Session 3: Financial Agent-Based Models

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Day 3: Agent-Based Models

- Part 1: ABM With Rationing Equilibrium [Georg (2013a)]
- Part 2: ABM With Bayesian Equilibrium [Georg (2013b)]
- Part 3: "ABM" with Nash Equilibrium [Ahnert and Georg (2012)]

Motivation: forms of systemic risk

- In **financial networks** a node represents a bank while an edge represents a relationship between two banks.

Assets		Liabilities	
Loans to Customers	100	Retail Deposits	130
Loans to B	30	Borrowing from B	30
Loans to C	30	Borrowing from C	30
Other securities	40	Equity Capital	10
Total	200		200

Table: Balance sheet of bank A

Motivation: forms of systemic risk

Assets		Liabilities	
Loans to Customers	100	Retail Deposits	130
Loans to A	30	Borrowing from A	30
Loans to C	30	Borrowing from C	30
Other securities	40	Equity Capital	10
Total	200		200

Table: Balance sheet of bank B

Assets		Liabilities	
Loans to Customers	100	Retail Deposits	130
Loans to A	30	Borrowing from A	30
Loans to B	30	Borrowing from B	30
Other securities	40	Equity Capital	10
Total	200		200

Table: Balance sheet of bank C

Motivation: forms of systemic risk

- The banks are completely symmetric w.r.t. deposits, borrowings, securities and equity.

The domino case

- Suppose that A makes a **loss** of 40 on it's loans.
- This **wipes out** it's equity.
- It has a **shortfall** of 30 on it's liabilities.
- This shortfall is divided up amongst B and C, each suffering a shortfall of 15 on their **interbank lendings**.

$\Rightarrow$ **B and C are wiped out as well!**

- However: limits on large exposure make direct contagion **highly unlikely**
- However however: this holds true for **regulated** financial intermediaries

Motivation: forms of systemic risk

Beyond the domino model...

- Bank A makes losses of 5 on it's loan book, halfing it's equity capital to 5.
- The leverage ratio (ratio of assets to equity capital) of A increases from 20 (200/10) to 39 (195/5), putting the bank close to, or below the capital adequacy ratio.
- This forces A to sell some of it's securities.
- They were originally worth 40, but since A has to get rid of them in a fire-sale, the bank sells half of them and recoups only 18.
- This reduces the bank's equity capital to 1.

Motivation: forms of systemic risk

Beyond the domino model (ctd.)...

- B and C are now hit with **two problems**:
  1. Since A has been selling it's securities in a fire-sale, the securities of B and C are now worth only 36. This **reduces their equity capital** to 6.
  2. Needing to shrink their balance sheets and worried about A's solvency, they decide **not to roll-over their loans** to A.
- A now has to repay the loans to B and C, but with **almost no equity** and the **value of it's securities falling**, it fails to do so.
- B and C now realize losses on their loans to A and also on their securities.

$\Rightarrow$ **B and C are just as vulnerable as A**

Systemic Risk is Dynamic and Takes Various Forms

- Two dimensions of systemic risk
  1. Systemic risk slowly builds in tranquil times and abruptly unravels in times of crisis

     $\Rightarrow$ **time-dimension**
  2. Systemic risk can be transmitted through various channels

     $\Rightarrow$ **cross-sectional dimension**
- Systemic risk channels:
  - financial contagion: Allen and Gale (2000), Freixas, Parigi, and Rochet (2000)
  - common shocks: Acharya and Yorulmazer (2008)
  - informational spillovers: Acharya and Yorulmazer (2008b), Nier et al. (2007) Ahnert and Georg (2012)

Modelling Systemic Risk is a Challenge

Four reasons why modelling systemic risk is a challenge for economists:

1. **Heterogeneous agents** $\rightarrow$ No representative agent(s)
2. Complex interactions
3. Dynamic structural change
4. Deviations from rationality

Financial Intermediaries are Heterogeneous

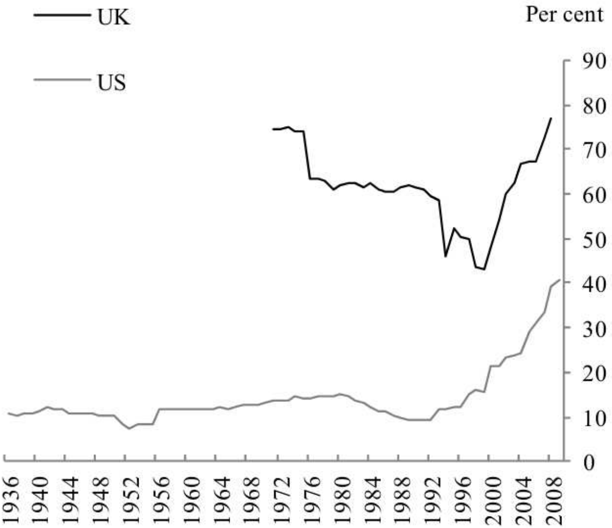


Figure: Concentration of the UK and US banking system. Source: Gai, Haldane and Kapadia (2011).

Modelling Systemic Risk is a Challenge

Four reasons why modelling systemic risk is a challenge for economists:

1. Heterogeneous agents
2. **Complex interactions** $\rightarrow$ incomplete markets
3. Dynamic structural change
4. Deviations from rationality

Interbank Loans Form a Network Structure

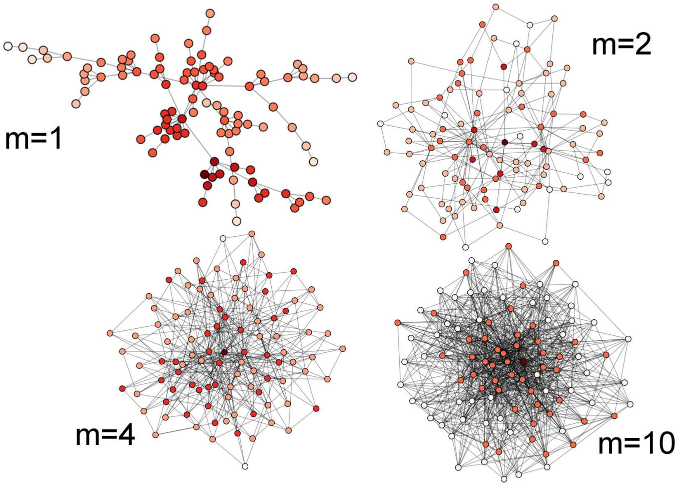


Figure: Different scale free networks

Modelling Systemic Risk is a Challenge

Four reasons why modelling systemic risk is a challenge for economists:

1. Heterogeneous agents
2. Complex interactions
3. **Dynamic structural change** $\rightarrow$ Processes on different time scales
4. Deviations from rationality

The Financial System is Highly Interconnected

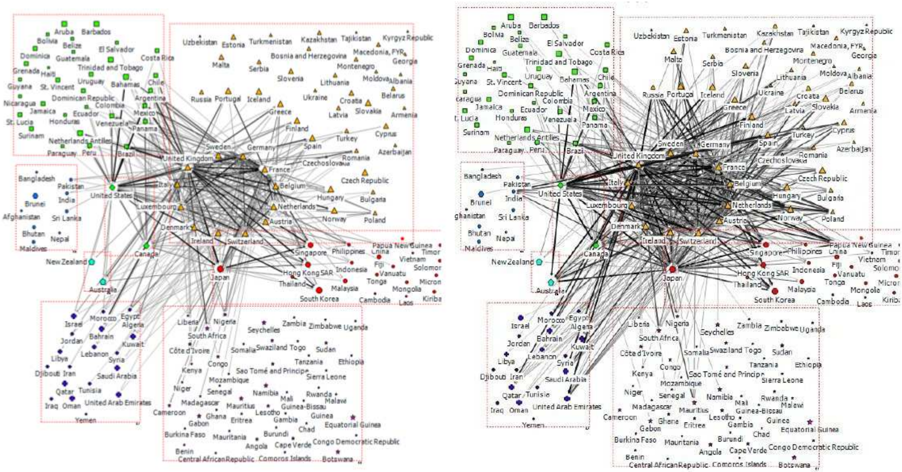


Figure: Interconnectedness of the international banking network in 1980 (left) and 2007 (right). Source: Minoiu and Reyes (2011) using BIS data.

Modelling Systemic Risk is a Challenge

Four reasons why modelling systemic risk is a challenge for economists:

1. Heterogeneous agents
2. Complex interactions
3. Dynamic structural change
4. **Deviations from rationality** $\rightarrow$ Agent behaviour matters

Modelling Systemic Risk is a Challenge

Four reasons why modelling systemic risk is a challenge for economists:

1. Heterogeneous agents
2. Complex interactions
3. Dynamic structural change
4. Deviations from rationality

Multi-Agent Simulations can help understand systemic risk

Relation to the Literature

Literature on Financial Networks

- Allen and Gale (2000), Freixas et al. (2000)
- Haldane and May (2011), Gai, Haldane, and Kapadia (2011), Gai and Kapadia (2008)
- Becher et al. (2008), Gabrieli (2011), Chang et al (2011), Brink and Georg (2011), Markose et al. (2010), Craig and von Peter (2010)

Literature on Fire-sales

- Shleifer and Vishny (1992): specialised asset holders are simultaneously in distress and sell to non-specialists
- Allen and Gale (1994): endogenous market participation

Literature on Multi-Agent Models:

- Iori et al. (2006), Nier et al. (2007), Ladley (2011), Bluhm et. al. (2012)
- **However:** risk-free investments, no central bank, mechanistic agent behaviour, "fine-tuning"

