EUROPEAN CENTRAL BANK

BANKING SUPERVISION

Systemic Risk in Finance

Public Lecture Series

Lecture 3
Shock transmission channels and behaviors

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Agenda

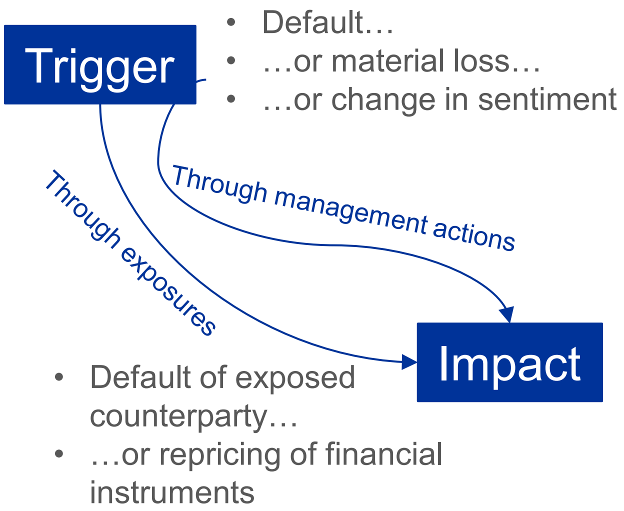
5. Shock transmission in financial network: contagion mechanisms and simulations

6. Financial agents' behaviours and emergence of systemic risk: Portfolio choice, ALM, and endogenous systemic risk

Shock transmission

From trigger to impact

- The network connecting agents (e.g., financial institutions) is conducive to shock propagation…
- …and mechanisms of the **shock transmission** can be very diverse, depending on:
  - Type of exposures
  - Contractual / legal or regulatory (resolution) / accounting rules
  - Management actions / business or recovery plans
  - Investor behaviours (risk management or market practice
- This all determines and differentiates the origine and magnitude of systemic risk



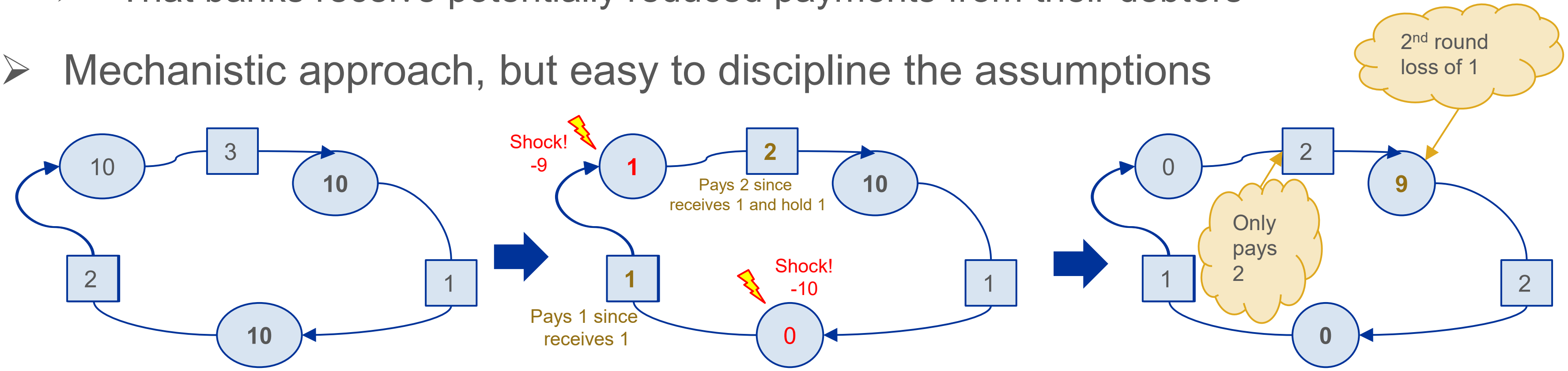
Points related to transmission channels to consider when modeling systemic risk

- Static (mechanistic) or dynamic (considering how agents and macro-environment would react to stress and its propagation)
- Simple, contractual loss incurred by the exposed counterparty or loss amplified by legal/ contractual/ market friction/ lost opportunity costs
- Monetary loss or loss in trust (maybe also quantifiable in terms of funding spreads)
- Would exposure be as seen at the onset of the stress conditions or it would change (e.g., increase due to wrong-way-risk*)

*) Risk that exposure increases with the deterioration of the risk factors, e.g., default probabilities, unfavorable moves in interest rates

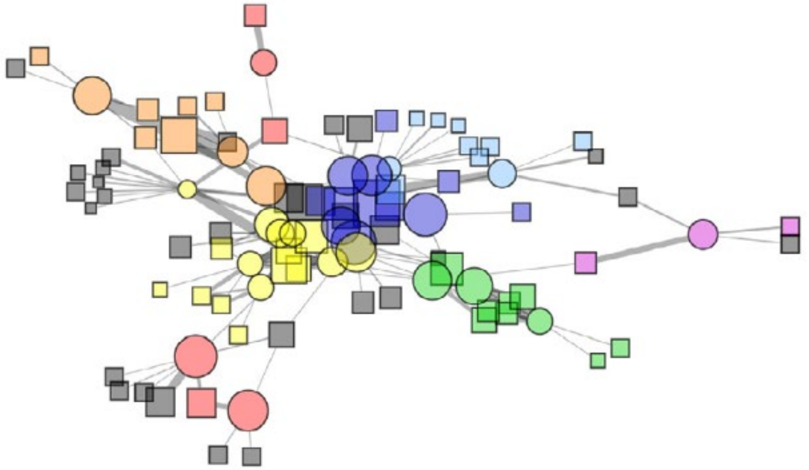
Simulation methods – trace propagation of shocks

