# From Banks' Strategies to Financial Instability


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# Where We Are: A Course Recap

**Heterogeneous Agent Models:**

- Brock & Hommes (1998): fundamentalists vs. chartists, intensity of choice $\beta$, routes to chaos
- Naimzada & Ricchiuti (2008, 2012): heterogeneous fundamentalists, bifurcations, ambiguous role of heterogeneity

**Networks:**

- Centrality measures: degree, betweenness, closeness, PageRank, Katz
- Community detection: modularity $Q$, Louvain, Girvan–Newman
- Small-world and scale-free networks: topology shapes resilience
- BH on a network: local herding amplifies instability

## The question for today

What if the **network itself evolves endogenously** as banks compete for clients? And what if banks' **strategies** shape both the topology and the system's resilience to shocks?

# Why Networks Matter for Financial Stability

Network Theory links the **MICRO** to the **MACRO** dimension:

- Global phenomena (crises, bubbles) are the **irreducible result of local interactions**
- Macro properties are **self-organised outcomes** of micro interactions — they do not exist at the individual level

**Two modelling paradigms:**

- **Walrasian**: complete network, simultaneous and costless information exchange
- **Agent-Based**: heterogeneous local neighbourhoods, bounded rationality

**Once the network is reconstructed, we can:**

- Test its **robustness** to shocks (resilience)
- Implement policies to reduce **vulnerability** and cascading failures
- Avoid the **“too interconnected to fail”** problem
- Introduce **firewalls** between dense communities

# Stylized Facts: Financial Markets

**Asset prices:**

- **Fat tails**: extreme returns far more frequent than a normal distribution predicts
- **Volatility clustering**: large moves tend to follow large moves
- **Bubbles and crashes**: sustained deviations from fundamental value

**Financial cycles and contagion:**

- Pro-cyclical leverage: banks expand credit in booms, contract in busts
- **Contagion**: failure of one institution spreads through credit links
- **Systemic risk**: network structure amplifies idiosyncratic shocks
- "The crisis was a **network event**" (ECB, 2010)

## The key insight

Individual bank behaviour does not explain crises. It is the **interaction structure** — the network — that turns idiosyncratic shocks into systemic events.

# From Banks' Strategies to Financial Instability

## Berardi & Tedeschi, *IREF* 2017 — Research question

Which interbank market architecture is most **resilient** to liquidity shocks? How does the choice of banks' **strategy** shape both the network topology and the system's fragility?

**Key ingredients:**

- $N = 100$ heterogeneous banks over $T = 1000$ periods
- Interbank market with **endogenous** network formation via preferential attachment
- Banks compete via a **fitness function** combining liquidity and interest rate
- Random liquidity shocks from deposit motion

**Two key parameters:**

- $\eta \in \{0, 0.5, 1\}$: bank **strategy** — pure interest rate / mixed / pure liquidity
- $\beta \in [0, \infty]$: **intensity of choice** — how strongly banks follow the fitness signal

# Two New Ideas in This Paper

Everything we have seen so far assumed a **given, fixed** network topology. Today we go one step further.

**New idea 1 — Endogenous network:**

- The network is **not imposed**: it emerges from banks' own decisions
- At each period, banks **rewire** their credit links based on the fitness of potential lenders
- Topology is an **outcome**, not an assumption

**New idea 2 — Strategy $\rightarrow$ topology $\rightarrow$ fragility:**

- Banks choose a **strategy** (compete on liquidity, on interest rate, or both)
- That strategy determines what kind of **network emerges**
- That network determines how **resilient** the system is to shocks
- It is a **feedback loop**: strategy $\rightarrow$ topology $\rightarrow$ stability $\rightarrow$ strategy

# Why This Matters: Connecting the Dots

**What we knew from the course:**

- HAMs: heterogeneous agents generate instability endogenously (BH, Naimzada–Ricchiuti)
- Networks: topology shapes contagion, resilience, information diffusion
- BH on a network: local herding amplifies price swings

**What Berardi & Tedeschi add:**

- The topology is **not exogenous** — it is the product of competitive behaviour
- Systemic risk is **not bad luck** — it is the **endogenous outcome** of rational strategies under herding
- Individual banks do nothing "wrong" — instability **emerges** from interaction

## The policy implication

You cannot fix systemic risk by regulating individual banks in isolation. You have to regulate the **network** — its topology, its hubs, its community structure.