The Financial System from a Complex Systems Perspective

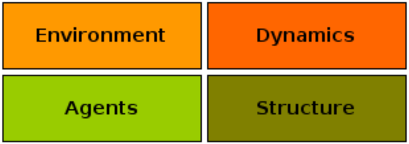


Figure: The building blocks for a simulation of the financial system

The Financial System from a Complex Systems Perspective

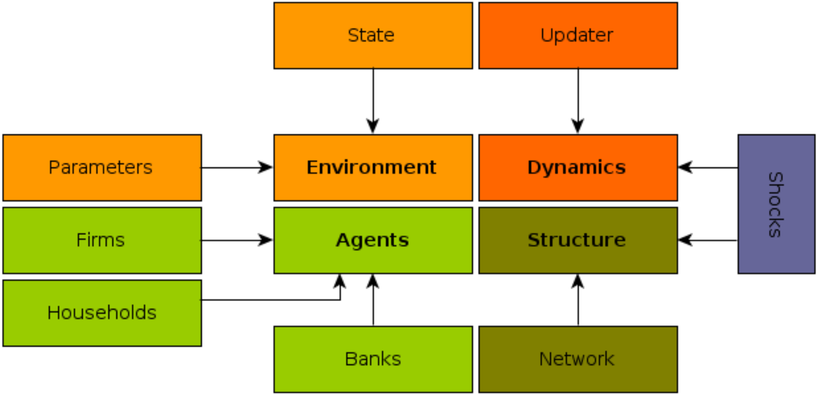
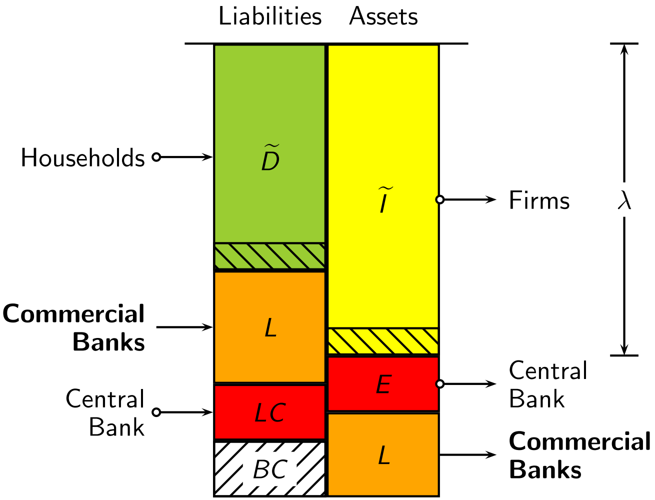


Figure: The building blocks for a simulation of the financial system

Microfoundations of Banks Determine Model



The Network Structure Matters

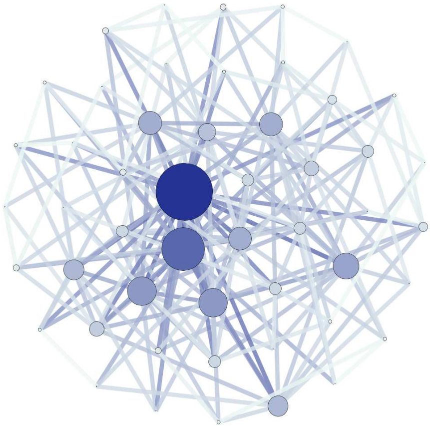


Figure: A scale-free network ($k = 4$) of contracts amongst 50 banks.

Agent Behaviour (and Model Dynamics)

- Banks optimize their **portfolio structure and -volume** according to CRRA preferences

$$u = \frac{1}{1-\theta}\left(V(1+\lambda\mu - \frac{1}{2}\theta\lambda^2\sigma^2)\right)^{(1-\theta)}$$

where θ is risk-aversion parameter, μ and σ^2 expected return and variance of risky assets

- **Deviation from Rationality**: agents become more (less) risk averse if there are (no) bank defaults in previous period

$\Rightarrow$ Information Contagion

Possible extensions:

- Bayesian updating for expected return and variance of real (and financial) assets
- Agent behaviour is key: alternative implementation with risk neutral agents (see e.g. Baltensperger (2002))

Model Dynamics – The Update Algorithm

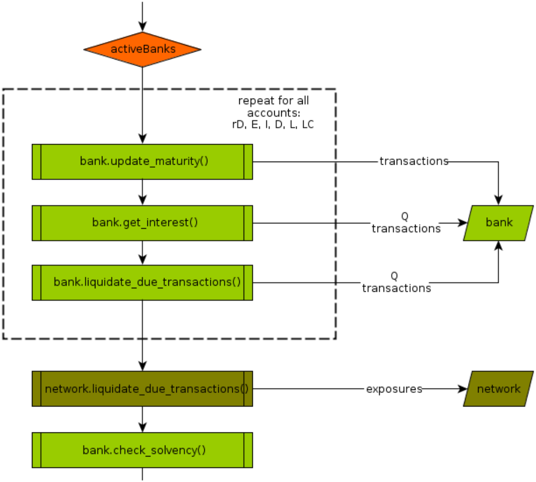


Figure: The first part of the update algorithm.

Model Dynamics – The Update Algorithm

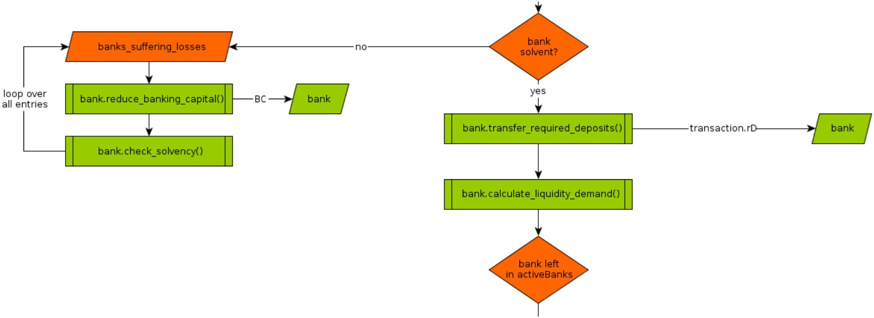


Figure: The second part of the update algorithm.

Model Dynamics – The Update Algorithm

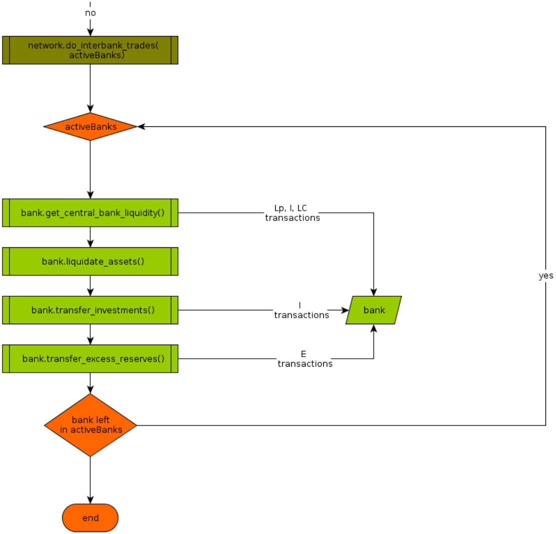


Figure: The third part of the update algorithm.

Model Parameters

Upside: model is very flexible – 26 parameters
Downside: model will be hard to calibrate (if at all possible)

Parameter type	Parameter name
Simulation	numSweeps, numSimulations, numBanks, contractsNetworkFile shockType, **liquidationDiscountFactor**, **riskAversionDiscountFactor** **riskAversionAmplificationFactor**
Interest rates	rb, rd
Central bank	collateralQuality
Firm	successProbabilityFirms, positiveReturnFirms, firmLoanMaturity assetNumber
Household	scaleFactorHouseholds
Bank	dividendLevel, successProbabilityBank, positiveReturnBank **thetaBank**, xiBank, interbankLoanMaturity
Regulation	r, **sifiSurchargeFactor**, **leverageRatio**, requiredCapitalRatio

Table: Overview of model parameters

Central Bank Liquidity Stabilizes in the Short-Run...

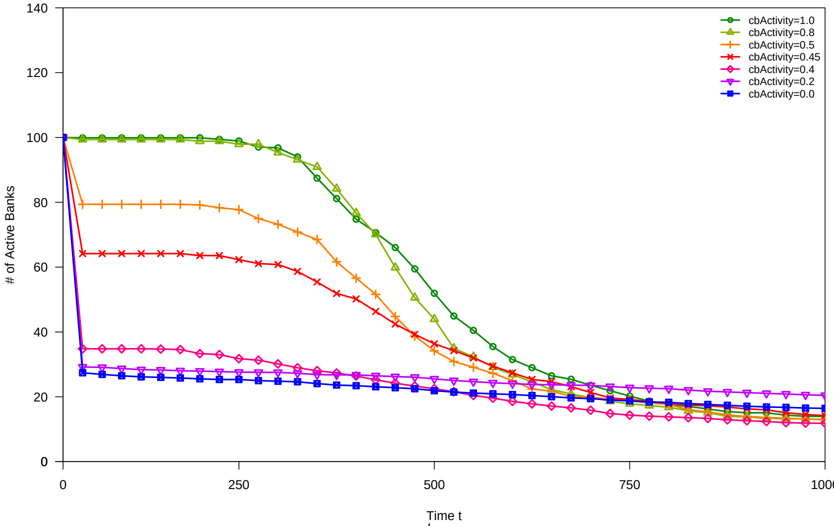


Figure: The effect of central bank activity α^k on financial stability in a crisis scenario ($\rho_f^+ = 0.09, \rho_f^- = -0.08$)

...but the Effect is Non-Monotonic

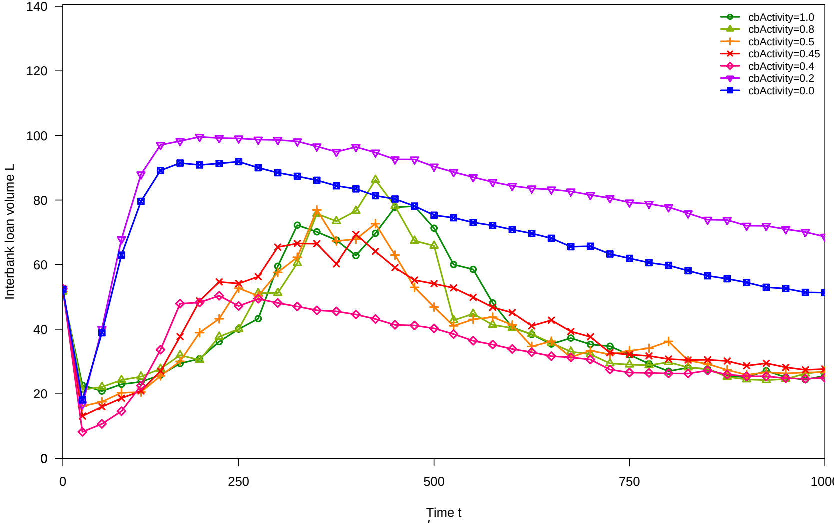


Figure: The effect of central bank activity α^k on interbank liquidity in a crisis scenario $(\rho_f^+ = 0.09, \rho_f^- = -0.08)$