- Eisenberg-Noe (2001) algorithm: clearing payments vector approach computing how much can be paid back by the banks in the financial network given:
  - A financial shock to the banks, reducing their capacity to absorb losses or sunspot defaults of some vulnerable banks on their interbank obligations
  - That banks receive potentially reduced payments from their debtors
- Mechanistic approach, but easy to discipline the assumptions



Case study – systemic exposures: Network Valuation

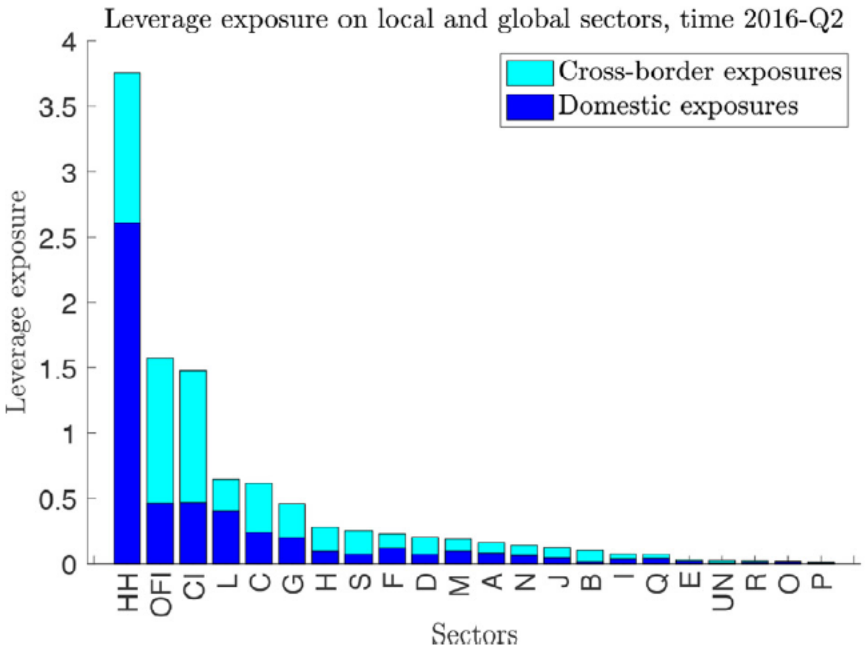
- Economic (fair value) of exposures depends on counterparty's quality:
  - Like in Merton model…
  - …but endogenously in the network
- Network Valuation (NEVA) captures that:
  - A simulation tool, integrating **direct and indirect channels of contagion**
  - Calibration might be tricky: assumptions on how prices react to transacted volumes, what leverage measure to use



Bi-partite network of the banks and firms in EU. Circles = banks; Squares = sectors; Colors = domicile
Source: Roncoroni et al. (2021)

Case study – systemic exposures: leverage overlap

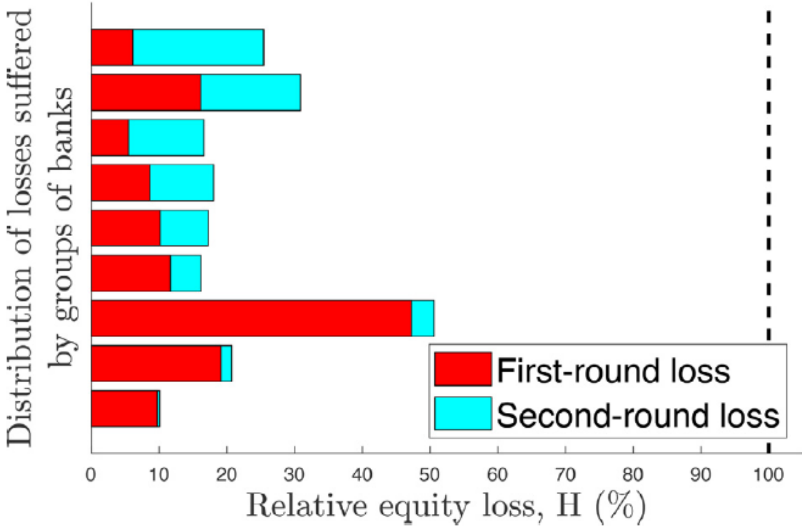
- What determines the amplification of the shocks is the amount of leverage:
  - More exposure taken with higher leverage will magnify the losses
- Instead of running the full NEVA machinery, one can approximate the measure of systemic risk by looking at leverage exposures:
  - Exposure_{counterparty}/capital_{bank}
  - Useful indicator to monitor systemic risk



The blue bar shows the ratio of exposures allocated to domestic sectors, while the cyan bar shows the ratio of exposures allocated to cross-border sectors

Case study – systemic exposures: scenario analysis, i.e., tracing paths of shock propagation

- What if the system is subject to a financial shock:
  - E.g., a set of banks experience losses to its credit portfolios
- NEVA helps to assess how these initial losses change the credit worthiness of banks:
  - The exposures would be worth less
  - Caveat: many of the exposures would not be remarked immediately (like loans and deposits), so the exact impact may be overestimated
  - However, the estimates are an indication of sentiment-based channels of contagion (SVB)