# The Model: Time Schedule

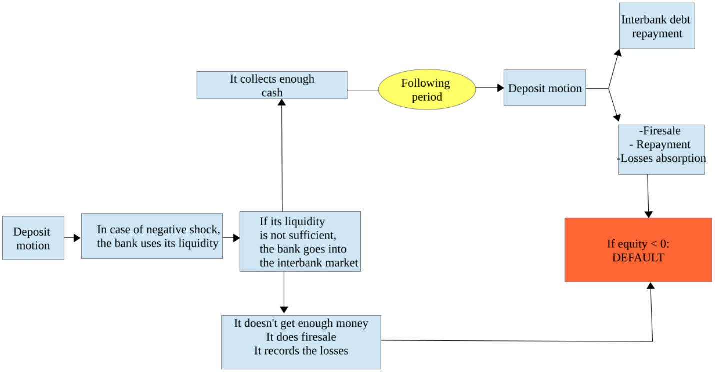


**Fig. 1.** Model time schedule.

Figure: Model time schedule — Berardi & Tedeschi (2017), Fig. 1

# Balance Sheet and Deposit Shock

**Balance sheet identity** for bank $i$ at time $t$:

$$L_t^i + C_t^i + R_t^i = D_t^i + E_t^i$$

$L$ = long-term assets, $C$ = liquidity, $R$ = reserves, $D$ = deposits, $E$ = equity.

**Deposit motion** (stochastic shock):

$$D_t^i = D_{t-1}^i \left(\mu + \omega \mathcal{U}(0,1)\right)$$

## Default mechanism (four steps)

1. Negative shock $\Rightarrow$ bank uses its liquidity $C_t^i$
2. If insufficient $\Rightarrow$ enters the **interbank market** as borrower
3. If still short $\Rightarrow$ **fire-sale** of long-term assets at price $\rho < 1$, recording losses
4. If equity $E_t^i < 0 \Rightarrow$ **DEFAULT**

# Bank Behaviour: Expected Profit and Interest Rate

**Expected profit** of lender $i$ on a loan to borrower $j$:

$$\mathbb{E}[\Pi_t^{i,j}] = p_t^j \, (r_t^{i,j} \, c_t^{i,j}) + (1 - p_t^j)(\xi A_t^j - c_t^{i,j}) + \varphi A_t^j - \chi A_t^i$$

- $p_t^j = 1 - E_t^j / E_t^{\max}$: default probability (higher leverage $\Rightarrow$ higher risk)
- $r_t^{i,j}$: interest rate; $c_t^{i,j}$: maximum loan; $\xi, \varphi, \chi$: cost parameters

**Optimal interest rate** (zero-profit condition):

$$r_t^{i,j} = \frac{\chi A_t^i - \varphi A_t^j - (1 - p_t^j)(\xi A_t^j - c_t^{i,j})}{p_t^j \, c_t^{i,j}}$$

## Financial accelerator

Rate **increases** with the lender's size and the borrower's leverage. More fragile borrowers pay higher rates $\Rightarrow$ their condition worsens further $\Rightarrow$ amplification.