Central Bank Liquidity Stabilizes in the Short-Run

- Central bank liquidity provision has **non-linear** effect on financial stability
  - $\Rightarrow$ Close threshold value, small changes have significant impact
  - $\Rightarrow$ Away from threshold value, even large changes can be ineffective
- Stabilizing effect in the **short-run** only
- Abundant central bank liquidity **crowds out** interbank liquidity

Some Network Structures are More Resilient Than Others

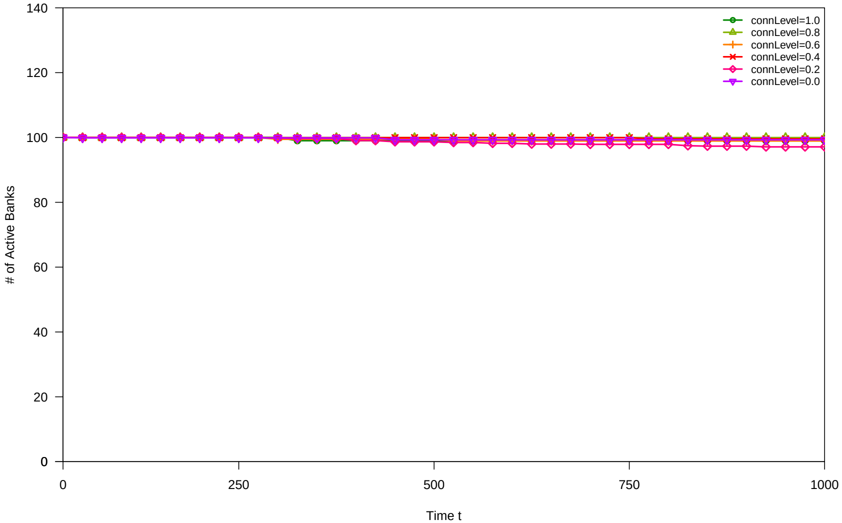
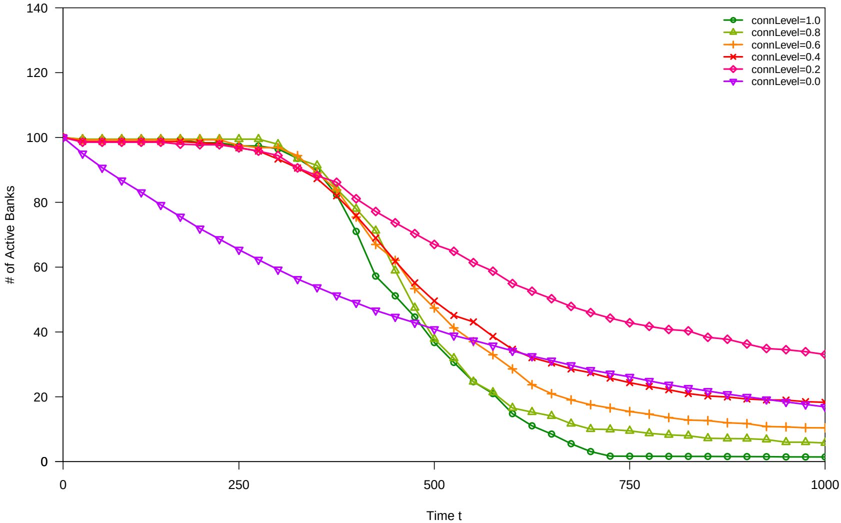


Figure: The impact of the network topology on financial stability in a normal scenario ($\rho_f^+ = 0.09, \rho_f^- = -0.05$) in a random network.

Some Network Structures are More Resilient Than Others



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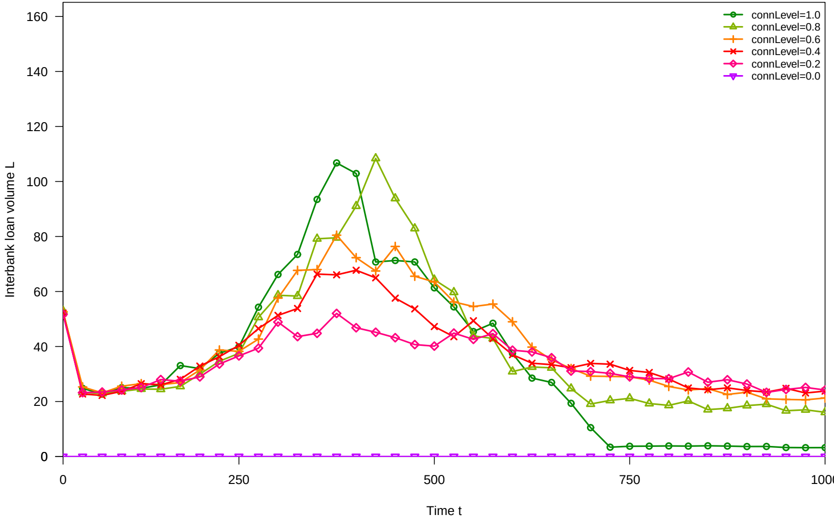

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Some Network Structures are More Resilient Than Others

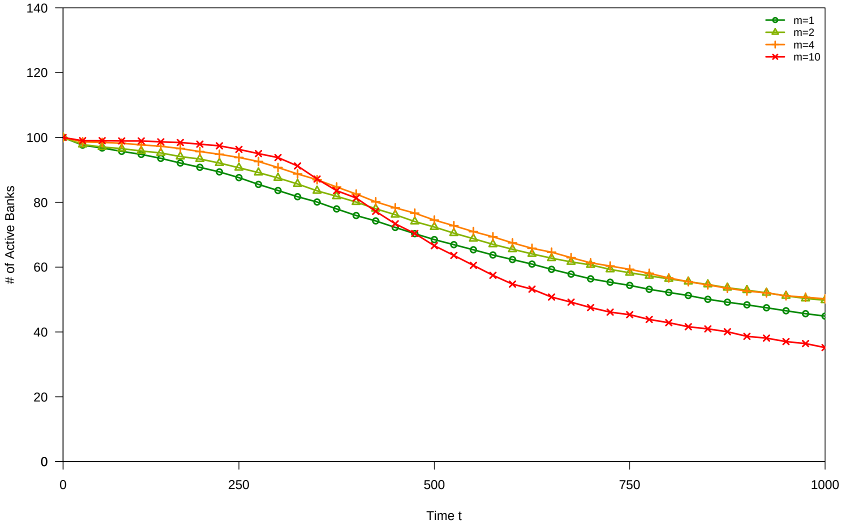

Figure: The impact of the network topology on financial stability in a crisis scenario ($\rho_f^+ = 0.09, \rho_f^- = -0.08$) in a BA network

Some Network Structures are More Resilient Than Others

- Network **structure matters** in crises
- Relationship between financial stability and interconnectedness in random networks is **non-monotonic**
- Scale-free networks tend to be **more stable** than random networks
- Interbank networks are **robust-yet-fragile**
  $\Rightarrow$ Size of endogenous fluctuations matter

Different Forms of Systemic Risk Require Different Answers

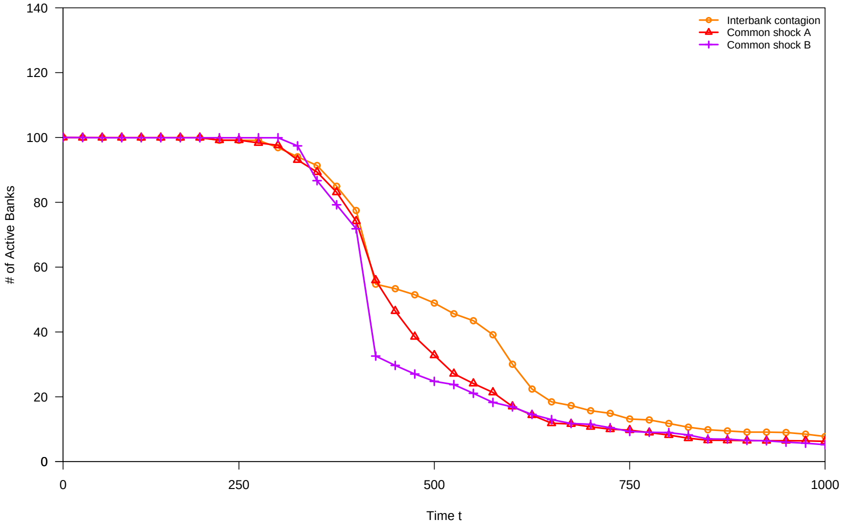

Figure: The impact of different forms of systemic risk on financial stability in a crisis scenario ($\rho_f^+ = 0.09, \rho_f^- = -0.08$) in a random network (`connLevel`=0.8)

Different Forms of Systemic Risk Require Different Answers

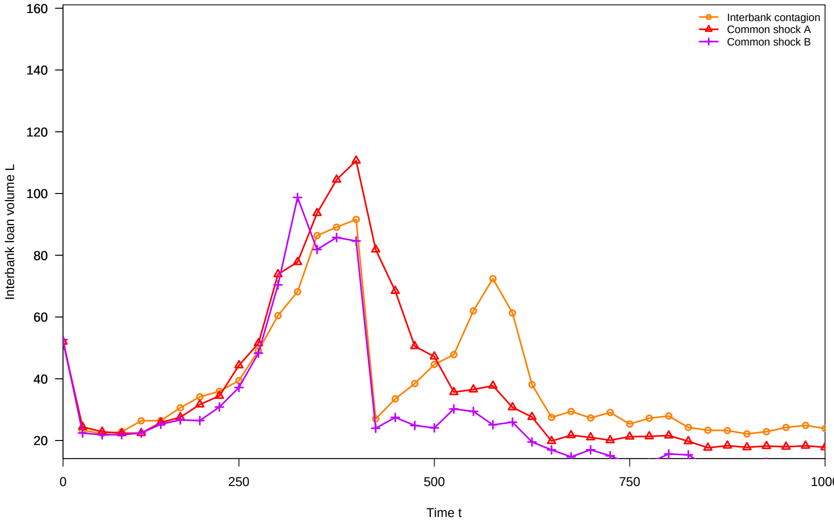

Figure: The impact of different forms of systemic risk on financial stability in a crisis scenario ($\rho_f^+ = 0.09, \rho_f^- = -0.08$) in a random network (`connLevel`=0.8)

Different Forms of Systemic Risk Require Different Answers

- Common shocks can pose greater threat to financial stability
- Contagion mainly reduces **liquidity** available in the system
- Common shock mainly reduces **banking capital** and increases (relative) size of endogenous fluctuations