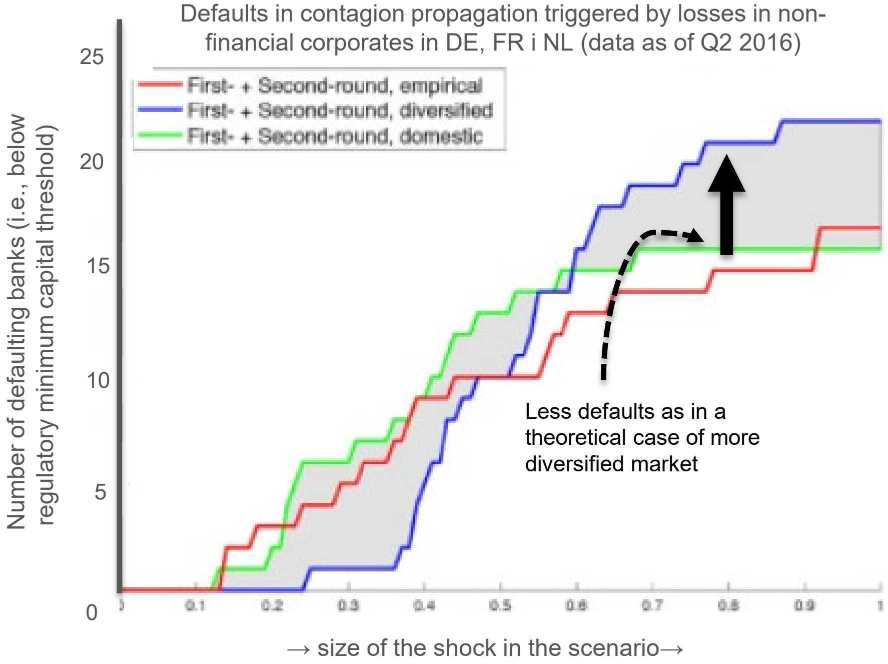


Distribution of relative equity losses suffered by banks in a consistent macro-financial scenario designed for the EBA 2016 EU-wide stress-test exercise
Source: Roncoroni et al. (2023)

Case study – systemic exposures: diversification / fragmentation effects

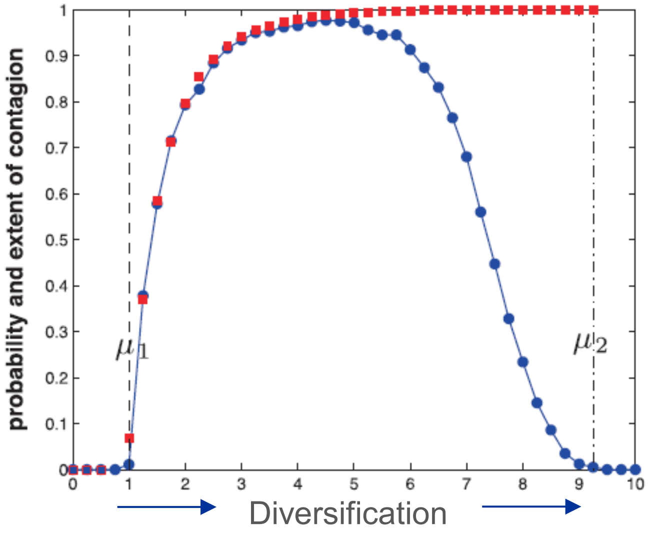
- **Observation: banks are interconnected on various levels**, as depicted by data in regulatory reporting (deposits, shares, derivatives, asset commonality, similar funding sources)
- **Question:** how to measure **banks sensitivity to financial shocks in euro area**, applying **stress test techniques?**
- **Approach: calibration of** NEVA model and assessment of the impact of the EBA Stress Test outcomes on 2nd round losses

- **Significance:** assess the importance of transmission channels => identifying banks that are more vulnerable because their balance sheets are similar in structure to many other banks; showing that the fragmentation of the European market can make the system more resistant to large-scale shocks



Case study – phase transition: systemic risk jump with a small change in some properties of the network

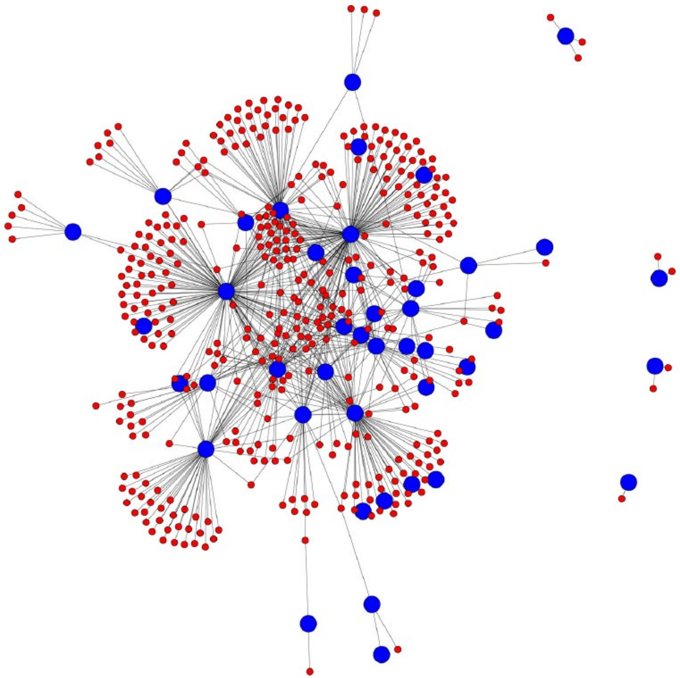
- As the diversification of the banks' portfolios increases, the system undergoes two phase transitions, with a region in between where global cascades occur (robust-yet-fragile system).
- In between these two transitions, banks are both vulnerable to shocks in their asset prices, and interconnected enough for these shocks to spread.



