

Bank Networks: Contagion, Systemic Risk and Prudential Policy

Iñaki Aldasoro¹ Domenico Delli Gatti² Ester Faia³

¹Goethe University Frankfurt & SAFE

²Università Cattolica Milano

³Goethe University Frankfurt, CFS & SAFE

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Motivation

- Trade off: *efficiency* (maximize banks' investment in non-liquid risky assets) and *financial stability* (minimize systemic risk).
- Contribute to measurement and analysis of *systemic risk*, to help devise an "appropriate" regulatory framework.
- Replicate stylized facts about real world interbank networks with a micro-founded model and market equilibrium
- Effects of different matching mechanisms on systemic risk

(Most closely) related literature

- Cifuentes, Ferrucci & Shin 2005 (CFS): network model of the interbank market (à la Eisenberg & Noe 2001) with endogenous price adjustment (see also Bluhm & Krahn, 2014).
- Bluhm, Faia & Krahn (current draft: 2014) (BFK) extend CFS introducing
 - *risk neutral optimizing banks,*
 - *ex post (after shocks) measure of systemic risk*
- Halaj & Kok (2014) + others on endogenous networks

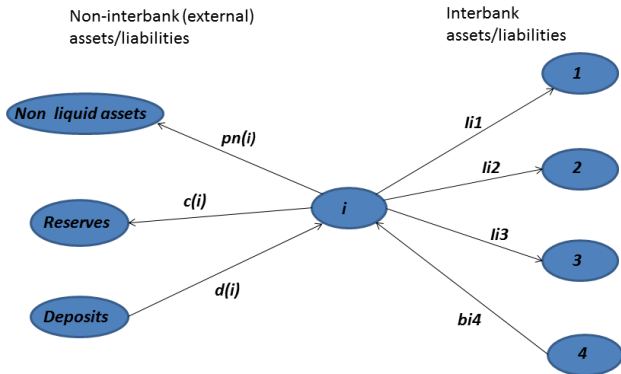
Our contribution

- We extend BFK introducing
 - *Risk averse optimizing* banks,
 - *Ex ante* measures of systemic importance: *network centrality* or *input-output* measures (see Aldasoro and Angeloni 2013) and
 - *Ex post* (after shock) measures of systemic risk: *Shapley value*.
 - Network metrics for different matching mechanisms
- Effects of changes in prudential policy
 - On systemic risk
 - Banks' investments, interest rate, etc.

Financial contagion

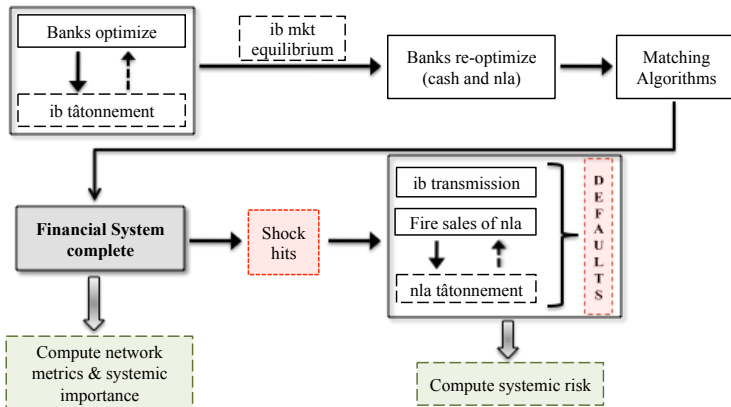
- Channels of financial contagion (risk transmission):
 - 1 *Credit interlinkages (network externalities)*
 - 2 *Fire sale of common non-liquid assets (pecuniary externalities)*
 - 3 *Liquidity hoarding*
- Systemic risk is due to the spreading of defaults through these channels.