$\Rightarrow$ Different optimal responses, for different forms of systemic risk

Channels of Systemic Risk

Interbank contagion

- Interbank contagion is a source of systemic risk, but not the major one

Fire-sale

- Common shocks are quantitatively the greater threat
- Fire-sales can be caused by cash-in-the-market pricing:

$$p(\gamma, t, I_l(t)) = \exp\left(-\gamma \cdot \frac{(I(0) - I(t) + I_l(t))}{I(0)}\right)$$

where γ is the liquidationDiscountFactor

Information contagion

- Risk aversion θ depends on history of loan repayments

Endogenous Fire Sales – No Information Contagion

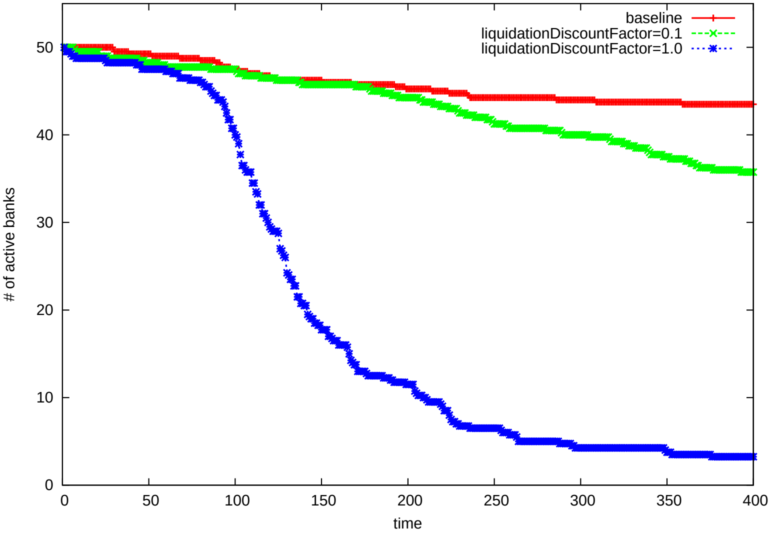

Figure: Number of active banks over time for different strengths of fire sales.

Information Contagion – No Fire Sales

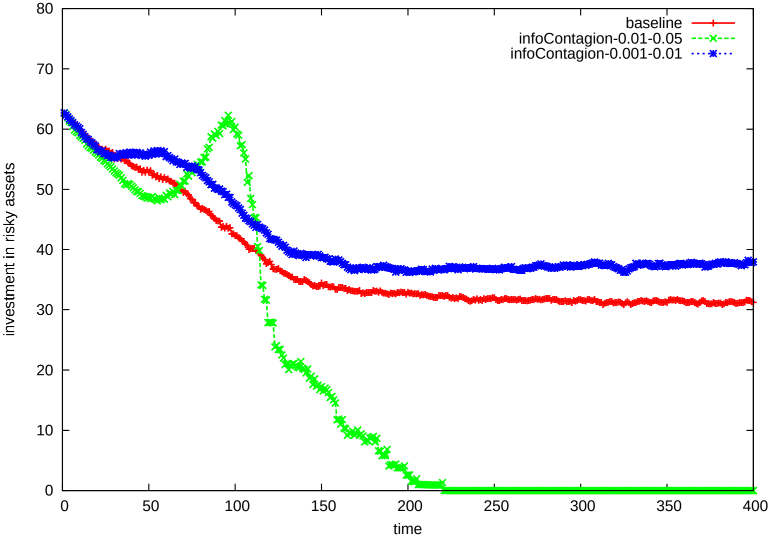

Figure: Investment level over time for different strengths of risk aversion discount and amplification.

Macroprudential Tools to Alleviate Systemic Risk

A number of tools has been proposed to alleviate systemic risk:

- Time-dimension: **countercyclical capital buffer**, leverage ratio, dynamic risk-weights, dynamic provisioning, **liquidity ratios: LCR, NSFR**, reserve requirements
- Cross-sectional dimension: higher capital requirements, concentration limits, **SIFI surcharge**

How these measures are implemented:

- LCR: highly liquid assets → limit on liquidationDiscountFactor
- NSFR: stable funding sources → limit on scaleFactorHouseholds
- Countercyclical capital buffer → varying required capital during simulation
- Leverage ratio → limit on portfolio expansion when banks are euphoric
- SIFI surcharge → additional capital requirements based on interconnectedness

Countercyclical Capital Buffers

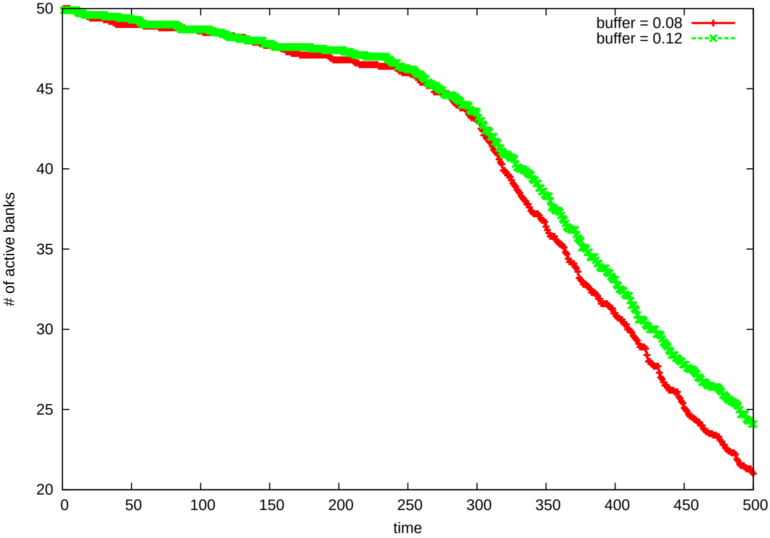

Figure: Number of active banks over time with a countercyclical capital buffer.

Countercyclical Capital Buffers

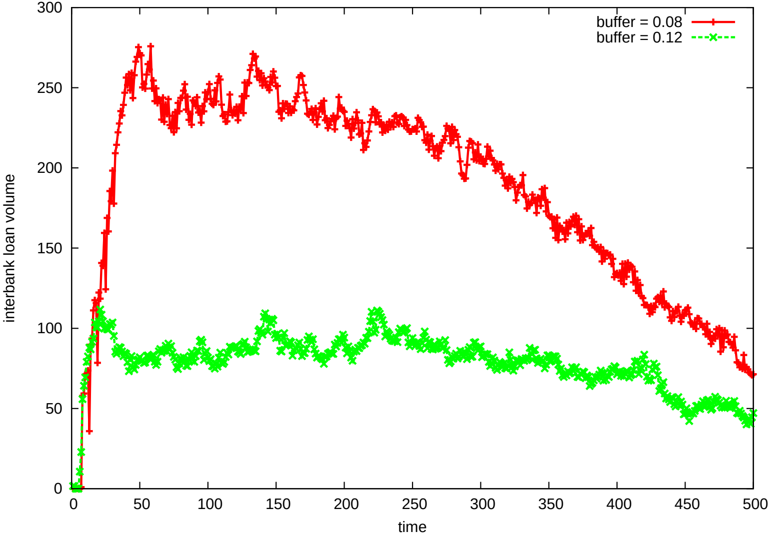

Figure: Amount of interbank lending over time with countercyclical capital buffer.

Leverage Ratio

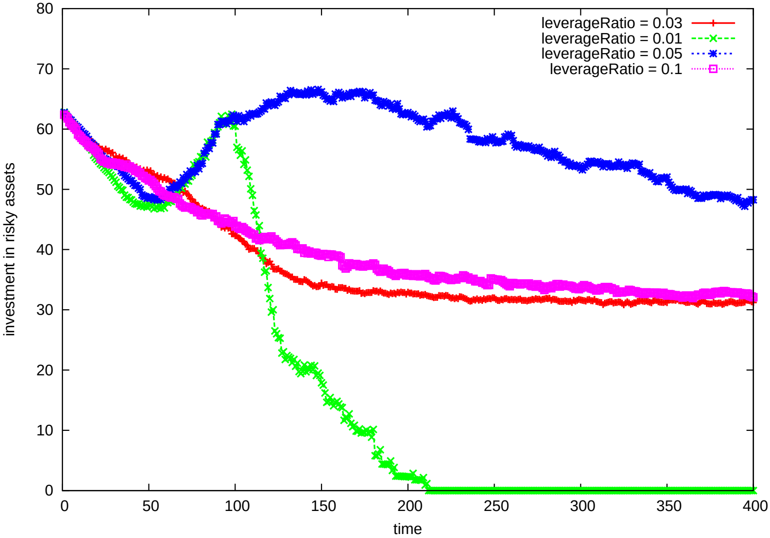

Figure: Investment in risky assets over time for different leverage ratios.

Is a SIFI Surcharge Better than Higher Capital Ratios?

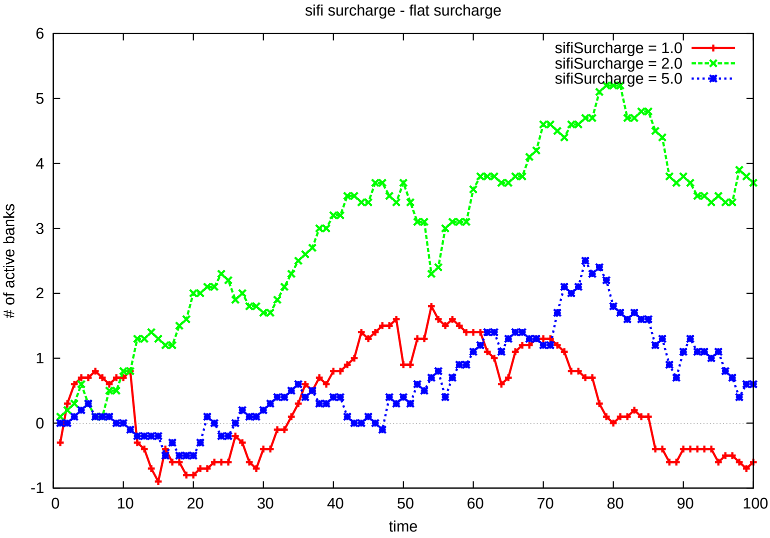

Figure: The effect of a SIFI surcharge vs. a flat increase in capital requirements.