Banks randomly default causing vulnerable connected banks to fail, which creates a cascade. Vulnerable: exposed to the same asset classes as the defaulting banks and that are subject to fire sale revaluation exceeding their capital. So, results would depend on the impact function. Gai and Kapadia (2010)

Case study – portfolio overlaps: role of indirect contagion channel

- Network of N banks and M asset classes, liquidated to raise cash when needed but with price impact externalities (Caccioli et al, JBF 2014)
- Key property: diversification of exposures across different asset classes
- Measure of instability: does contagion effect the whole system or is contained locally?

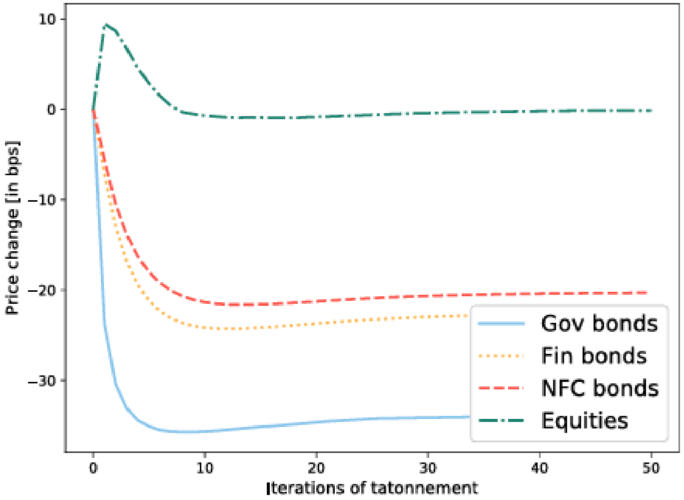


Bi-partite network of the banks and firms in Mexico.

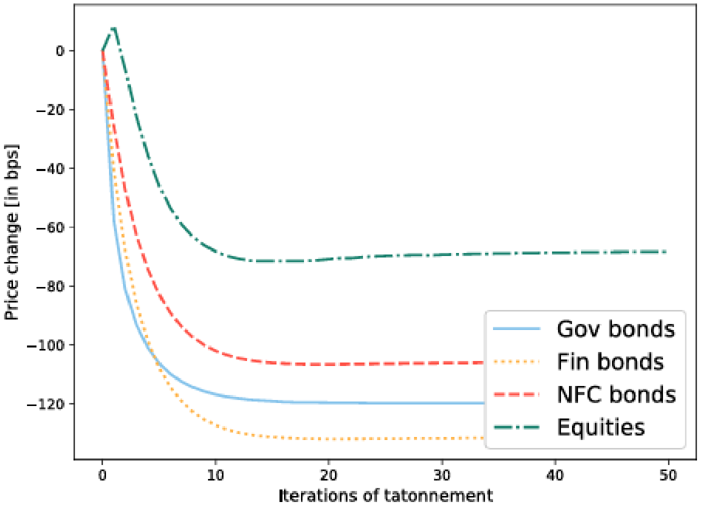
Case study – fire sales: how much to sale and which assets first?

- Pecking order – a holy grail of fire sale models?
- Ad-hoc approaches:
  - proportional selling (investment funds' balanced asset holdings commensurate with investment strategy)
  - From most liquid to least liquid (the least market price impact on the system)
- Model of the decision-making process (Feinstein et al, 2023)
- Liquidate such that risk-adjusted return on assets sold and remaining is maximized, considering other agents liquidating following the same principle

Case study – fire sales: strategy matters…



Change in equilibrium prices when banks optimize liquidation of assets considering their risk-return characteristics and impact of liquidation on market prices of assets
Source: Feinstein and Halaj (2023)



Change in equilibrium prices when banks follow a proportional liquidation strategy.
Bottom line: much higher estimated of contagion impact

…so, lets move to the next section

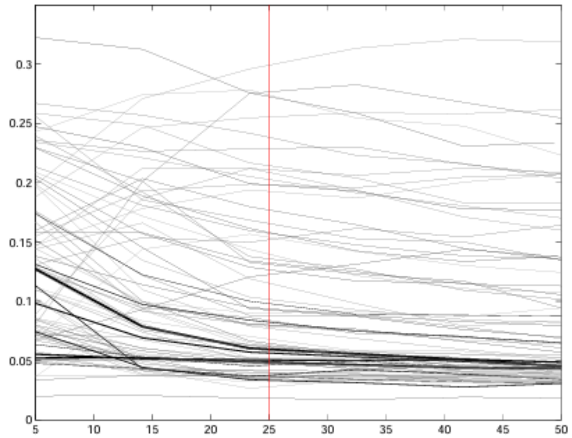
Financial agents' behaviors and emergence of systemic risk

Simulation methods – embed management actions

- Subjected to a shock, financial actors would most likely react, following some management action strategy
  - Stop losses, contingency plans, panic of investors triggering defensive actions
    - \+ Rebalance their positions to increase buffers or raise cash, also temporarily adjusting their business objective to survive, e.g., by cutting lending to counterparties
    - \- On a flip side, their action would have externalities; what if major players hoard cash and deprive other institutions, that fund or hedge themselves this way, of resources? What if actions change market value of assets, e.g., when large players start to sale (fire-sale)?