The connections of bank i



$$c_i + n_i p + \underbrace{l_{i1} + l_{i2} + \dots + l_{iN}}_{\equiv l_i} = d_i + \underbrace{b_{i1} + b_{i2} + \dots + b_{iN}}_{\equiv b_i} + e_i \quad (\text{BSI})$$

A bird's eye view of the model



The problem of the bank

- Choose c_i , n_i , l_i , b_i to maximize CRRA utility of *expected* profits:

$$V_i = V(E(\pi_i)) = \frac{\left(n_i \frac{r_i^n}{p} + l_i r^l - b_i r_i^b\right)^{1-\sigma}}{1-\sigma}$$

- Subject to (BSI), liquidity and equity requirements (+ n.n.c.)

$$c_i \geq \alpha d_i \quad (\text{LR})$$

$$\varepsilon_i := \frac{c_i + n_i p + l_i - d_i - b_i}{\omega_n p n_i + \omega_l l_i} \geq \gamma + \tau \quad (\text{ER})$$

- Given d_i and e_i , optimization yields supply and demand for interbank loans l_i and b_i given the current rate r^l (price of $nl_a = 1$ in setting up financial system)

Tâtonnement on the interbank market

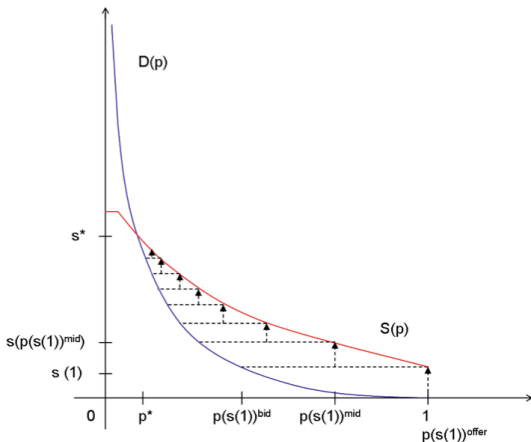
- Why? Demand and supply will not be mutually consistent after initial optimization (given starting value of r^l)
- Auctioneer evaluates *total* demand (B) and supply (L) of ib loans
- If $B > L$ ($B < L$) $\implies \uparrow r^l$ ($\downarrow r^l$)
 - Let banks optimize again given the new r^l
 - continue until equilibrium is achieved
- We obtain two vectors $\mathbf{l} = [l_1, l_2, \dots, l_N]$ and $\mathbf{b} = [b_1, b_2, \dots, b_N]$ that are mutually consistent, such that $B = L$
- But ...*who is lending to whom and who is borrowing from whom?* (i.e. how does the *matrix of ib exposures* look like?)

Matching and the formation of the network

- To answer this we experiment with three *matching algorithms*:
 - *Maximum Entropy (MEA)*: distributes lending and borrowing as evenly as possible,
 - *Closest Matching (CMA)*: associates closest demand and supply,
 - *Random Matching (RMA)*: random pairing of banks with a load factor.
- The algorithm determines the *topology of the network*.
- By construction, MEA yields very high density, CMA yields very low density, RMA yields a density which falls in between.

Life after a shock: *n/a* mkt tâtonnement

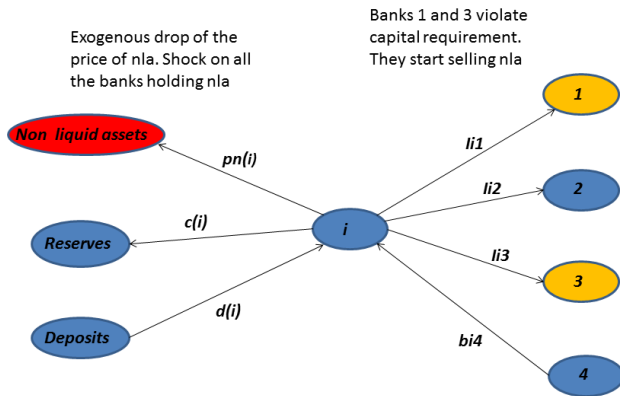
- Pre-shock, $p = 1$
- Post-shock, supply and price of *n/a* are affected
- Banks sell *n/a* to fulfill ER
- $s'_i(p) < 0 \implies s'_n(p) < 0$
- CFS inverse demand
 $\rightarrow p = \exp(-\beta d_n)$
- Equilibrium $s_n = d_n$
 $\rightarrow \Theta(p) = \exp(-\beta s(p))$