Conclusion (II)

- Heterogeneous agents, complex interactions, and dynamic structural change calls for a more flexible set of models $\Rightarrow$ **Multi-Agent Network Models**
- Network models to assess systemic risk can be used to analyse recently proposed **macroprudential measures**:
- Going forward: consistent agent behaviour and clear notion of equilibrium

Conclusion (II)

- Heterogeneous agents, complex interactions, and dynamic structural change calls for a more flexible set of models $\Rightarrow$ **Multi-Agent Network Models**
- Network models to assess systemic risk can be used to analyse recently proposed **macroprudential measures**:
- Going forward: consistent agent behaviour and clear notion of equilibrium

All simulations done with black rhino: open source MAS
`http://cabdyn.ox.ac.uk`

Learning in ABMs

Motivation

- Banks should have private information about their borrowers and learn from their peers
- How did such a large fraction of banks end up investing in toxic assets, i.e. choosing the "wrong" investment strategy?

Institutional background: two key developments:

1. Direct linkages (e.g. interbank loans, repos, CDS) amongst financial intermediaries increased in the past decade
2. Banks increasingly invested into similar assets (e.g. MBS)

This paper:

1. Develops an agent-based model (ABM) of the financial system with social learning and endogenous network formation
2. Methodological contribution: ABM with clear(er) notion of equilibrium

Summary of Key Results

Three main results:

- I show the existence of a *contagious regime* in which banks are connected in an exogenously fixed network and synchronize their investment strategies on a state non-matching action. The contagious regime is lager when the signal structure becomes less informative

- I characterize the equilibrium network structures as the result of an endogenous network formation process. The density of the equilibrium network in the pure coinsurance-counterparty risk case ($\alpha = \gamma = 0, \beta > 0$) decreases with the informativeness of the signal structure

- In the full model increasing informativeness reduces the contagious regime more than it is increased via the reduction in network density

Distinction from Literature

- Starting point: agent based models of financial networks: Iori et al. (2006), Nier et al. (2007), Georg (2013), Bluhm et al. (2013)
  $\rightarrow$ mechanistic agent behaviour, no clear notion of equilibrium
- Endogenous network formation: Jackson and Wollinsky (1996), Castiglionesi and Navarro (2011), Babus (2011), Cohen-Cole et al. (2013)
  $\rightarrow$ no information spillovers and learning
- Related literature on money market freezes: Acharya and Skeie (2011), Acharya, Gale, and Yorulmazer (2011), Afonso, Kovner, and Schoar (2011), Acharya and Merrouche (2013)
  $\rightarrow$ how to understand the persistency of money markets?
- Bayesian (social) learning: Banerjee (1992), Gale and Kariv (2003), Acemoglu, Dahleh, Lobel, and Ozdaglar (2010)
  $\rightarrow$ fixed networks, asymptotic learning

Model - States and Agents

- Countable number of dates $t = 0, 1, \ldots$ and n agents. State of the world $\theta \in \{0, 1\}$ is revealed at each point in time with probability $p > 0$
- $\theta = 1$ corresponds to boom, $\theta = 0$ to bust
- Banks choose one of two investment strategies $x^i \in \{0, 1\}$
- Bank i's individual utility given as:

$$u^i(x^i, \theta) = \begin{cases} 1 & \text{if } x^i = \theta \\ 0 & \text{else} \end{cases}$$

- Once the state of the world is revealed, it changes with probability $\lambda = \frac{1}{2}$

Model - The Network

- Banks can form connections in the form of mutual lines of credit
- The set of banks to which bank i is connected is called the neighborhood of i and denoted $K^i \subseteq N$
- Bank i has $k^i = |K^i|$ neighbors
- A network of banks $\mathfrak{g}$ is a set of banks together with a set of unordered pairs of banks, called links:

$$L = \cup_{i=1}^{n} \{(i,j) : j \in K^i\}$$

- The network is implemented through an adjacency matrix g^{ij}

Model Timeline

- In $t = 0$ there is no endogenously formed link and banks decide their action in autarky
- Banks receive a signal $s^i \in \overline{S}$ about the state of the world and form private belief determining their action x^i
- Signals are independently generated according to probability measure $\mathbb{F}_\theta$
  $\rightarrow$ Signal structure $(\mathbb{F}_0, \mathbb{F}_1)$
- $\mathbb{F}_0$ and $\mathbb{F}_1$ are informative, not identical, and absolutely continuous w.r.t. each other
- After receiving the signal, banks decide about mutual lines of credit and network is endogenously formed for the first time

Model Timeline

- In $t = 1, \dots$ banks receive a private signal
- Banks now also observe the actions of their neighbors in the previous period
- Banks update their actions
- New network structure is based on banks' decisions
- This is repeated until state of the world is revealed every $1/p$ periods
- If state of the world is revealed, banks realize their utility

Private and Social Beliefs

- For each t bank i receives private signal s^i generated according to $(\mathbb{F}_0, \mathbb{F}_1)$
- Banks observe actions of their previous neighbors K^i_{t-1}. Bank i's information set is:

$$I^i_t = \left\{ s^i_t, K^i_{t-1}, x^j_{t-1} \forall j \in K^i_{t-1} \right\}$$

  and the set of all possible information sets is denoted as $\mathcal{I}^i$
- A strategy for bank i is a mapping $\sigma^i : \mathcal{I}^i \to x^i = \{0, 1\}$

Definition

A strategy profile $\sigma = \{\sigma^i\}_{i \in 1,\dots,n}$ is a pure strategy Bayesian equilibrium of this game of social learning for a bank i's investment if σ^i maximizes the expected pay-off of bank i given the strategies of all other banks σ^{-i}.

Optimal Strategy

- For every σ the expected pay-off of i from $x^i = \sigma^i(I^i)$ is $\mathbb{P}_\sigma(x^i = \theta | I^i)$
- For any equilibrium σ, i chooses x^i according to:

$$x^i = \sigma^i(I^i) \in \arg\max_y \mathbb{P}_{(y,\sigma^{-i*})}(y = \theta | I^i) \quad , \quad y \in \{0,1\}$$

Proposition

Let σ be an equilibrium of the single bank investment game and let $I_t^i \in \mathcal{I}^i$ be the information set of bank i at time t. Then the strategy decision of bank i, $x_t^i = \sigma^i(I_t^i)$ satisfies

$$x^i = \begin{cases} 1, \ \textit{if} & \mathbb{P}_\sigma(\theta = 1 | s^i) + \mathbb{P}_\sigma(\theta = 1 | K_{t-1}^i, x^j, j \in K_{t-1}^i) > \overline{x}(k^i, n) \\ 0, \ \textit{if} & \underbrace{\mathbb{P}_\sigma(\theta = 1 | s^i)}_{\textit{private belief}} + \underbrace{\mathbb{P}_\sigma(\theta = 1 | K_{t-1}^i, x^j, j \in K_{t-1}^i)}_{\textit{social belief}} < \overline{x}(k^i, n) \end{cases} \tag{1}$$

and $x^i \in \{0,1\}$ otherwise

Optimal Strategy

- The threshold $\overline{x}(k^i, n)$ is given as:

$$\overline{x} = \frac{1}{2}\left(1 + \frac{k^i}{(n-1)}\right)$$

- The private belief of bank i can be obtained using Bayes' rule:

$$\mathbb{P}(\theta = 1|s^i) = \left(1 + \frac{d\mathbb{F}_0}{d\mathbb{F}_1}(s^i)\right)^{-1} = \left(1 + \frac{f_0(s^i)}{f_1(s^i)}\right)^{-1}$$

- Social belief is formed by averaging over the actions of all neighbors $j \in K^i_{t-1}$:

$$\mathbb{P}_\sigma(\theta = 1|K^i_t, x^j, j \in K^i_{t-1}) = 1/k^i \sum_{j \in K^i_{t-1}} x^j$$

$\rightarrow x^i = 1$ is chosen whenever private + social belief exceed threshold

Endogenous Network Formation

- Banks gain utility from being interconnected through social learning but face a fixed cost per link
- Net benefit of bank i from establishing a link with bank j:

$$\alpha g^{ij} \quad , \quad \alpha \in \mathbb{R}^+$$

- Banks that selected a state non-matching action suffer liquidity shortfall
- A mutual line of credit allows a bank with liquidity shortfall to draw liquidity from a bank without liqudity shortfall
- When bank i has a private belief of $p^i = \frac{1}{2}$ it is entirely uncertain about the underlying state of the world and coinsurance is most valuable
- If bank i is certain about the state of the world, it will not value coinsurance at all:

$$q^i(p^i) = \begin{cases} 2p^i & \text{for } p^i \leq \frac{1}{2} \\ 2(1-p^i) & \text{for } p^i \geq \frac{1}{2} \end{cases}$$

Endogenous Network Formation

- Expected utility from coinsurance is given as:

$$\beta q^i(p^i) g^{ij} \quad , \quad \beta \in \mathbb{R}^+$$

- Analogous, the expected loss from counterparty risk is given as:

$$-\beta \left(1 - q^i(p^i)\right) g^{ij} \quad , \quad \beta \in \mathbb{R}^+$$

- This implies the total expected utility, respecting the coinsurance-counterparty tradeoff:

$$\beta(2q^i(p^i) - 1)g^{ij}$$

- Natural interpretation: when bank i is certain about the state of the world, it will fear counterparty risk more than it will value coinsurance

Endogenous Network Formation

- I assume that losses are amplified if they occur in bulk:

$$-\gamma|g|q^i(p^i)g^{ij} \quad , \quad \gamma \in \mathbb{R}^+$$

- The total number of connections in the financial system are given as:

$$|g| = \sum_{i,j} g^{ij}$$

- Bank i's total utility of being interconnected:

$$u^i(g^{ij}=1) = \alpha + \beta\left(2q^i(p^i) - 1\right) - \gamma|g|q^i(p^i)$$

utility from learning

coinsurance/counter-party risk trade-off

disutility of amplification

Endogenous Network Formation

- An update step consists of agents chosing an optimal strategy based on their private and social beliefs, and a network formation process
- Following Jackson and Wollinsky (1996), an equilibrium of the network formation process can be characterized using the notion of pairwise stability

Definition

A network defined by an adjacency matrix g is called pairwise stable if

(i) For all banks i and j directly connected by a link, $l^{ij} \in L$: $u^i(g) \geq u^i(g - l^{ij})$ and $u^j(g) \geq u^j(g - l^{ij})$

