Asset Pricing Implications of Systemic Risk in Network Economies

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Introduction

- This paper extends a dynamic endowment DSGE to allow for network structures among firms. This is usually difficult due to the curse of dimensionality of network economies
- Main Questions:
    1. Are DSGE cash-flow *dynamics* robust to the introduction of network effects? What is the impact of cash-flow externalities?
    2. Are equilibrium *Lucas' asset prices and risk premia* robust to the existence of network effects? How are interest rates and risk premia affected by these externalities?
    3. What can we learn from a network-based DSGE model in terms of *optimal design of financial network*? Which network is the most *stable*? What is the maximal *debt capacity* of a network?

Main findings

- To model network effects, we introduce a contact matrix in a DSGE model where cash-flow growth of one firm depends on its distress state, whose transition intensities depends on the state of distress of all other firms in the network according to a specific topology.
- Answers:
  1. No. There exist two distinct dynamics:
     - Subcritical dynamics: If firm-to-firm interaction strength is below a critical threshold the Lucas assumption holds true. Clusters of firm-specific shocks are transitory, only aggregate shocks matter.
     - Supercritical dynamics: Above the critical threshold, a "domino effect" induces non-linear amplification of micro-shocks and a violation of the Lucas assumption. Risk of persistent cascades of firm-specific shocks is priced by investors.

Main findings

- 2. No. There exist two distinct equilibria:
    - C-CAPM fails in the supercritical equilibrium
    - Risk premium includes a non-linear component that is network specific
    - Emergence of a cross-section of risk premia.

3. We propose two spectral-based measures of stability and economic resilience. We show that:
    - It is possible to introduce a tractable reduced-form model that captures first order dynamics
    - There exists a trade-off between stability and resilience:
      (a) Star network are the most stable and least resilient;
      (b) Complete networks are least stable and most resilient.
    - Compute the equilibrium Libor spread and cost of equity capital in financial networks.
    - Derive link between bank debt on the interbank basis spread and bank cost equity accounting for network externalities.

Some Related Literature

1. *Networks and Systemic Risk:* Allen and Gale (2000), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015, 2016), Eisenberg and Noe (2001), Giesecke and Weber (2006), Elliott, Golub, and Jackson (2014), Cabrales, Gottardi, and Vega-Redondo (2014), Denbee, Julliard Li and Yuan (2018).
2. *Asset Pricing in Lucas Orchards and Long Term Risk:* Santos and Veronesi (2009), Cochrane, Longstaff, and Santa-Clara (2008), Martin (2011), Buraschi and Porchia (2013).
3. *Networks in Production and Asset Pricing:* Scheinkman and Woodford (1994), Horvath (1998), Gabaix (2011), Acemoglu, Carvalho, Ozdaglar, and A. Tahbaz-Salehi (2012), Barrot and Sauvagnat (2016), Altinoglu (2016), Herskovic (2017).
4. *Distress Risk and Contagion:* Giesecke, Longstaff, Schaefer, and Strebulaev (2014), Feldhütter and Schaefer (2016), Azizpour, Giesecke, and Schwenkler (2017).
5. *Epidemic spreading and Contact Models:* Van Mieghem Omic and Kooij (2009), Grosskinsky (2009).

Benchmark specification of the dividend distribution dynamics

Dividend follows $D_t^i = Y_t x_t^i$:

- The aggregate shock is log-normal: $\frac{dY_t}{Y_t} = \mu dt + \sigma dW_t$.
- The firm-specific component x_t^i follows a Markov chain:

$$x_t^i = \begin{cases} x_t^i = x^i(0) & \text{healthy state } H_t^i = 0 \\ x_t^i = x^i(1) & \text{distressed state } H_t^i = 1. \end{cases}$$

The evolution of firm-specific shock x_t^i is defined by transition rates:

$$\begin{aligned} 0 \to 1 &: \lambda_i(\mathbf{H}_t) \text{ distress rate,} \\ 1 \to 0 &: \eta \text{ (constant) healing rate} \end{aligned}$$