Centrality measures – adaptive structure of the network in a stress testing framework

- As a result of management actions, the network structure would change*
- Endogenous network formation
  - In times of stress or shift in regulation, banks decide to change lending patterns or to limit funding based on **risk management criteria** (e.g., minimizing risk, targeting specific risk/return mix)
  - This implies a change to a pattern in connections between agents



Note: x-axis: limit on exposures relative to the capital level (in %) y-axis: Out-degree of the networks. The darker the line, the larger the bank.

Source: Halaj & Kok (2015), QF

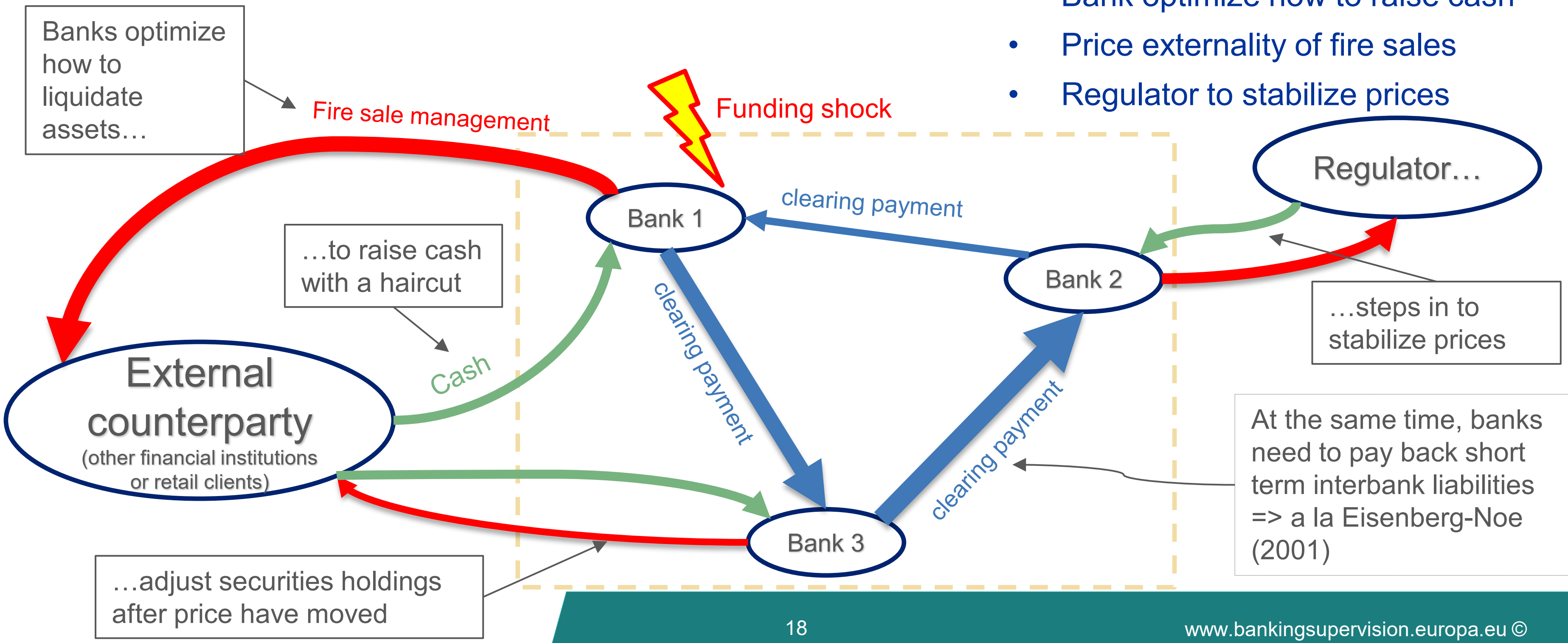
*) the whole branch of research dedicated to strategic decisions on links and stability of the resulting networks (**not covered in this lecture**), see e.g., Jackson & Wolinsky (1996), JET

Addressing gaps on liquidity and solvency interactions with dynamic balance sheet – fire sales

Based on Feinstein & Halaj (2023, JEDC)

Features:

- Bank optimize how to raise cash
- Price externality of fire sales
- Regulator to stabilize prices



Data for calibrations

FINREP 20.06 (Liabilities by country)