(ii) For all banks i and j not directly connected by a link, $l^{ij} \ni L$: $u^i(g + l^{ij}) < u^i(g)$ and $u^j(g + l^{ij}) < u^j(g)$

Simulation Results – Fixed Network Structure

- Limiting case with fixed network structure first
- Fully connected network: signals are informative, thus banks coordinate on state-matching action in the long-run
- In an empty network the probability of all banks choosing a state-matching action increases with signal informativeness
- Interim levels of connectivity feature a *contagious regime* in which all banks choose state non-matching action
- Intuition: positive probability that bank i has a neighborhood with more than half of the banks choosing state non-matching action
  $\rightarrow$ this can offset private signal of bank i
- Size of contagious regime increases with decreasing signal informativeness

Simulation Results – Fixed Network Structure

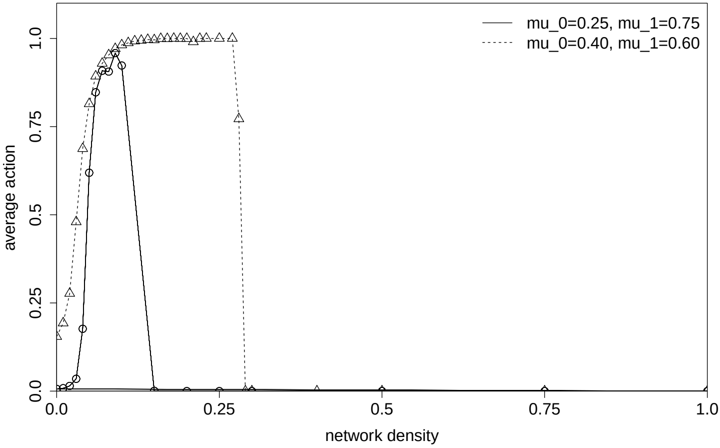

Figure: Average actions of agents in $t = 20$ for $\theta = 0$, varying network densities, and different signal structures: (i) high informativeness, $\mu_0 = 0.25, \mu_1 = 0.75, \sigma^2_{\{0,1\}} = 0.1$; and (ii) low informativeness, $\mu_0 = 0.4, \mu_1 = 0.6, \sigma^2_{\{0,1\}} = 0.1$.

Simulation Results – Highly Informative Signal

- Second limiting case with highly informative signal and endogenous network formation
- Two trivial network structures
  1. $\beta = \gamma = 0$: complete network for $\alpha > 0$ and empty network for $\alpha = 0$
  2. $\alpha = \beta = 0$: empty network for all γ
- For $\alpha = \gamma = 0$, $\beta > 0$ bank i's utility from establishing a link is:

$$\beta(2q^i(p^i) - 1) \quad \Leftrightarrow \quad u^i > 0 \Leftarrow q^i(p^i) > \frac{1}{2}$$

- For very uninformative signal structures $\mu_1 - \mu_0 \approx 0$ banks are almost never certain about the state and coinsurance dominates counterparty risk
- For very informative signal structures $\mu_1 - \mu_0 \approx 1$ resulting network is empty

Simulation Results – Highly Informative Signal

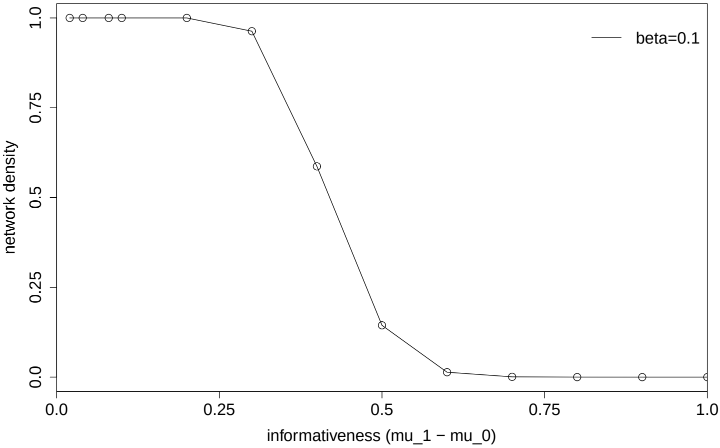

Figure: Average equilibrium network density as a function of signal informativeness $(\mu_1 - \mu_0)$ for $\alpha = \gamma = 0.0, \beta = 0.1$. Each point is the average of 500 simulations with $n = 20$ agents and $\sigma^2_{\{0,1\}} = 0.1$.

Simulation Results – Star Networks

- Another limiting case is that of a star network which is obtained for $\beta = 0, \alpha > 0, \gamma > 0$
- Star network is characterized by (i) small average shortest path length $l \simeq 2$; (ii) density $\delta = 1/n$; and (iii) a clustering coefficient of zero
- Shortest average path length is defined as:

$$l(i,j) = \sum_{i,j} \frac{d(i,j)}{n(n-1)}$$

- The local clustering coefficient of a node is given as:

$$c^i = \frac{|\left\{ l^{jk}, j, k \in K^i, l^{jk} \in L \right\}|}{k^i(k^i - 1)}$$

- Real world interbank networks are a superposition of these basic types

Simulation Results – Star Networks

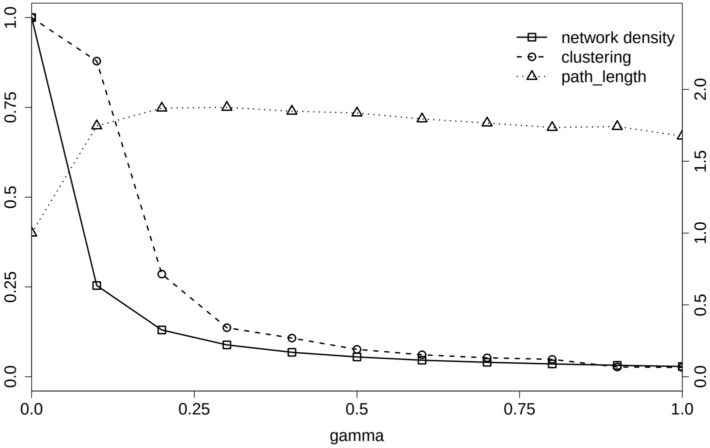

Figure: Network density, average clustering coefficient, and average shortest path length for varying amplification parameter $\gamma \in [0.0, 1.0]$ and fixed learning parameter $\alpha = 0.01$. Each point is the average of 500 simulations with $n = 20$ agents and $\mu_0 = 0.4, \mu_1 = 0.6, \sigma^2_{\{0,1\}} = 0.1$.

Simulation Results – Star Networks

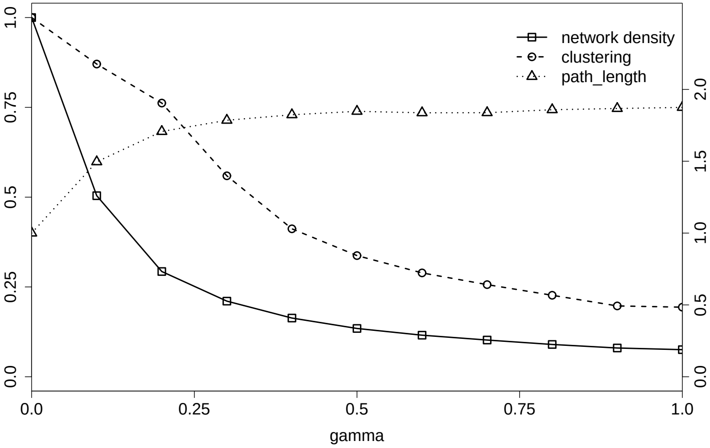

Figure: Network density, average clustering coefficient, and average shortest path length for varying amplification parameter $\gamma \in [0.0, 1.0]$ and fixed learning parameter $\alpha = 0.01$. Each point is the average of 500 simulations with $n = 20$ agents and $\mu_0 = 0.25, \mu_1 = 0.75, \sigma^2_{\{0,1\}} = 0.1$.

Simulation Results – Social Learning and Endogenous Network Formation

- Trade-off for less informative signals between social learning (larger contagious regime) and endogenous network formation (higher density)
  $\rightarrow$ Which effect dominates?

- Total utility of the model financial system:

$$U = \sum_i \left[\underbrace{u^i(x^i, \theta)}_{\text{state-matching action}} + \underbrace{u^i(g)}_{\text{interconnectedness}} \right]$$

Simulation Results – Social Learning and Endogenous Network Formation

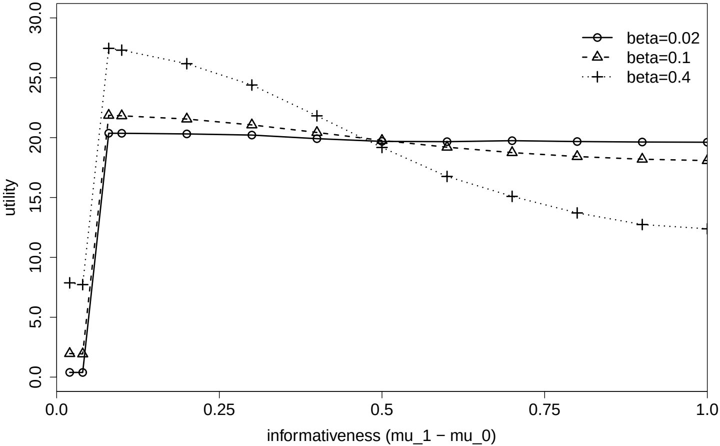

Figure: Total utility (individual + network) as a function of signal informativeness $(\mu_1 - \mu_0)$ for $\alpha = \gamma = 0.0, \beta = \{0.02, 0.1, 0.4\}$. Each point is the average of 500 simulations with $n = 20$ agents and $\sigma^2_{\{0,1\}} = 0.1$.

Summary of Key Results

Ingredients:

- Social learning about previous actions of neighbors
- Endogenous network formation due to three motifs

Three main results:

- The Bayesian equilibrium with exogenous network structure exhibits a *contagious regime* in which all agents choose a state-non-matching action. The contagious regime is lager when the signal structure becomes less informative.
- The density of the pairwise stable equilibrium network that is obtained in the pure coinsurance-counterparty risk case ($\alpha = \gamma = 0, \beta > 0$) decreases with the informativeness of the signal structure.
- In the full model increasing informativeness reduces the contagious regime more than it is increased via the reduction in network density.