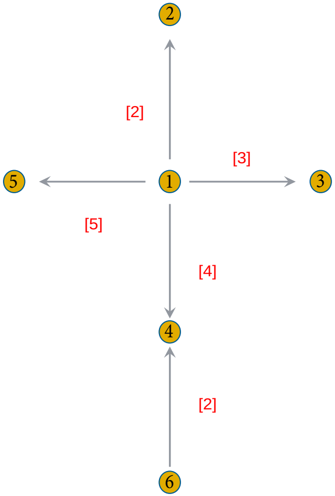
Key innovation $\Longrightarrow \lambda_i(\mathbf{H}_t)$ is network dependent:

$$\frac{\lambda^i(\mathbf{H}_t)}{\eta} = \varepsilon_i + \frac{\lambda}{\eta} \sum_{j=1}^{N} \Delta_{ij} H_t^j, \qquad \varepsilon_i := \lambda_i / \eta$$

$$\mathbf{H}_t = \left(H_t^1, H_t^2 \ldots, H_t^N\right), \qquad \Delta_{ij} \text{ network matrix.}$$

A reduced form description of distress propagation channels

- The level of $\Delta_{ij} > 0, i \neq j$ determines the increase in the likelihood of distress of firm i due to a distress of firm j.



$$\Delta = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0 & 0 \\ 4 & 0 & 0 & 0 & 0 & 2 \\ 5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Distress dynamics in the benchmark specification

- The number of accessible configurations is 2^N and increases exponentially wth N. Two consecutive configurations differ at most for the state of one firm.
- Firm-specific distress evolution can be represented in terms of a transition rate matrix $A^{(N)}$ of size $2^N \times 2^N$ that specifies the transition rate between any two configurations H and H'.
- In the benchmark specification all the firms are identical and spontaneous transition to distress is set to zero. Hence:
  - The firms have all the same β risk exposure to aggregate log normal factor Y_t.
  - The state $H = 0$ is absorbing, hence firm specific shocks are transitory.

thus in the long-term steady state each firm endomwent dynamics is equivalent to the one of a single tree Lucas model.

Cascades

- Let network G of N firms, H_0^S initial state with cluster of firms S in distress.
- Let $T^S(\mathbf{H}) = E\left[\tau_{\mathbf{H}} \mid \mathbf{H}_0^S\right]$ be the conditional expected time required to reach configuration H starting from configuration H_0^S
- Mean return time to steady state:

$$\mathcal{T}^{\mathcal{G}}(S) := \sum T^S(\mathbf{H})\,\pi^{\mathbf{A}}(\mathbf{H})$$

  $\pi^{\mathbf{A}}(\mathbf{H})$ are the ss probabilities identified by left-eigenvector of the transition matrix $\mathbf{A}$.
- $\mathcal{T}^{\mathcal{G}}$ is determined by the eigenvalues of $\mathbf{A} \Longrightarrow \mathcal{T}^{\mathcal{G}} = \sum_{n=2}^{2^N} \frac{1}{\lambda_n^{\mathbf{A}}}$.
- The higher $\mathcal{T}^{\mathcal{G}}$, the greater the amplification.

Definition (Cascade)

Process H_t^S is a cascade if there exist two constants c, $N_0 > 0$ such that:

$$\mathcal{T}^{\mathcal{G}} > e^{cN} \qquad \text{for } \forall N > N_0$$

i.e. the mean return time to steady state is longer than a characteristic time e^{cN} which grows exponentially with the number of firms in the economy $N > N_0$.

Theorem (Existence of Critical Dynamics)

Consider a finite CONNECTED NETWORK $\mathcal{G}$ *with a number of firms* $N > 2$. *Then there exists a finite critical threshold* $K^{\mathcal{G}}$ *separating two types of dynamics:*

- *Supercritical* Dynamics. *When* $\frac{\lambda}{\eta} > K^{\mathcal{G}}$, *there exists a set of firms* $S \subset V^{\mathcal{G}}$ *whose distress generates a contagion process* H_t^S *that drives a* CASCADE *of distress shocks with positive probability.*
- *Subcritical* Dynamics. *When* $\frac{\lambda}{\eta} < K^{\mathcal{G}}$ *the probability of occurrence of a cascade is zero.*

The presence of cascades is a generic feature of network dynamics for a broad class of topologies when the level of the distress-to-recovery intensity $\frac{\lambda}{\eta}$ overcomes a critical threshold $K^{\mathcal{G}}$.

