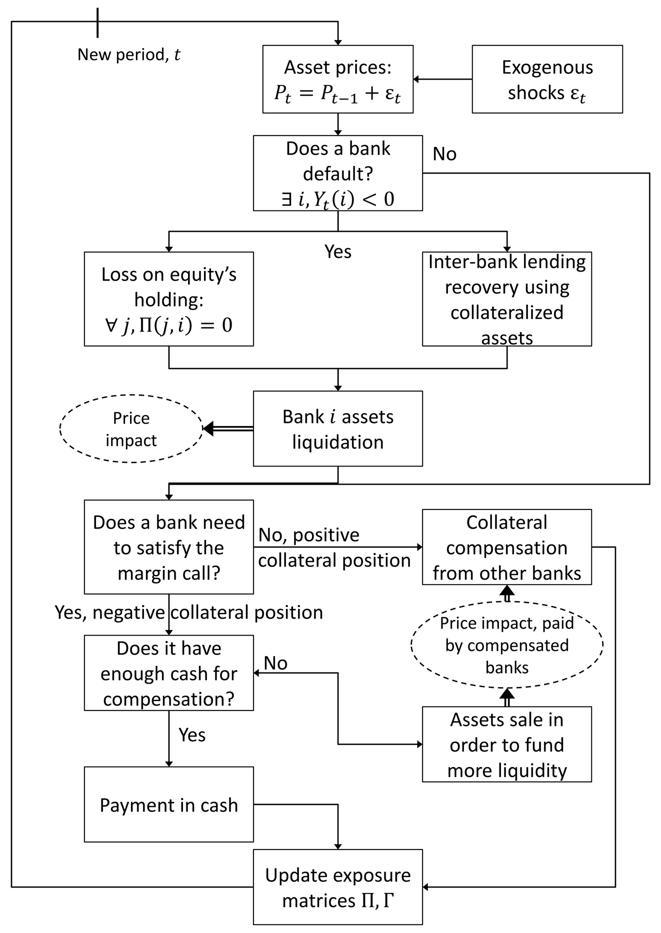

Figure 3: General framework

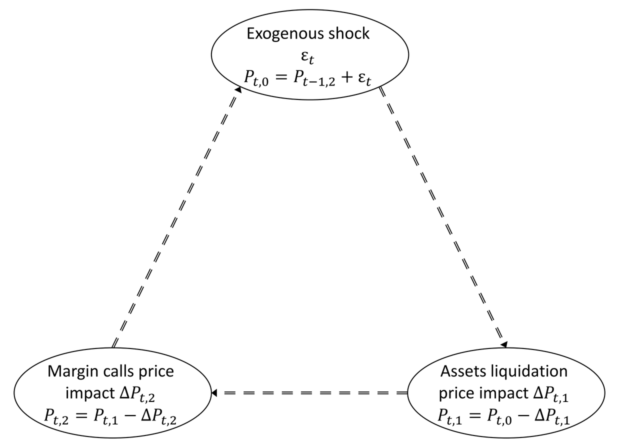

Figure 4: Asset prices variations

Results

When probabilities of default reflect contagion effects...
First round probabilities of default are high for banks directly impacted by the shocks (role of margin calls on collateralized loans and losses of equity value).
Then, banks with a low probability of default in the first round may be more severely affected in the second round: the highest probabilities of default are not obtained on first round losses as shown in Fig 2.