# Fitness Function and Preferential Attachment

**Fitness** — bank $i$'s attractiveness in the interbank market:

$$\mu_t^i = \eta \left( \frac{C_t^i}{C_t^{\max}} \right) + (1-\eta) \left( \frac{r_t^{\min}}{r_t^i} \right)$$

- $\eta = 1$: attract clients via **high liquidity supply**
- $\eta = 0$: attract clients via **low interest rate**
- $\eta = 0.5$: **mixed** strategy — balance the two

**Link rewiring**: bank $j$ cuts its link to $i$ and switches to $k$ with probability

$$P_t^j = \frac{1}{1 + e^{-\beta(\mu_t^k - \mu_t^i)}}$$

- $\beta = 0$: links rewired at random $\Rightarrow$ **random network**
- $\beta \to \infty$: always switch to the best lender $\Rightarrow$ **star / scale-free**: "too interconnected to fail"
- Same role as intensity of choice in BH (1998)!

# Simulation Results: Network Topology

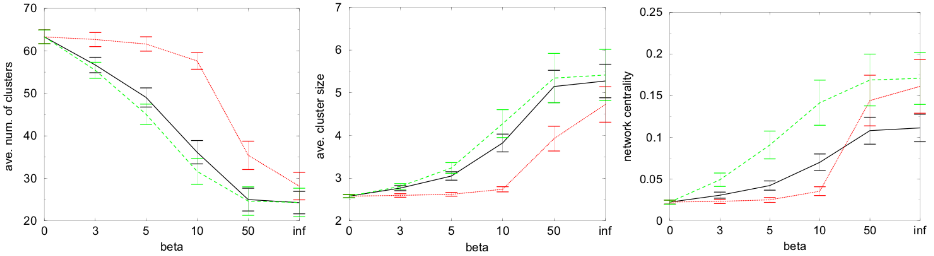


**Fig. 2.** Average number of clusters (left), average size of clusters (middle), and network centrality (right), over all times and all simulations as a function of $\beta$. The lowest interest rate strategy (i.e $\epsilon$=0) is highlighted in black solid line, the mixed strategy (i.e $\epsilon$=0.5) in red dotted line, and the highest liquidity one (i.e $\epsilon$=1) in green dashed line. Colors are available on the web site version. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure: Average number of clusters (left), cluster size (centre), network centrality (right) as a function of $\beta$. Black: $\eta = 0$; red dotted: $\eta = 0.5$; green dashed: $\eta = 1$.

# Network Topology: Discussion

**Key findings:**

- Increasing $\beta \Rightarrow$ network **centralises**: fewer and larger clusters, higher centrality
- Pure strategies ($\eta = 0$ and $\eta = 1$) centralise **fast and linearly** with $\beta$
- Mixed strategy ($\eta = 0.5$) stays **decentralised** up to $\beta \approx 10$, then undergoes a sudden **phase transition**

## Phase transition at $\beta = 10$

For the mixed strategy, the network jumps abruptly from fragmented to highly concentrated. This non-linearity is a key result: the mixed strategy appears safe but can collapse suddenly under strong herding.

**Connection to community detection:** the cluster structure here is exactly the community structure we studied with Louvain. High $\beta$ destroys community structure $\Rightarrow$ fewer natural **firewalls** $\Rightarrow$ higher contagion risk.

# Simulation Results: Core–Periphery Structure

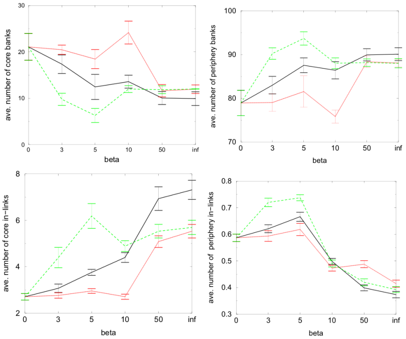


**Fig. 3.** Average number of banks belonging to the core (top left panel) and to the periphery (top right panel) and their average number of in-coming links(bottom left and right for core and periphery respectively), over all times and all simulations as a function of $\beta$. The lowest interest rate strategy (i.e $\epsilon$=0) is highlighted in black solid line, the mixed strategy (i.e $\epsilon$=0.5) in red dotted line, and the highest liquidity one (i.e $\epsilon$=1) in green dashed line. Colors are available on the web site version. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure: Average number of core and periphery banks and their in-links as a function of $\beta$.