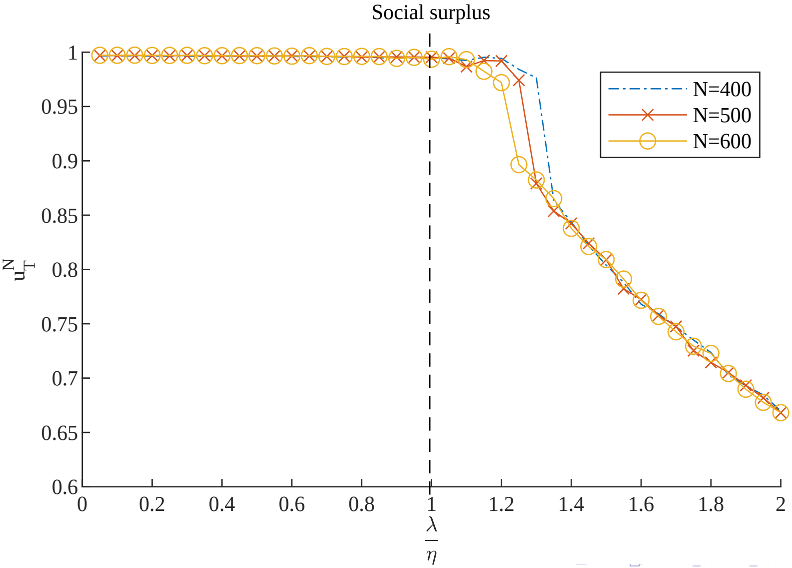
Application: Distress in Interbank Networks

We embed the two period model by Acemoglu et al. (2015) in our continuos time economy to study its dynamic properties:

- Δ_{ji} represents the interbank (short-term) liability that bank i owes to bank j
- Bank j cash flows are the sum of cash flows generated by risky projects and by payments of interbank debt from non distressed banks.
- In normal times ($H_t^j = 0$) bank j distributes dividends to equity holders since the difference between cash flows and liabilities is positive.
- Bank j is in distress ($H_t^j = 1$) and dividends are not paid if cash flows are insufficient to meet its obligations.
- Financial Stability is measured by a dynamic extension of the surplus function as follows:

$$u_T^N := \frac{1}{T} E_{\mathbf{H}_0}^{\mathbb{P}} \left[\int_0^T \left(1 - \frac{1}{N} \sum\nolimits_{j=1}^N H_t^j \right) dt \right].$$

Social Surplus for different levels of aggregate debt



Cascades without Fire-Sales

Numerical simulation of dynamics in a complete undirected network: X-axis = level of interconnectedness $\frac{\lambda}{\eta}$; T = 1000 years.

- Subcritical equilibrium: distress shocks quickly average out, i.e. $\frac{1}{N}\sum_{j=1}^{N} H_t^j \simeq 0$ and $u_T^N\left(\frac{\lambda}{\eta}\right) \simeq 1$.
- Supercritical equilibrium: cascades induce lack of convergence of social surplus to its expected steady state value: $u_T^N\left(\frac{\lambda}{\eta}\right) \nrightarrow 1$
- Cascades form even in the absence of fire sales. We hold Δ fixed; it's not endogenous to the state.
- What are the key characteristics that impact on: (a) distance to critical threshold and (b) social loss upon distress?
- For this we need a tractable model that allows for closed-form solutions.

Endogeneity and Empirical Implications

Institutions optimally set the level of debt and the lending counterparties independently of each other. However, this firm-specific decision creates network externalities (see, e.g., Jackson and Pernaud (2019)).

- As firms adapt to environment changes, financial network structure is endogenous and may change over time.
- Firms may have incentive to live close to the critical point $K^{\mathcal{G}}$ (fiscal advantage of debt; convex managerial incentives), spontaneously pushing $\frac{\lambda}{\eta} > K^{\mathcal{G}}$ creating endogenous fluctuations.
- Welfare considerations may motivate the mandate for a regulator to keep the network in a subcritical equilibrium.