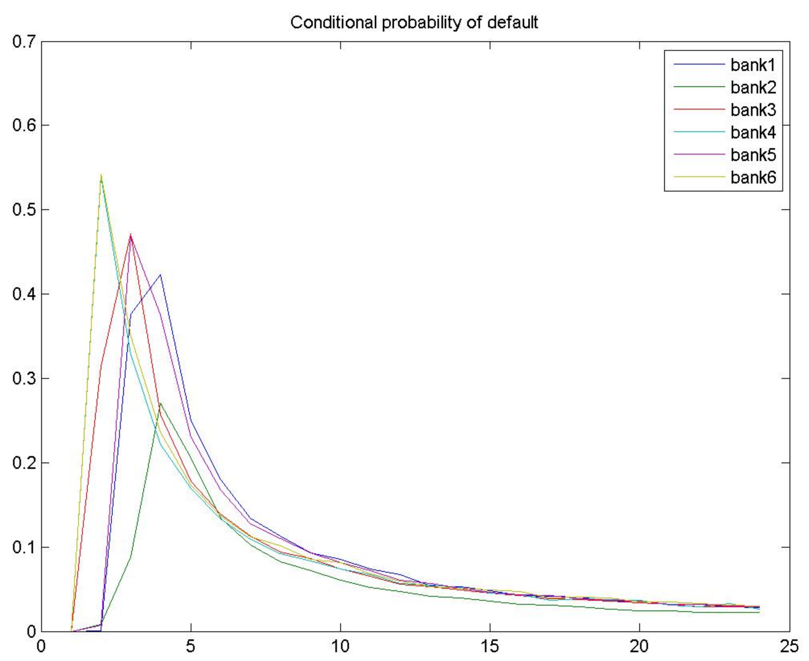

Figure 2: Banks PDs evolution as the number of bank defaults at time t across simulations over the number of non defaults of bank i at time t-1.

Which turns out to be caused by bad equilibrium
Next figures present the evolution over time of equity distributions characterized by multimodality. We decompose, on the right panel, for a given date, the multi modal distributions of equity according to the number of failed banks at the former period. This partition help us to understand how contagion effects due to former failure may weaken surviving institutions.