# Simulation Results: Leverage and Interest Rates

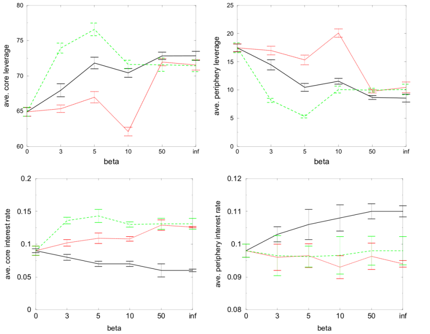


**Fig. 5.** Average core and periphery leverage (top left and right panel, respectively), average core and periphery interest rate (bottom left and right panel, respectively), over all times and all simulations as a function of $\beta$. The lowest interest rate strategy (i.e $\epsilon$=0) is highlighted in black solid line, the mixed strategy (i.e $\epsilon$=0.5) in red dotted line, and the highest liquidity one (i.e $\epsilon$=1) in green dashed line. Colors are available on the web site version. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure: Average core and periphery leverage (top) and interest rates (bottom) as a function of $\beta$.

# Simulation Results: Bank Failures

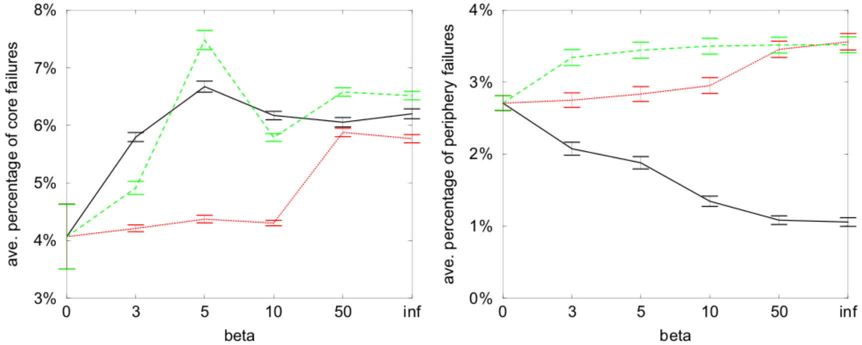


**Fig. 6.** Average percentage of core and periphery banks failures (left and right panel, respectively), over all times and all simulations as a function of $\beta$. The lowest interest rate strategy (i.e $\epsilon$=0) is highlighted in black solid line, the mixed strategy (i.e $\epsilon$=0.5) in red dotted line, and the highest liquidity one (i.e $\epsilon$=1) in green dashed line. Colors are available on the web site version. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure: Average percentage of core (left) and periphery (right) bank failures as a function of $\beta$.

# Simulation Results: Aggregate Fragility

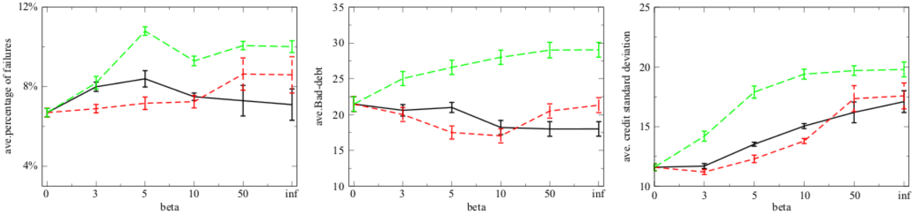


**Fig. 7.** Average percentage of banks failures (left), average bad-debt (middle) and average credit standard deviation (right), over all times and all simulations as a function of $\beta$. The lowest interest rate strategy (i.e $\epsilon$=0) is highlighted in black solid line, the mixed strategy (i.e $\epsilon$=0.5) in red dotted line, and the highest liquidity one (i.e $\epsilon$=1) in green dashed line. Colors are available on the web site version. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Figure: Average failures (left), bad debt (centre), credit standard deviation (right) as a function of $\beta$.