Econometrician observes two distinct dynamics complicating estimation methods. With supercritical dynamics he sees infrequent clusters of large distress. See Giesecke et al. (2011) and Feldhutter and Schaefer (2015).

A Reduced-form Model

Question: "Possible to capture dynamics in a tractable reduced-form model?"

- Important to distinguish two types of information: (a) "*Systemicness*", ν_j^L, economic information/state that affects other nodes, and (b) "*Vulnerability*", ν_i^R, economic information/state that depends on others.
- They are mutually linked:
  1. Bank j *Systemicness* ν_j^L increases if $\sum_i \nu_i^R \Delta_{i,j}$ increases
  2. Bank i *Vulnerability* ν_i^R increases if $\sum_j \Delta_{i,j} \nu_j^L$ increases
- Linearity assumption:

$$\nu^R = c_1 \Delta \nu^L \qquad \text{and} \qquad \nu^L = c_2 \Delta' \nu^R$$

  Solution:

$$v^R = (c_1 c_2) \Delta \Delta' v^R \qquad \text{and} \qquad v^L = (c_1 c_2) \Delta' \Delta v^L$$

- Natural link between $[v^R, v^L]$ and right left singular vectors of Δ: Kleinberg (1999) first to introduce notion of "hub" and "authority" scores.
- Different from Eigenvalue Centrality that applies only to symmetric Δ: not suited for directed networks.

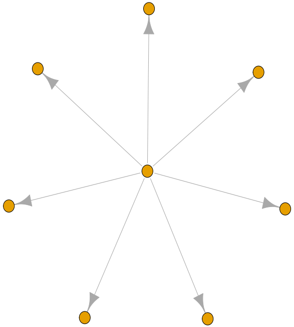
Low Rank Representation of the Model

- Given ν_i^R and ν_j^L from right and left singular vectors of Δ, we can obtain an optimal lower rank aproximation of Δ:

$$\Delta_{i,j}^{\mathcal{G}} \sim \alpha^{\mathcal{G}} \nu_i^R \nu_j^L \quad i,j = 1,..,|\mathcal{G}|$$

  The N^2 elements of $\Delta^{\mathcal{G}}$ of a generic network can be represented in terms of the $2N+1$ components of $[\nu_i^R, \nu_j^L, \alpha^{\mathcal{G}}]$.
- This specific rank-reduction preserves economic interpretation: vulnerability and systemicness of firm i is still the same; these measures still depend on the global properties, not on just local links.

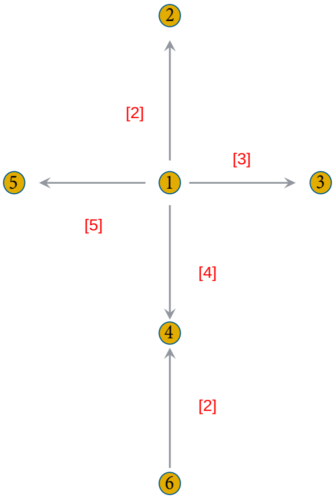
Example: a Directed Star Network



$$
\begin{aligned}
\Delta^{SN} &= \alpha_0 \left(\nu^R\right)^T \cdot \nu^L \\
&= \begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}
\end{aligned}
$$

$$
\begin{aligned}
\alpha_0 &= 1, \\
\nu^L &= [1, 0, ..., 0], \\
\nu^R &= [0, 1, ..., 1],
\end{aligned}
$$

Systemicness and Vulnerability vs Eigenvector Centrality



$$\Delta = \alpha_0 \left(\nu^R\right)^T \cdot \nu^L \simeq \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 3 & 0 & 0 & 0 & 0 & 2 \\ 4 & 0 & 0 & 0 & 0 & 0 \\ 5 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Kleinberg Hub and Authority:

$$\begin{aligned} \alpha_0 &= 7.0433 \\ \nu^L &= [0.98, 0, 0, 0, 0, 0.15]\,, \\ \nu^R &= [0, 0.27, 0.40, 0.57, 0.66, 0]\,. \end{aligned}$$