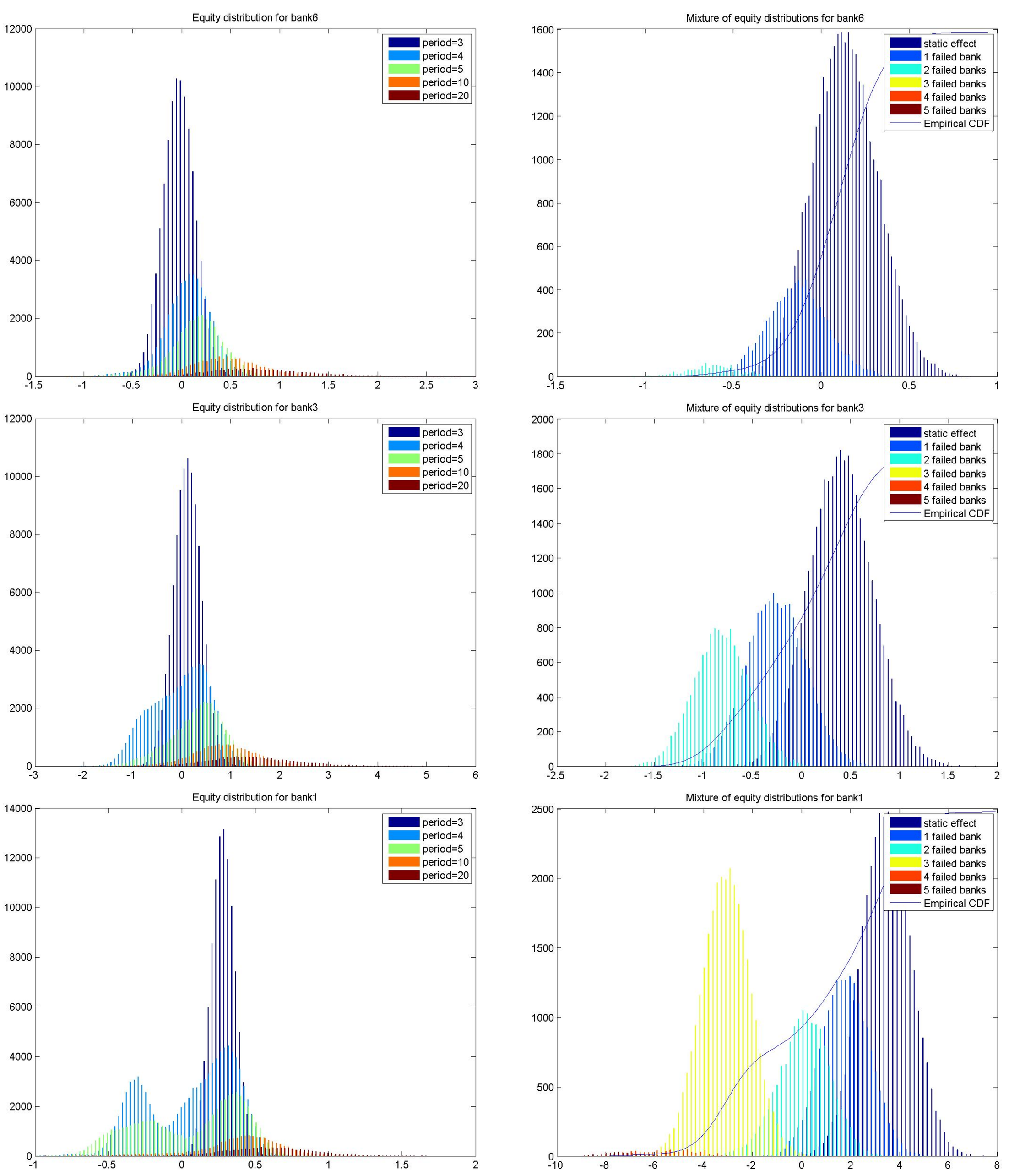

Table 1: Banks 6, 3 and 1 complete equity distributions over time (left panel) and its partition at period 4 conditional on the default of other banks at period t-1 (right panel).

Bad equilibrium appears when former defaults may shift the mean equity toward negative values. They are characterized by multimodal distributions observed in the right part of table 1 for banks 3 and 1. Notice that the multimodal distribution appears for vulnerable banks, *id est* banks that do not fail in the second round but because of contagion effects.

How do systemic institutions impact the network solvency
The model can also be used to reveal the role of systemic institutions. Table 2 presents the evolution of probabilities of default conditional to banks 2 and 3 failures: systemic institutions failures have a higher impact on the system than the one of rather small institutions.

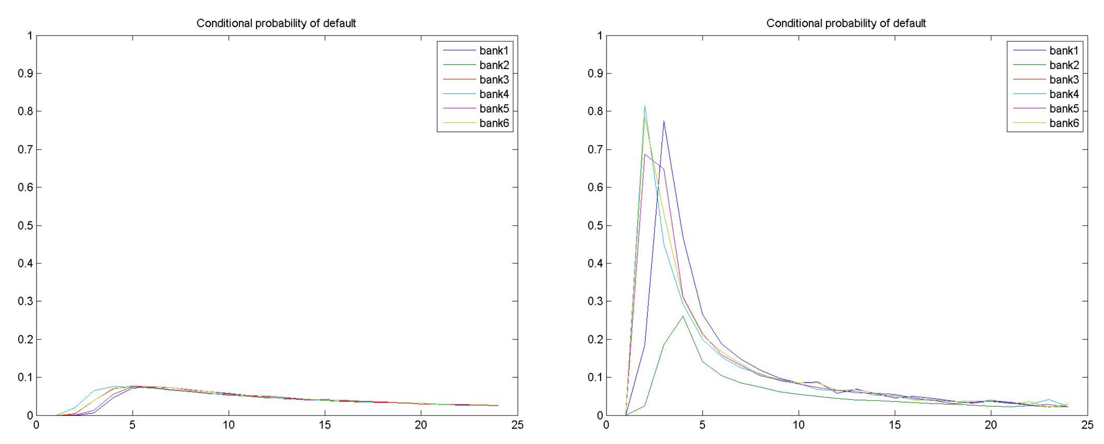

Table 2: Note: Banks PDs evolution with the initial failure of a credit institution: Bank 2 fails in the left graph whereas bank 3 fails in the figure at the right