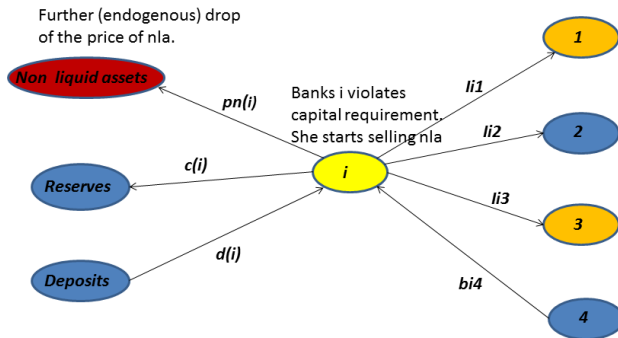
Systemic importance and systemic risk

- *Ex ante* measures of vulnerability
 - Network centrality measures (degree (in, out), closeness, betweenness, eigenvector)
 - Input-output based measures (Aldasoro & Angeloni (2013))
 - (i) stress originating in non-interbank lending
 - (ii) stress originating in (non-interbank) funding side (d_i)
 - (iii) systemic effect from bank i being cut ib financing
 - (iv) systemic effect from bank i cutting interbank financing
 - (v) combination of (iii) & (iv)
 - (vi) systemic effect of cut-off from ib mkt
- *Ex post* measures (Shapley value)

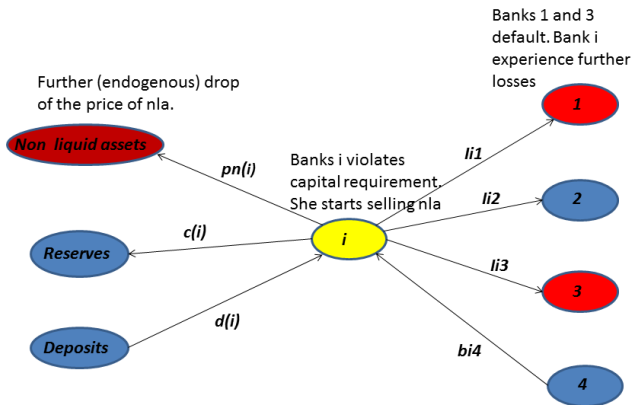
Shock: exogenous increase in nla supply $\Rightarrow \downarrow p$



Self-reinforcing downward pressure on price of nla



Collapse in mkt value of banks' assets might lead to default



Ex post measure

- The after shock measure of systemic risk is the ratio of the value of assets of defaulting banks (grouped in the set Ω) to total assets:

$$\Phi = \frac{\sum_{\Omega} assets_{\Omega}}{\sum_i asset_i}$$

- Contribution of each bank to systemic risk \rightarrow *Shapley value*:

$$\Xi_i(v^{\Psi}) = \frac{1}{N!} \sum_{O \in \pi_N} (v^{\Psi}(\Delta^i(O) \cup i) - v^{\Psi}(\Delta^i(O)))$$

- Curse of dimensionality: approximate SV by the average contribution of banks to systemic risk over k randomly sampled permutations

Calibration

Par./Var.	Description	Value
N	Number of banks in the system	20
α	Liquidity requirement ratio	0.10
ω_n	Risk weight on non-liquid assets	1
ω_l	Risk weight on interbank lending	0.20
γ	Equity requirement ratio	0.08
τ	Desired equity buffer	0.01
d_i	Bank deposits	Top20 EA
e_i	Bank equity	Top20 EA
σ	Bank risk aversion	2
r_i^n	Return on non-liquid assets	$U(0, 0.15)$
Ψ	Shocks to non-liquid assets	$\mathcal{N}(5, 25 * \mathbf{I})$

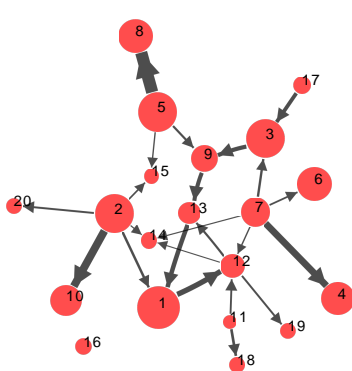
Table 1 : Baseline calibration

Network metrics

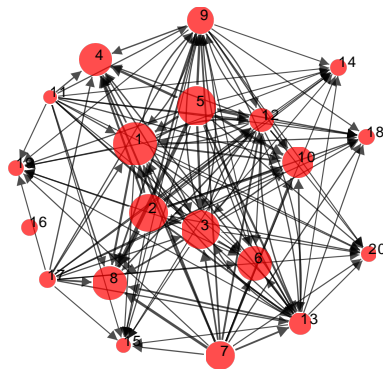
	RAS	CMA	RMA
Density (%)	35.53	6.05	17.11
Degree (Av.)	6.75	1.15	3.25
Av. Path Length	1.20	2.66	1.58
Betweenness Cent. (Av.)	0.25	4.05	8.55
Eigenvector Cent.(Av.)	0.13	0.14	0.08
Clustering Coeff. (Av.)	0.14	0.0003	0.07
Assortativity			
<i>out-in degree</i>	-0.94	-0.31	-0.39
<i>in-out degree</i>	-0.05	0.09	-0.12
<i>out-out degree</i>	-0.52	-0.65	-0.43
<i>in-in degree</i>	-0.40	-0.19	-0.32