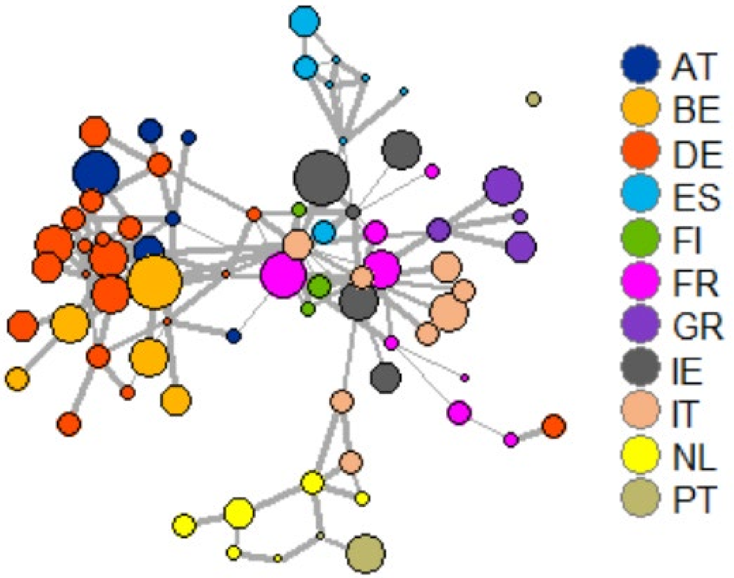
- Hint: funding shocks likely to spread to banks in adjacent countries and with similar funding structure
- Network contagion based on distance matrix
- Distance based on k-mean clustering considering:
    - I. Liability structure (~ Business model)
    - II. Country

(e.g., share of domestic/non-domestic deposits, market funding)

COREP 66.01.a (Deposit amount and historical outflow calibration)

COREP 27 (Large exposures)

Similarity: Distance network based on liability structure

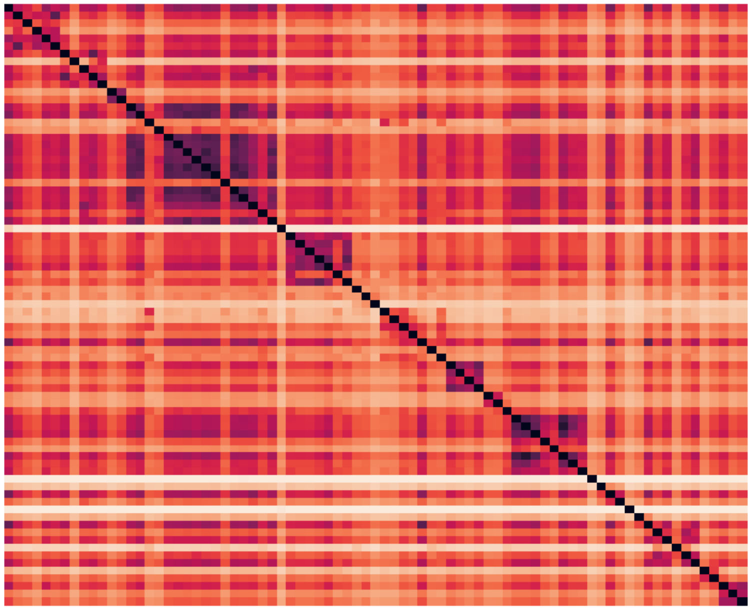


Source: Authors computations based on FINREP (F.20.06)
Note: Network filtered for normalized distances larger than 0.95, size of nodes proportional to degree (with upper trim bound)

Features of funding shock: duration and business model similarities

- Duration of the shock (how many days of the cumulative deposit outflows):
  - 1 day to 60 days
  - Severity controlled by the assumed quantile of historical deposit outflow distribution
- Information channel of contagion (*Clerc et al, 2016*, *NBER*):
  - Stressed run-offs for similar banks
  - Similar business models = similar balance sheet structures

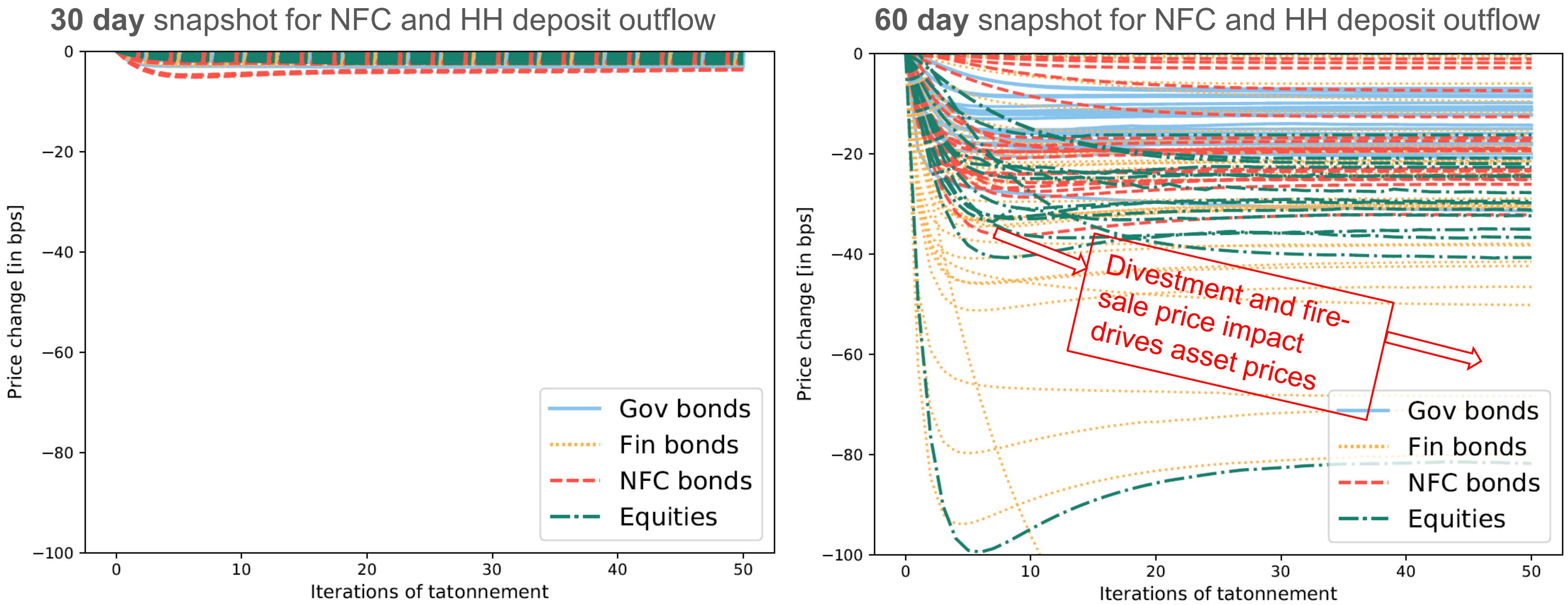
Heatmap of similarity based on k-means clustering of balance sheet compositions