Emergency liquidity from the Central Bank
Contagion effects are more harmful in this model than first round losses, with a key role a systemic institution, even if they are not directly hit by the initial shock. Given the role of liquidity in amplification channels, Central banks may play a role in protecting the system by providing emergency liquidity. Next table presents the same figures than Table 1 when the Central Bank rescues the three most systemic institutions after the shock by funding their losses in cash (liquidity emergency rescue).

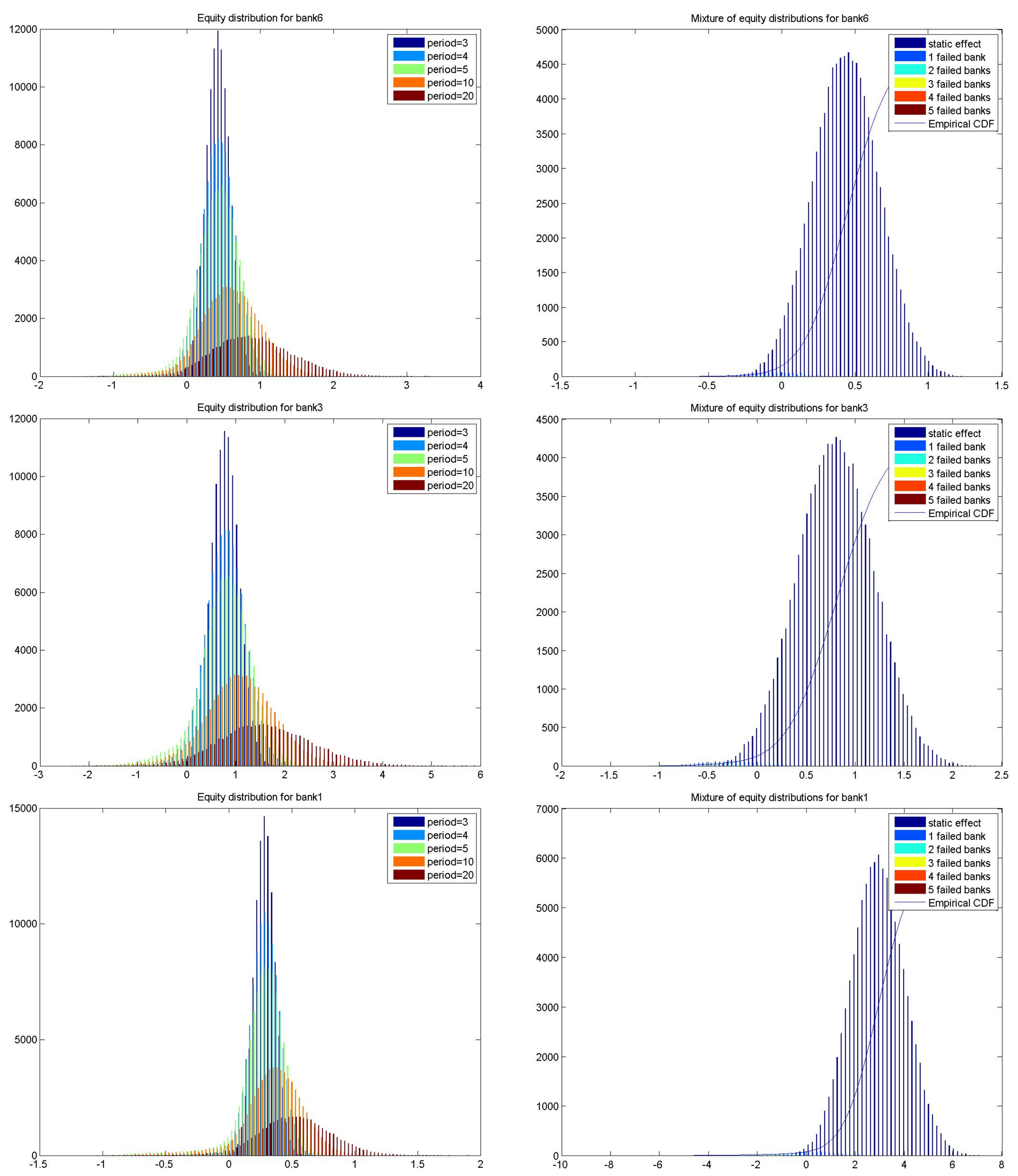

Table 3: Banks 6, 3 and 1 complete equity distributions over time (left panel) and its partition at period 4 conditional on the default of other banks at period t-1 (right panel) when CB intervenes.

If this intervention can be efficient, it is very costly since it should perfectly compensate the losses and target the most systemic institutions. This calls for a proper regulation of too big to fail institutions, for solvency and liquidity aspects.

Protocol

- A sample of 6 European banks is used, exploiting public balance sheet information. part of these banks are G-SIB institutions mostly involved in trading activities whereas others do more lending businesses. Each bank has bilateral relation to others, either through interbank loans or equity cross-holdings.
- Exposure matrix X is split into 6 different exposures:

$$X = \begin{pmatrix} Loans_1 & Debt\ intruments_1 & Equity_1 & Derivatives_1 & Other\ securities_1 & cash_1 \\ \vdots & \vdots & \vdots & & & \\ Loans_6 & Trading\ book_6 & cash_6 & & & \end{pmatrix}$$

- While prices are scaled at 1 at the beginning of the stress test, we consider a shock of 6% on trading assets. This size is chosen in order to avoid first round default without preventing margin calls and cascading failures in further periods.
- Shocks ϵ_t change prices at the beginning of every period as highlighted in figure 3. They follow a Gaussian distribution $\mathcal{N}(0,\sigma)$, where σ is in line with asset markets volatility. Banking book prices volatility is three times smaller than trading assets.
- 100,000 simulations are then performed to compute equity distributions and mean probabilities of default.