Table 2 : Network characteristics - Baseline setting

Example of network configuration



(a) CMA



(b) RAS (Maximum Entropy)

Figure 1 : Baseline network configuration examples

Contribution to systemic risk

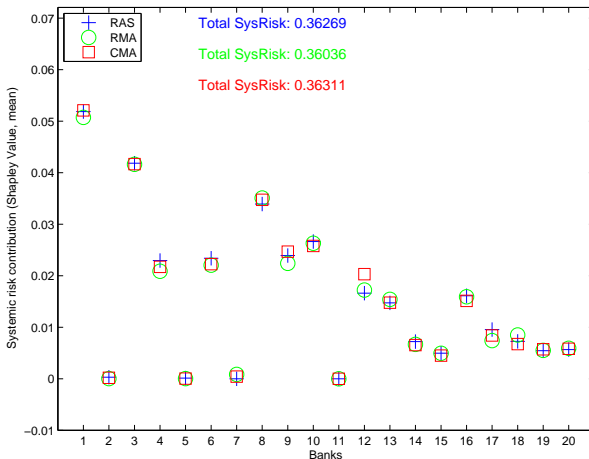


Figure 2 : Contribution to systemic risk (mean SV), by bank and network

Shapley value vs. bank characteristics

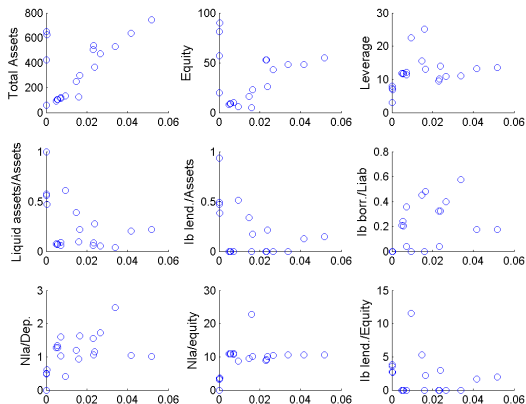


Figure 3 : RAS network

IO measures vs. bank characteristics

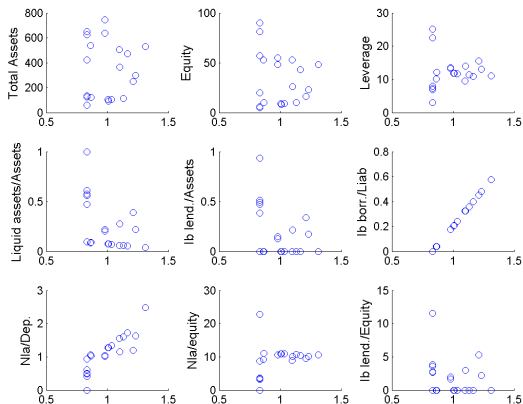


Figure 4 : RAS network - RH Backward index (case (i))