Note: the darker the color the more similar the banks

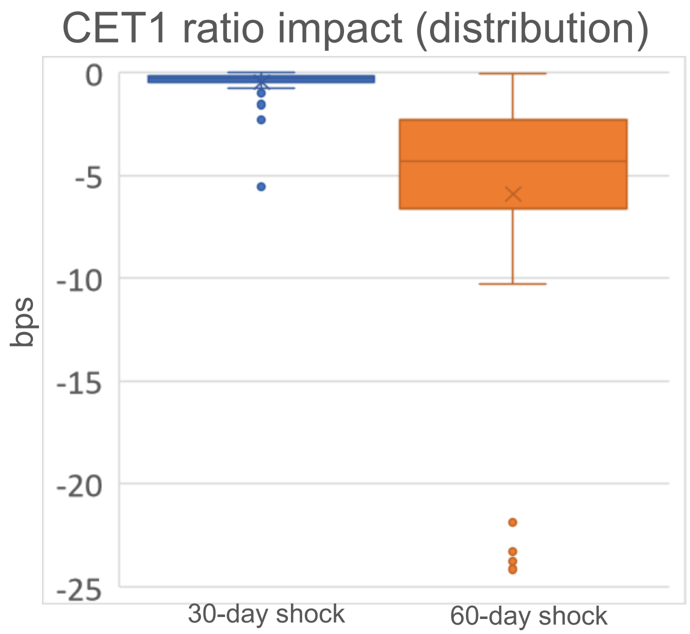
Useful metric for a structural vulnerability: asset price dynamics

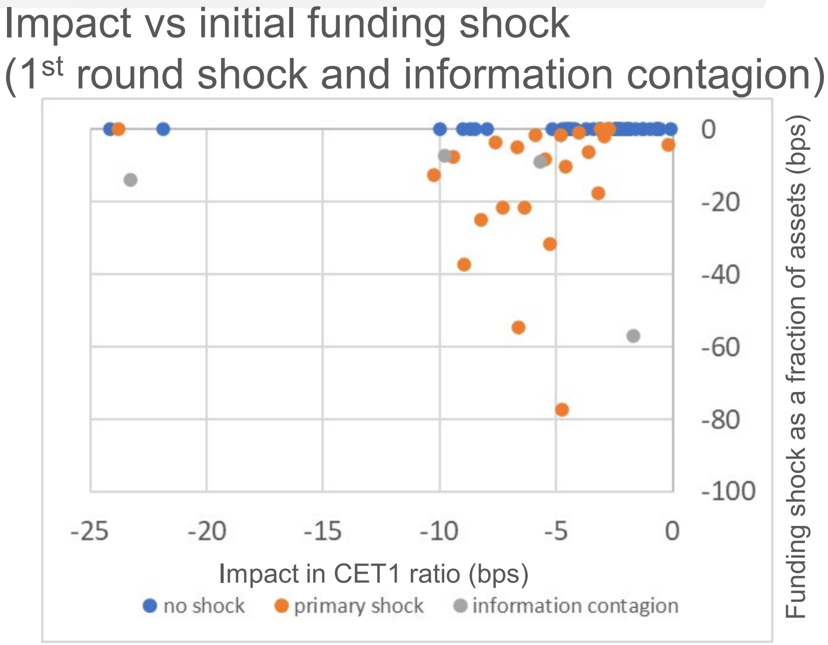
Evolution of prices after funding shock with different duration (in days)



Note: Each line represents the price evolution for one asset category in 4 asset classes (depicted in colors). Iterations of fictitious (tatonnement) algorithm describing banks gradual adjustment of securities portfolio composition, based on Feinstein & Halaj (2023, JEDC).

Solvency impact: losses in fire sales and systemic risk materialisation





Note: **Steep increase of impact when the magnitude of the funding shock increases** to match a severe deposit run-off rates observed historically (**cliff effect**)

Note: Each dot represent a bank, colored to indicated how the funding shock impacts them. Importantly, also **banks impacted by the initial shock (blue) incur losses from revaluation of assets** subject to fire sales

For those who'd like to experiment further

GitHub repository of code to run simulations based on a stylized (toy) system: https://github.com/greghalaj/Optimized_Fire_Sales

Potential questions to answer to (I invite researcher to use the code as a springboard for their projects):

1. What if banks can trade only with a subset of counterparties (CCR limits, geographical proximity, relationship trading)? How does it impact price dynamics after stress?
2. When can we have multiplicity of equilibria? How do they depend on the sequence in trading, delay, portfolio overlaps, etc.?
3. Can we embed different optimization rules? How would this impact behaviour in equilibrium?
4. Can we generalize the code to other market players (funds)?