Data

- Banks equity cross-holdings: SNL data
- Bank debt cross-holdings: non public - need proxies extracted form public balance sheets (as of 2014). Aggregated loans to other credit institutions and deposit from other banks are in there. These two Figures do not match because our 6 banks are only a fraction of the system. To restrict our universe to the 6 banks under consideration, we rescale everything on the size of deposits that are used as inter-bank liability L^I. Therefore, debt holding from bank i to bank j, Γ is calculated as a share of bank i total interbank loans divided by the sum of possible loans to bank j.

$$\Gamma(i,j) = \frac{loans(i)}{\sum_{k=1}^{6} loans(k) - loans(j)}$$

- Exposure matrix X is composed of 6 assets: SNL data on loans to non banking players, debt instruments, equity instruments, derivatives instruments, other securities and cash. To not double count bank equity both in "equity instrument" class data (used as X_t) and in $\Pi * Y_t$ we subtract the corresponding amount of cross holding equity from the equity class instrument amount for each bank.
- Remaining liability L^* is estimated as the difference between the sum of the portfolio of exogenous assets, the inter-bank liability and equity, minus the amount of equity.

Conclusion

We have designed a dynamic model of network for stress testing, including many transmission channels. We show that bad equilibrium may increase contagion through the network. Central bank can efficiently remove the bad equilibrium by rescuing systemic institution. However it is highly costly as it implies to fund all systemic bank losses with liquidity. Besides, we developed a framework flexible enough to account for many scenarios and players, and whose precision relies on the financial information available.
Future research will focus on the design of the liquidity emergency policy, and the introduction of regulatory buffers in the framework to assess their effectiveness on the network's solvency. Besides, we work on extending the model to a larger number of European banks in order to give rise to more complex equity distributions and contagion spreading.

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