Shapley value vs. IO measures

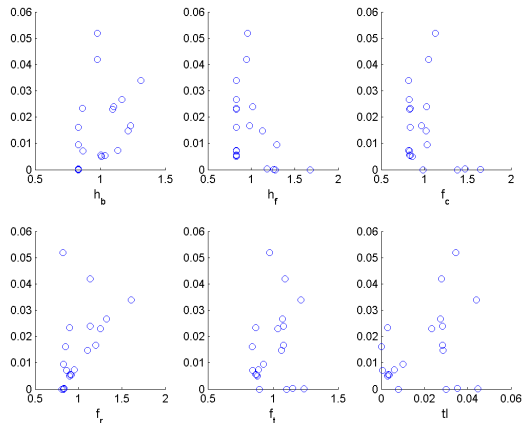


Figure 5 : RAS network

Systemic risk as a function of LR and ER

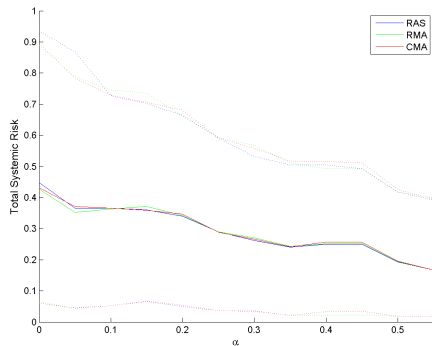


Figure 6 : Total Systemic Risk for different values of α

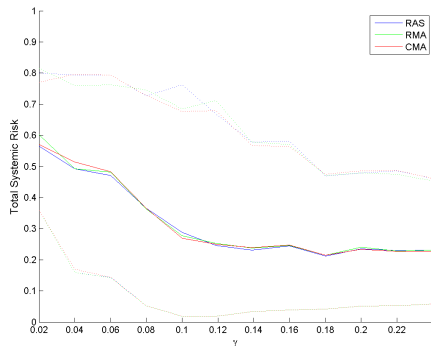
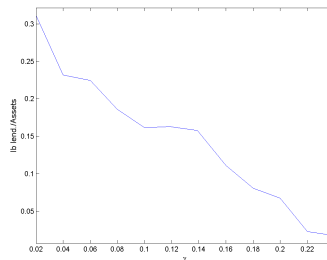
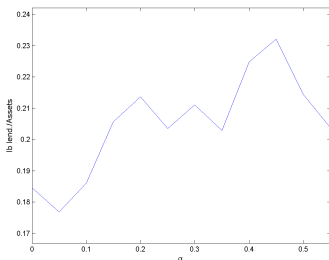
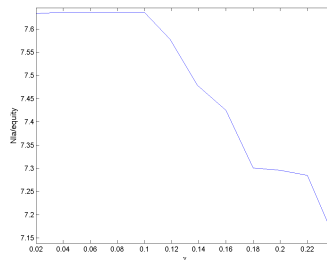
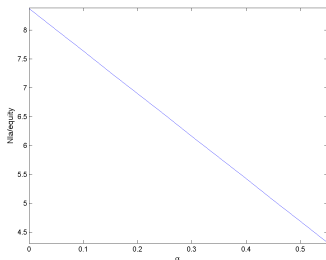
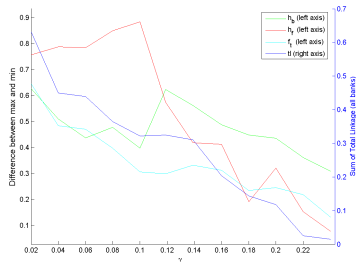
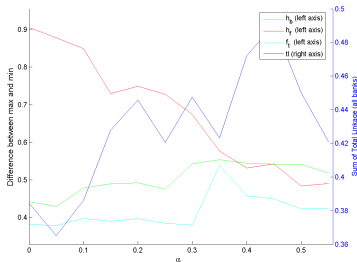
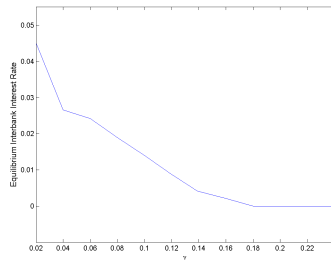
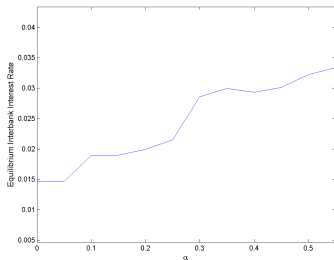


Figure 7 : Total Systemic Risk for different values of γ

$Nla/equity$ and $iblend/ta$ as a function of LR and ER



Ib rate and IO measures as a function of LR and ER



To do list (to name just a few...)

- Study the effects of risk coming from the liability side
 - liquidity crises (information-based bank runs)
 - arrival of information dependent on post-shock ability of the bank to service depositors
- Refine the partner's choice
- Endogenize net worth (go dynamic)
- Study interaction of fiscal/monetary policy measures with capital/liquidity requirement

THANK YOU!

- ✉ aldasoro@safe-uni-frankfurt.de
- ✉ domenico.delligatti@unicatt.it
- ✉ faia@wiwi.uni-frankfurt.de