Eigenvector Centrality:

$$\begin{aligned} \alpha_0 &= 0 \\ C &= [1, 0, 0, 0, 0, 0]\,. \end{aligned}$$

Low Rank Representation

- STAR network: cash-flow transition of non-central firms i depends on central ($\star$) firm:

$$A^{(i)}_{\nu,H^\star_t} = \begin{bmatrix} -\lambda H^\star_t & \lambda H^\star_t \\ \eta & -\eta \end{bmatrix} \quad \forall i.$$

- GENERIC network:

$$A^{(i)}_{\nu^R,H^\nu_t} = \begin{bmatrix} -\lambda\alpha\nu^R_i H^\nu_t & \lambda\alpha\nu^R_i H^\nu_t \\ \eta & -\eta \end{bmatrix}$$

- COMMON NETWORK FACTOR: linearity allows construction of (systemicness) ν^L_i-weighted mean of each firm distress indicators H^i_t:

$$H^\nu_t := \frac{\sum_{i=1}^{+\infty} \nu^L_i H^i_t}{\sum_{i=1}^{+\infty} \nu^L_i}.$$

Closed form solutions

Theorem

Consider the large economy limit $N \to +\infty$ of a sequence of reduced form GENERIC DIRECTED NETWORKS *satisfying Condition 1. Then:*

a *The critical threshold is given by:*

$$K^{\mathcal{G}} = \frac{1}{\overline{\alpha}}, \quad \overline{\alpha} = L\left(\nu^L \cdot \nu^R\right)$$

b *The long term probability of distress $h^i_\infty := \lim_{t\to\infty} E\left[h^i_t\right]$ of firm i is given by:*

- *for $\frac{\lambda}{\eta} \leq K^{\mathcal{G}}$, $h^i_\infty = 0$.*
- *for $\frac{\lambda}{\eta} > K^{\mathcal{G}}$, h^i_∞ and h^ν_∞ are strictly positive and are the unique solution to:*

$$h^i_\infty = \frac{\alpha \frac{\lambda}{\eta} \nu^R_i}{1 + \alpha \frac{\lambda}{\eta} h^\nu_\infty \nu^R_i} h^\nu_\infty, \qquad \sum_{k=1}^{K} p_k \frac{\nu^L_k \nu^R_k \frac{L\lambda}{\eta}}{\frac{L\lambda}{\eta} \nu^R_k h^\nu_\infty \left(\nu^L \cdot \mathbf{1}\right) + 1} = 1.$$

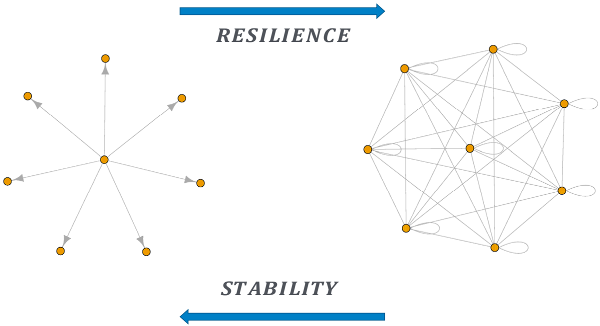
Debt bearing capacity and financial network architectures

- STABILITY. Debt capacity is $K^{Debt} := \frac{\eta}{\lambda} \frac{1}{(\nu^R \cdot \nu^L)}$. If leverage $L < K^{Debt}$, the dynamics is STABLE.
  - Maximum debt bearing capacity is achieved by the class of directed star networks. In fact, in this case $\nu^R \cdot \nu^L = 0$ implies $K^{Debt} \to +\infty$.
  - Minimal debt bearing capacity is achieved by the complete undirected network. In fact, $\nu^R = \nu^L = 1$ and standardized $K^{Debt} = \frac{\eta}{\lambda}$.
- RESILIENCE. Social loss in supercritical reduces welfare to:

$$u_\infty = 1 - \left(\nu^R \cdot \mathbf{1}\right) \left(\mathbf{1} \cdot \nu^L\right) L \frac{\lambda}{\eta} h_\infty^\nu$$

  - The most resilient network is the uniform complete undirected network, with $\nu_i^L = \nu_i^R$.
  - The least resilient network is a star network with a central institution having non-zero vulnerability. Resilience is decreasing with increasing vulnerability of the central institution.