Conclusion

Possible extensions:

- Agent heterogeneity
- Two regions with different business cycles
- Individual learning in addition to social learning

Conclusion

- ABM with clear notion of equilibrium possible
- Model relates two sources of systemic risk: common shocks and money market freezes
- With heightened uncertainty about the state of the world, probability of banks synchronizing their investment strategies increases
- Banks become less interconnected if signal informativeness is high, this can explain persistency of money market links despite high counterparty risk

Information Contagion – Full Nash equilibria as an ABM

What this paper is about

Setting the stage

- Our notion of systemic risk: joint default probability of financial intermediaries (banks, mmmf, etc.)
- Information about other banks can be valuable for (at least) two reasons: counterparty risk and common exposures
- Information contagion is the spill-over of information about the health of one bank, adversely affecting other banks

Our main research question

- What is the effect of ex-post information contagion on banks' ex-ante optimal portfolio choice?
- What is the welfare loss implied by information contagion due to joint default?

Information contagion can reduce systemic risk

Sneak preview: our results

- Unanticipated information contagion will always increase systemic risk
- When banks are subject to common exposures, information contagion increases systemic risk
- When banks are subject to counterparty risk, anticipated information contagion can **reduce** systemic risk
- Applied to microfinance, our model predicts group loan default rates to be lower and households holding more durable goods

Intuition for our main result

- Banks are more prudent when they anticipate information spillover

Motivation

- Systemic risk comes with large social costs: BIS estimates the cost of systemic bank crises ranging from 3% GDP (US savings and loans) to 30% GDP (Chile 81-87)
- After Lehman insolvency only the Reserve Primary Fund "broke the buck". However, Dumontaux and Pop (2012) show that NBFIs were most affected
- When investors are sensitive to the health of the financial system, information contagion can be a major source of systemic risk
- Two reasons why information about other banks can be useful: **counterparty risk** and **common exposures**
- Information contagion is a major source of systemic risk

Relation to the literature

- Acharya and Yorulmazer (2008b): interlinkages through correlated portfolio holdings; information contagion creates incentive for correlated investments;
  ⇒ **our paper**: exogenous asset correlation, but endogenous portfolio choice (liquidity, interbank insurance, demand deposits)
- Allen, Babus, and Carletti (2012): interaction of asset commonality and funding maturity; portfolio overlap created by network formation model; bad news about aggregate state adversely affect debt roll-over
  ⇒ **our paper**: liability diversification; risky and risk-free assets; bank-specific information spillovers
- Allen and Gale (2000): financial contagion in unanticipated aggregate liquidity shock
  ⇒ **our paper**: solvency shocks with positive probability; optimal portfolio choice

Model: Timing, agents, and investment opportunities

- Three dates $t = 0, 1, 2$
- Two regions $k = A, B$
- Agents (in each region):
  - Continuum of depositors
  - A representative bank (e.g. investment bank, money market fund)

- Two investment opportunities
  - Storage: risk-free, matures after one period
  - Long-term investment project: risky, matures after two periods, yields (regional) return R_k:

$$R_k = \begin{cases} R & \text{w.p. } \theta_k \\ 0 & \text{w.p. } 1 - \theta_k \end{cases}$$

    where θ_k is a solvency shock to region k
  - Costly liquidation: $\beta \in [0, 1)$

Model: Depositors

- Liquidity preferences as in Diamond and Dybvig (1983)
  - Uncertainty about liquidity preference at date $t = 0$
  - Uncertainty resolved at the beginning of $t = 1$
  - Early despositors of mass λ, late depositors of mass $1 - \lambda$
- Risk averse depositors:

$$U(c_1, c_2) = \begin{cases} u(c_1) & \text{w.p.} \quad \lambda \\ u(c_2) & \text{w.p.} \quad 1 - \lambda \end{cases}$$

- Unit endowment
- Store or deposit at bank

Model: Banks

- Collects deposits by offering a demand deposit contract (d_1, d_2) at $t = 0$
  - insurance against idiosyncratic liquidity risk for risk-averse depositors
- Choice of interbank insurance $b \geq 0$ and liquidity y at $t = 0$
- Free entry $\Rightarrow$ maximize depositors expected utility
  - deposit in full at bank
- Distributes proceeds equally at $t = 2$ (mutual bank)
- Focus on essential bank-runs $\rightarrow$ no co-ordination failure

Model: Information structure

- All prior distributions are common knowledge
- Depositors receive independent public signals about returns in both regions which are perfectly revealing with probability q_k
- Information about the other region can be valuable for two reasons: counterparty risk and common exposures
- Information contagion occurs if information about the other region's fundamentals is payoff-relevant in your region

Model: Timeline

Date 0	Date 1	Date 2
1. Endowed depositors invest or deposit at regional bank	1. Regional liquidity shocks are publicly observed	1. Investment projects mature
2. Banks choose portfolio and initiate interbank deposits	2. Banks settle date-1 interbank claims	2. Banks settle date-2 interbank claims
	3. Depositors privately observe liquidity preference	3. Banks service remaining withdrawals
	4. Depositors observe regional solvency signals	
	5. Depositors decide whether to withdraw	

Equilibrium: Outline

Outline

- Depositors compare payoffs from withdrawing and not withdrawing, using regional signals
- Essential bank-runs take place if $\theta < \overline{\theta}$
- Compute expected utility from thresholds
- Globally optimise expected utility w.r.t. (d_1, y, b) **numerically**

Equilibrium: Payoffs

- In high liquidity demand region H, payoffs are independent of L:

$$\begin{aligned} d_H &\equiv y + (1-y)\beta + b \\ c_{2H}^{\mathbf{G}} &\equiv \frac{(\mathbf{1-y})\mathbf{R} + y - \lambda_H d_1 - (\phi - 1)b}{1-\lambda_H} \end{aligned}$$

- In low liquidity demand region, payoffs depend on repayment of b:

$$\begin{aligned} d_L^{N,D} &\equiv y + (1-y)\beta - b + \beta\phi\widetilde{b}, \quad \text{where } \widetilde{b} \in \{b, 0\} \\ c_{2L}^{\mathbf{GN}} &\equiv \left(\frac{(\mathbf{1-y})\mathbf{R} + (y - \lambda_L d_1) + (\phi - 1)b}{1-\lambda_L}\right) \end{aligned}$$

Equilibrium: Counterparty risk

- With probability q_H depositors in H are informed about their region
- Signal thresholds are obtained by comparing payoffs from withdrawing and not withdrawing:

$$\overline{\theta}_{\mathrm{H}} \equiv \frac{u(d_H) - u(c_{2H}^B)}{u(c_{2H}^G) - u(c_{2H}^B)}$$

- Essential bank-run takes place if and only if $\theta_H < \overline{\theta}_H$
- When depositors are uninformed, they use prior distribution and not run the bank $\Rightarrow$ default probability $a_{1,H} \equiv q_H \overline{\theta}_H$
- Expected utility is given as:

$$\begin{aligned} EU_H \;&=\; (1-q_H)\left\{\lambda_H u(d_1) + (1-\lambda_H)\frac{1}{2}(u(c_{2H}^G) + u(c_{2H}^B))\right\} \\ &\quad + q_H\left\{\overline{\theta}_{\mathrm{H}} u(d_H) + (1-\overline{\theta}_{\mathrm{H}})\left(\lambda_H u(d_1) + (1-\lambda_H)\frac{1}{2}\left[u(c_{2H}^G) + u(d_H)\right]\right)\right\} \end{aligned}$$

Equilibrium: Counterparty risk

- In the low liquidity demand region L, the signal threshold depends on default in high liquidity demand region H:

$$\overline{\theta}_{1,\mathrm{L}} \equiv \frac{a_{1,\mathrm{H}}[u(d_L^D) - u(c_{2L}^{BD})] + (1 - a_{1,\mathrm{H}})[u(d_L^N) - u(c_{2L}^{BN})]}{a_{1,\mathrm{H}}[u(c_{2L}^{GD}) - u(c_{2L}^{BD})] + (1 - a_{1,\mathrm{H}})[u(c_{2L}^{GN}) - u(c_{2L}^{BN})]}$$

- This implies default probability in L to be $a_{1,L} = q_L\overline{\theta}_L$
- Systemic risk in the case of pure counterparty risk is then

$$A_{CR} = a_{1,\mathrm{L}}a_{1,\mathrm{H}} = q_H q_L \overline{\theta}_{\mathrm{H}}\overline{\theta}_{1,\mathrm{L}}$$

- Investment returns are independent $\rightarrow$ regional expected utilities separately:

$$EU_{CR} = \frac{1}{2}(EU_H + EU_{1,L})$$

Equilibrium: Counterparty risk and information contagion

- Depositors now receive a signal about returns in the other region too
- Behaviour and expected utility of depositors in H is unaffected
- When depositors in region L receive informative signal about H they **know** whether interbank loans are being repaid
- There are two thresholds for L now, one if H defaults and one if H survives:

$$\overline{\theta}^{N}_{2,\mathrm{L}} \equiv \frac{u(d_L^N) - u(c_{2L}^{BN})}{u(c_{2L}^{GN}) - u(c_{2L}^{BN})}$$

$$\overline{\theta}^{D}_{2,\mathrm{L}} \equiv \frac{q_H[u(d_L^D) - u(c_{2L}^{BD})] + (1-q_H)[u(d_L^N) - u(c_{2L}^{BN})]}{q_H[u(c_{2L}^{GD}) - u(c_{2L}^{BD})] + (1-q_H)[u(c_{2L}^{GN}) - u(c_{2L}^{BN})]}$$

Equilibrium: Counterparty risk and information contagion

- Thresholds are ranked: $\overline{\theta}^{N}_{2,\mathrm{L}} < \overline{\theta}^{D}_{2,\mathrm{L}}$
- Systemic risk in the CR + IC case is:

$$A_2 = q_H q_L \overline{\theta}_{\mathrm{H}} \overline{\theta}^{D}_{2,\mathrm{L}} > A_1$$

Result 1

If information spillovers are unanticipated, information contagion due to counterparty risk unambiguously increases systemic risk.

Similarly for **common exposures**

Result 2

If information spillovers are unanticipated, information contagion due to common exposures unambiguously increases systemic risk.