# Key Results: Why Does the Mixed Strategy Win?

**Pure liquidity ($\eta = 1$):**

- Core banks attract too many borrowers $\Rightarrow$ excessive leverage
- High interest rates $\Rightarrow$ bad debt erodes equity $\Rightarrow$ **most failures**

**Pure interest rate ($\eta = 0$):**

- Too-low rates $\Rightarrow$ margins eroded; small illiquid lenders $\Rightarrow$ high rationing
- **Thin margins and fragility**

## Mixed strategy ($\eta = 0.5$): the winner

+ Moderate client base $\Rightarrow$ leverage stays below critical threshold
+ Network does *not* condense (for $\beta \leq 10$) $\Rightarrow$ no "too interconnected to fail"
+ **Fewest failures and lowest bad debt**

**But**: at $\beta > 10$ the phase transition hits $\Rightarrow$ even the mixed strategy collapses. No strategy is safe under extreme herding.

# The Core–Periphery Tension

**Core banks (hubs):**

- High fitness ⇒ many borrowers ⇒ high leverage ⇒ more fragile than periphery despite larger equity
- Core failure ⇒ bad debt cascades to lenders ⇒ contagion
- Consistent with empirical evidence: Germany (Craig & Von Peter, 2014); e-MID (Fricke & Lux, 2015)

**Periphery banks:**

- Fewer clients ⇒ lower leverage ⇒ more resilient
- But under $\eta = 0$: periphery offers high rates ⇒ too high for borrowers ⇒ rationing

## The model identifies a safe corridor

There is a minimum and maximum interest rate. Below: profits too thin. Above: customers become insolvent. The mixed strategy keeps banks **inside the corridor**.

# Policy Implications

**From the model:**

- High $\beta$ (herding) $\Rightarrow$ centralised network $\Rightarrow$ fragility: systemic risk is **endogenous**
- The mixed strategy dominates — but can collapse under extreme herding ($\beta > 10$)
- No individual bank "does anything wrong" — instability emerges from **interaction**

**Regulatory tools:**

- **Limit hub size**: caps on interbank exposure concentration
- **Firewalls**: decouple sub-networks (use community structure as guide)
- **Discourage herding**: transparency requirements that reduce effective $\beta$
- **Incentivise mixed strategies**: penalise pure-rate or pure-liquidity competition
- **Modularity** $Q$ and **betweenness centrality** as systemic risk indicators

# Computational Economics: What We Have Learned

**The common thread across the entire course:**

- **Heterogeneity** is not noise — it is the source of dynamics
- **Interaction** is not a detail — it determines aggregate outcomes
- **Topology** is not given — it co-evolves with agent behaviour

**What we have built:**

- HAMs: BH (1998), Naimzada–Ricchiuti — instability from heterogeneous beliefs
- Networks: centrality, community detection, small-world, scale-free
- BH on a network: local herding amplifies price swings
- Endogenous networks: strategies shape topology shape fragility (Berardi & Tedeschi)

## The big picture

Complexity, heterogeneity, and network structure are not complications to be removed. They are the *source* of the phenomena we observe. **Computational methods let us study them rigorously.**

# Open Questions — and Good Luck!

**Extensions of today's model:**

- Add a **Central Bank**: what is the optimal policy to reduce interbank vulnerability?
- Microfounded utility functions for bank strategy selection
- Calibration to real interbank data (e-MID, German interbank market)
- Introduce **climate risk** shocks on bank balance sheets
- Agent-based macro models: DSGE vs. ABM

## References

Berardi & Tedeschi (2017), *IREF*, 47  Brock & Hommes (1998), *JEDC*, 22
Naimzada & Ricchiuti (2008), *AMC*, 199  Naimzada & Ricchiuti (2012), *CSF*, 45
Watts & Strogatz (1998), *Nature*, 393  Barabási & Albert (1999), *Science*, 286

**Good luck with the exam!** Mock exam: this afternoon.