Core-Periphery Structures: Stability vs Resilience Tradeoff



Valuation in a network economy

Our main interest is to model pricing of cash-flow risks. We introduce a simple preference structure and derive the intertemporal asset pricing equilibrium conditions.

- A representative agent maximizes a time additive Constant Relative Risk Aversion utility of intertemporal consumption.
- The separation of diversifiable from aggregate effects requires the analysis of the asymptotic long-term regime $t \to +\infty$ in the large economy limit $N \to \infty$.
- The analysis of expectations in supercritical dynamics requires the construction of a probability measure to characterize long-term contagion risk. Its construction follows the approach proposed in Hansen and Scheinkman (2009).

Network Irrelevance in subcritical equilibria

In the absence of "systemic firms" firm-specific distress shocks have marginal contributions to the stochastic discount factor of order $1/N$.

Theorem

Consider the large economy limit of a GENERIC NETWORK *of firms. Under the above assumptions, the risk free rate and the pure jump risk premia are unaffected by transitory shocks:*

$$r^{GN}(\mathbf{H}_t) \overset{N\to+\infty}{\simeq} r_f := \delta + \mu\gamma - \frac{1}{2}(1+\gamma)\gamma\sigma^2,$$

$$\theta^{GN,i}(\mathbf{H}_t) \overset{N\to+\infty}{\simeq} 1.$$

In the large economy limit, the dynamics of the SDF converges to the Lucas one:

$$\frac{d\xi_t^{GN}}{\xi_t^{GN}} = -r_f dt - \kappa dW_t,$$

If $\frac{\lambda}{\eta} < K^{\mathcal{G}}$ then distress shocks average out and the the network structure is irrelevant in the large economy limit.

Network Relevance in Supercritical Economies and Long-Run Risks

Theorem

Consider the large economy limit $N \to +\infty$ of a generic network. In supercritical economies with $\frac{\lambda}{\eta} > K^{\mathcal{G}}$, the idiosyncratic risk components dM_t^i are rationally compensated and the long-term expected risk premium of firm i is equal to:

$$\mu_\infty^i = \kappa\sigma + \left(1 - h_\infty^i\right) E\mu_\lambda^i + h_\infty^i E\mu_\eta^i,$$

where the two terms $E\mu_\lambda^i$ and $E\mu_\eta^i$, respectively the distress and recovery risk premia are:

$$E\mu_\lambda^i = \alpha\frac{\lambda}{\eta}\nu_i^R h_\infty^\nu \frac{a}{\left(1+\frac{a}{\eta}\right)}\left(1 - \frac{x^i(1)}{x^i(0)}\right),$$

$$E\mu_\eta^i = -a\left(1 - \frac{x^i(1)}{x^i(0)}\right).$$

CAPM fails

The Consumption CAPM fails:

- *Beta* does not capture risk premium even for simple preferences
- There is a cross-section of risk premia proportional to

$$\underbrace{\nu_i^R}_{\text{Vulnerability}} \times \underbrace{h_\infty^\nu}_{\substack{\text{Global Cashflow} \\ \text{Risk}}} \times \underbrace{\left[1 - \frac{x^i(1)}{x^i(0)}\right]}_{\substack{\text{Idiosyncratic Cashflow} \\ \text{Risk}}} .$$

- Note: the shape of the cross-section depends on global properties of the network, not just local $\Delta_{ij} = \alpha \nu_i^R \nu_j^L$. Indeed, each element of ν_i^R depends on all the elements of ν_j^L.

The impact of the interbank network on financial sector valuation

In a supercritical equilibrium the failure of the diversification argument has implications for asset valuation:

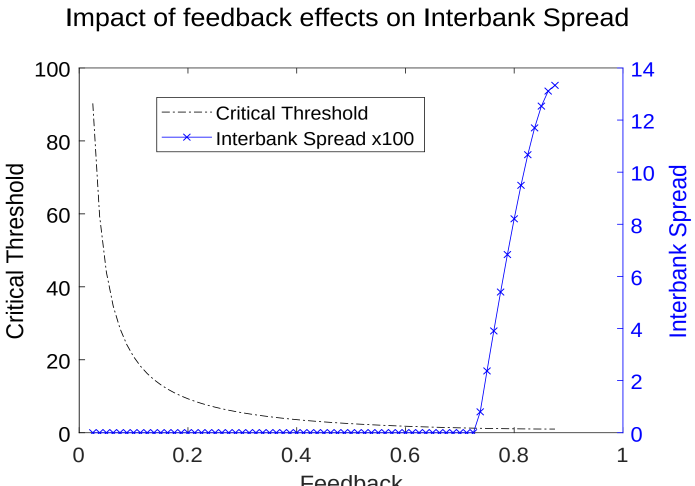
- *Interbank Basis Spread.* The fraction of borrowers that are not repayed is $E_{\Pi}^{\mathbb{P}}\left[\frac{1}{N}\sum_{j=1}^{N} H_t^j\right] > 0$ in a supercritical equilibrium. Then, the break-even interbank (Libor) spread over the risk-free rate is given by:

$$\ell := (1 + r_f)\left(\frac{E_{\Pi}^{\mathbb{P}}\left[\frac{1}{N}\sum_{j=1}^{N} H_t^j\right]}{1 - E_{\Pi}^{\mathbb{P}}\left[\frac{1}{N}\sum_{j=1}^{N} H_t^j\right]}\right).$$

Interbank basis spread for different financial architectures.

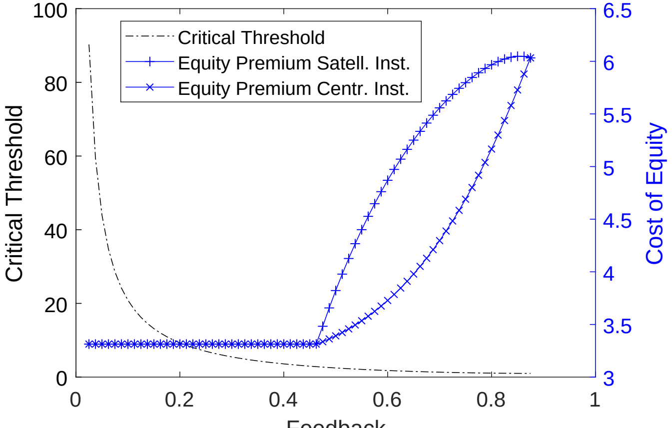
Consider convex combination of the two extreems architectures:

- STAR: $\nu^L = [1, 0, ..., 0]\,, \quad \nu^R = [0, 1, ..., 1]$
- COMPLETE: $\nu^L = \nu^R = [1, 1, ..., 1]$



Bank cost of equity for different financial architectures.

- *Bank cost of equity.* (a) More vulnerable banks have a higher cost of equity; (b) the greater the feedback effects (completeness) the greater the cost of equity:

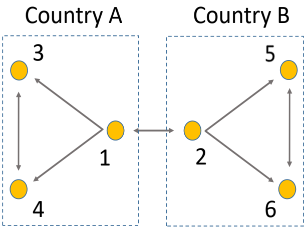


Cross-border Impact of Regulatory Changes

To illustrate the asset pricing implications of the exposure to network shocks, let us consider a two-country economy.

- The initial levels of interbank debt are given by matrix Δ^0:
- Banks 3 and 4 are subject only to country A local regulatory constraints; on the other hand, banks 5 and 6 are subject only to country B local regulatory constraints. Banks 1 and 2 operate cross-border and are subject to the same international regulatory standards.
- The two countries have homogeneous regulatory standards and international debt exchanges are symmetric.
- $\lambda/\eta = 0.045 < K^{\mathcal{G}} = 0.046$, the equilibrium is subcritical and risk premia are simply equal to $\kappa\sigma = 0.45\%$, since $h^i_\infty = 0 \; \forall i$.