Equilibrium: Optimal portfolio choice

- Because of free entry banks choose portfolio b, y and interim payment d_1 to maximize depositors' ex-ante expected utility
- It is never optimal to over-insure: $0 \leq b^* \leq \eta d_1^*$
- It is never optimal to face certain liquidation: $y^* \geq \lambda_H d_1^* - b^* \geq \lambda$
- d_1 is non-negative and bound from above
- We use CRRA utility function with risk-aversion parameter ρ
- Two reasons why an **analytical solution** of this problem is **infeasible**:
  1. corner solutions
  2. response of thresholds with respect to liquidity is non-monotonic

$\Rightarrow$ **Numerical solution!**

Results: Resilience effect

	cr only (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_1)	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{2,\mathrm{L}}^N$, $\overline{\theta}_{2,\mathrm{L}}^D$, A_2)
cr only	(**0.172**,0.88,0.73,0.08) (0.423,0.23,**0.048**)	(**0.096**,0.88,0.73,0.08) (0.423,0.212,0.252,**0.052**)
cr + ic		(0.107,0.94,0.8,0.02) (0.379,0.211,0.222,0.041)

Table: Parameters: β=0.7, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7

Results: Resilience effect

	cr only (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{1,\mathrm{L}}$, A_1)	cr + ic (EU, d_1^*, y^*, b^*) ($\overline{\theta}_{\mathrm{H}}$, $\overline{\theta}_{2,\mathrm{L}}^N$, $\overline{\theta}_{2,\mathrm{L}}^D$, A_2)
cr only	(**0.172**,0.88,0.73,0.08) (0.423,0.23,**0.048**)	(0.096,0.88,0.73,0.08) (0.423,0.212,0.268,0.052)
cr + ic		(**0.107**,0.94,0.8,0.02) (0.379,0.211,0.226,**0.042**)

Table: Parameters: β=0.7, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7

Results: Instability effect

	pure ce (EU, d_1^*, y^*, b^*) $(\overline{\theta}, A_5)$	ce + ic (EU, d_1^*, y^*, b^*) $(\overline{\theta}, A_6)$
ce only	(**0.13**,1.0,0.77,0.0) (0.328,**0.161**)	(0.137,1.0,0.77,0.0) (0.328,0.161)
ce + ic		(**0.137**,1.01,0.76,0.0) (0.344,**0.168**)

Table: Parameters: β=0.7, R=5.0, ϕ=1.0, λ=0.5, η=0.25, ρ=1.0, q_H=0.7

Results: Summary

Result 3: Resilience Effect

In the setup with counterparty risk, anticipating information contagion reduces systemic risk and expected utility.

Result 4: Instability Effect

In the setup with common exposures, anticipating information contagion increases systemic risk and expected utility.

Robustness of Results

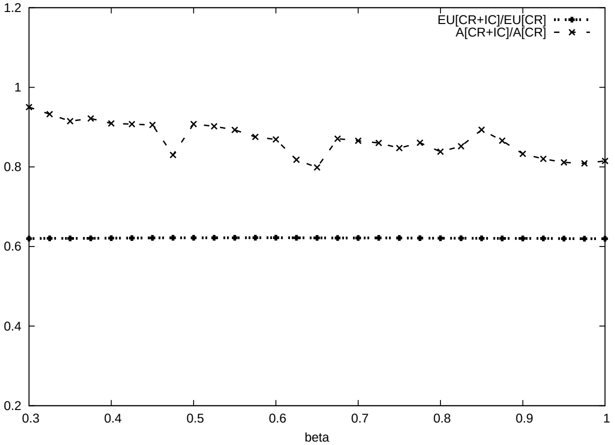

Figure: Robustness check for the resilience effect for a variation of β.

Robustness of Results

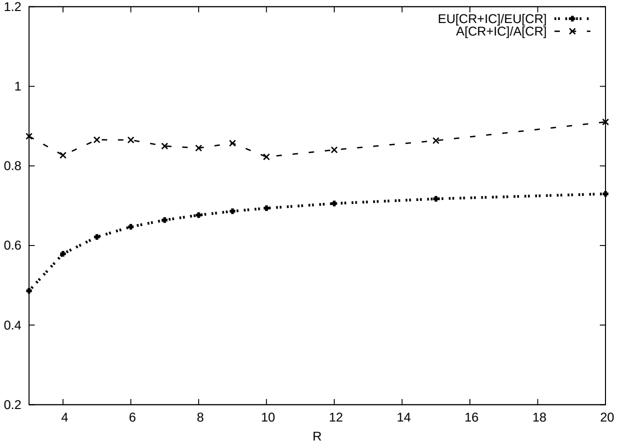

Figure: Robustness check for the resilience effect for a variation of R.

Robustness of Results

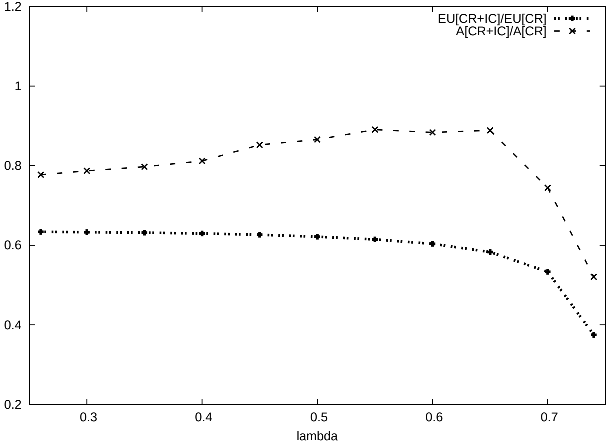

Figure: Robustness check for the resilience effect for a variation of λ.

Robustness of Results

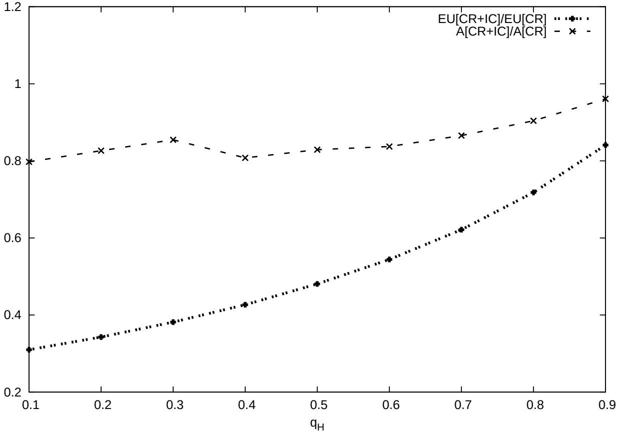

Figure: Robustness check for the resilience effect for a variation of q_H.

Robustness of Results

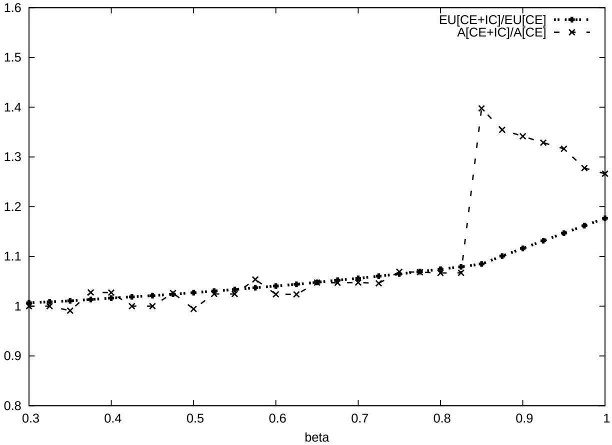

Figure: Robustness check for the instability effect for a variation of β.

Robustness of Results

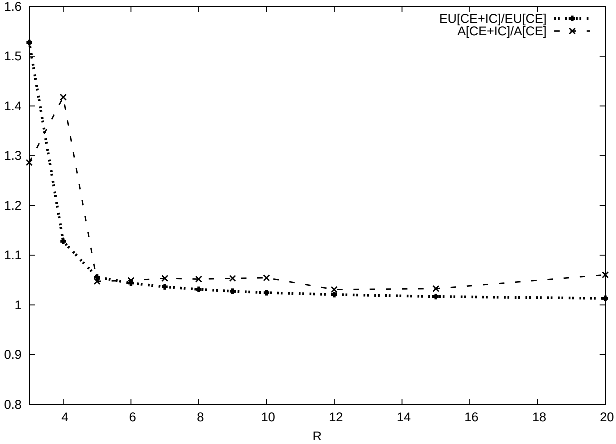

Figure: Robustness check for the instability effect for a variation of R.

Robustness of Results

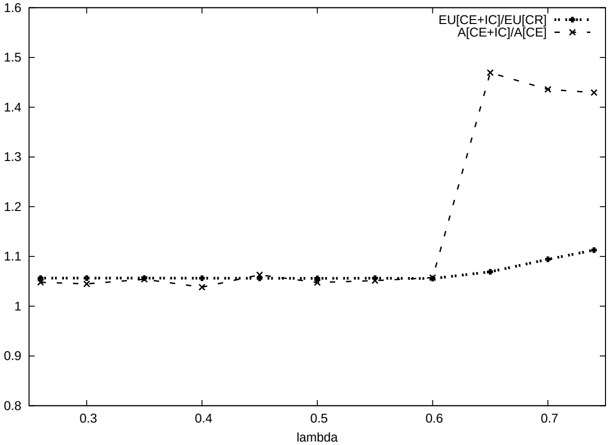

Figure: Robustness check for the instability effect for a variation of λ.

Robustness of Results

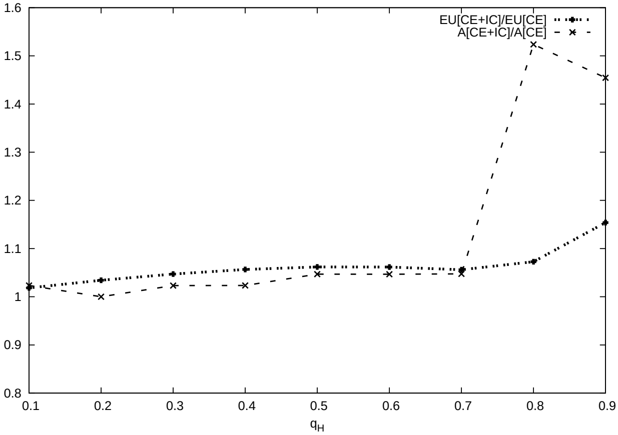

Figure: Robustness check for the instability effect for a variation of q_H.

Conclusion (III)

- Information contagion is a major source of systemic risk
- There are non-trivial equilibrium effects affecting overall systemic financial fragility
- Consequences for ABM: equilibrium behaviour relevant as benchmark; focus on agent-behaviour and system dynamics instead of contagion mechanics;