Cross-border Impact of Regulatory Changes



$$\Delta^0 = \begin{bmatrix} 10 & 10 & 20 & 20 & 0 & 0 \\ 10 & 10 & 0 & 0 & 10 & 10 \\ 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 0 & 0 & 10 & 0 \end{bmatrix}$$

$$\Delta^1 = \begin{bmatrix} 10 & 10 & 20 & 20 & 0 & 0 \\ 10 & 10 & 0 & 0 & 10 & 10 \\ 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 30 \\ 0 & 0 & 0 & 0 & 30 & 0 \end{bmatrix}$$

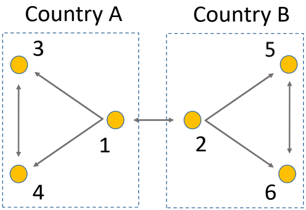
Δ^0	1	2	3	4	5	6	$\sum_{i=1}^{6}$
$\nu_i^{0,L}$	0.35	0.35	0.61	0.61	0.085	0.085	2.09
$\nu_i^{0,R}$	0.93	0.26	0.18	0.18	0.03	0.03	1.60
$\mu_i^{\infty} = \gamma\sigma^2$	0.45%	0.45%	0.45%	0.45%	0.45%	0.45%	–

Cross-border Impact of Regulatory Changes

Assume now that country B introduces a more relaxed domestic regulatory standards which allows local institutions 5 and 6 to take more counterparty risk and/or debt.

- Δ^1 is the new adjacency matrix after this regulatory shock
- $K^{\mathcal{G}}$ drops by 27% and $\lambda/\eta > K^{\mathcal{G}}$ so that the equilibrium becomes supercritical. Local banks 5 and 6 in country B scale up their borrowing/lending activity increasing both their level of systemicness and vulnerability.
- Externality generated by banks 5 and 6 propagates to the rest of the network. The regulatory framework and the books of global banks 1 and 2 and local banks 3 and 4 in country A do not change however, their vulnerability increases because the risk of their counterparties increases.
- The cost of equity of all banks raises. Bank 3 and 4 in country A increase to 2%. The largest risk premium increase occur for the global bank 1, which is the most vulnerable to the chain of negative externalities originating in country B, and goes to 7.85%

Cross-border Impact of Regulatory Changes



$$\Delta^0 = \begin{bmatrix} 10 & 10 & 20 & 20 & 0 & 0 \\ 10 & 10 & 0 & 0 & 10 & 10 \\ 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 10 \\ 0 & 0 & 0 & 0 & 10 & 0 \end{bmatrix}$$

$$\Delta^1 = \begin{bmatrix} 10 & 10 & 20 & 20 & 0 & 0 \\ 10 & 10 & 0 & 0 & 10 & 10 \\ 0 & 0 & 0 & 10 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 30 \\ 0 & 0 & 0 & 0 & 30 & 0 \end{bmatrix}$$

Δ^1	1	2	3	4	5	6	$\sum_{i=1}^{6}$
$\nu_i^{1,L}$	0.31	0.31	0.38	0.38	0.51	0.51	2.40
$\nu_i^{1,R}$	0.62	0.47	0.11	0.11	0.43	0.43	2.17
h_i	17%	14%	4%	4%	13%	13%	$h_\infty^\nu = 52\%$
μ_i^∞	7.9%	6.3%	2%	2%	5.9%	5.9%	–

Policy Implications

- Macro-Prudential Debt and Leverage constraints: this affects α, thus distance to criticality
- Bank specific policies $\Longrightarrow$ Bail-ins and Bail-outs:
  - When close to threshold $K^{\mathcal{G}}$, "Bail-ins" may take economy above threshold unless the bank is not systemic. This can be calculated from ν^L and ν^R. Thus, bail-ins depends on the spectral characteristic of teh network.
  - When distance to threshold $\left\|\lambda/\eta - K^{\mathcal{G}}\right\|$ is large enough, "Bail-ins" are possible.
  - When $\lambda/\eta > K^{\mathcal{G}}$, "Bail-out" might be the only solution.
- Derivative markets: centralized clearing market (Star) are the most stable.

Conclusions and extensions

- We show that concentrated directed networks are stable but not economically resilient. On the contrary, a complete network is unstable but economically resilient.
- The equilibrium unsecured interbank deposit rate includes a compensation for the undiversifiable risk that a clustering of bank distress transitions induces (endemic) distress.
- In the supercritical state the differential exposure to aggregate network risk is priced selectively and is higher for smaller more vulnerable banks.
- Future analysis will further refine testable empirical implications on: i) *Bailout Policies, Leverage, and Correlation Risk*, ii) *The Political Economy Banking Networks*, *The cross-section of risk premia*.