Addressing gaps in liquidity and solvency interactions with dynamic balance sheet – encumbrance matters

Based on Cuzzola, Barbieri, Bindseil (2023, ECB WP)

Features:

- Only "indirect" contagion via price adjustment
- Deposit-run triggered by weaker regulatory requirements

Initial exogenous shock to assets value
(a la Cont, Schaanning 2017)

Banks breaching regulatory requirements trigger some **depositors to run** (**endogenous funding shock**)

Bank strategies to meet requirements:
- Use repo in Central Bank Collateral Framework
- Use Repo via commercial market
- Resort to Unsecured lending
- Liquidate assets in Fire sales

Change in **asset prices** (**endogenous price shock**)

Policy
(CB accepted collateral and applied haircuts)

Encumbrance constraining available liquidity pools

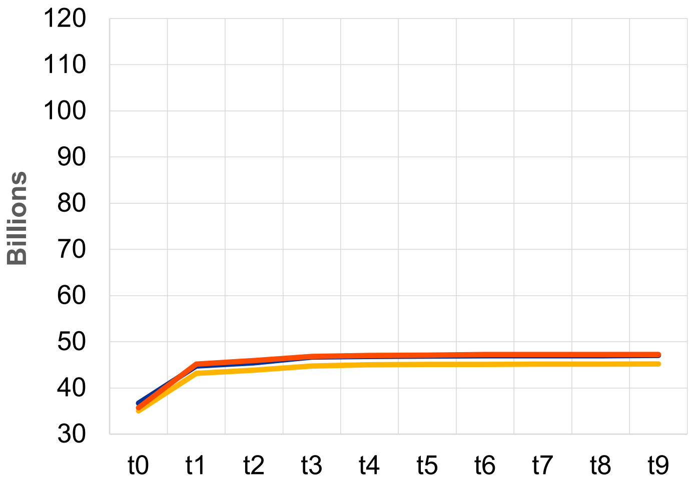
II. Encumbrance constraints in mobilizing liquidity

Based on Cuzzola, Barbieri, Bindseil (2023, ECB WP)

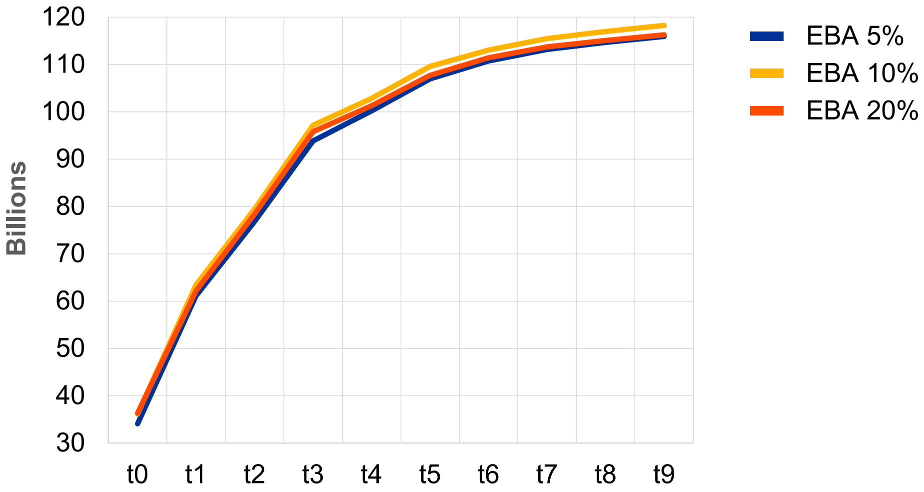
Dynamic encumbrance: given a specific fire sale loss, banks choose an asset liquidation strategy that implies the lowest level of asset encumbered in their balance sheets

- In their model, the CB channel is used more than the double of the Repo channel
- The volume of assets pledged at the CB triples in a ten-step simulation
- Preference for CB driven by more convenient haircuts than those in the Repo market

Additional collateral encumbered in Repo



Additional collateral encumbered at the Central Bank

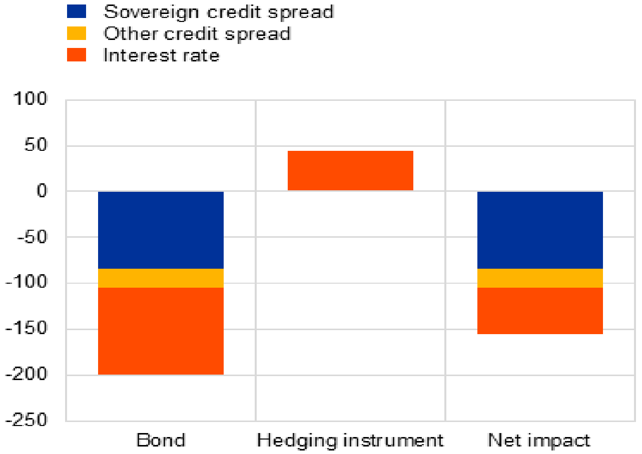


Source: authors results of simulation (average of 10 runs)
Scenarios calibrated to match the 5%, 10%, and 20% of the ST EBA 2021 final impact on LR

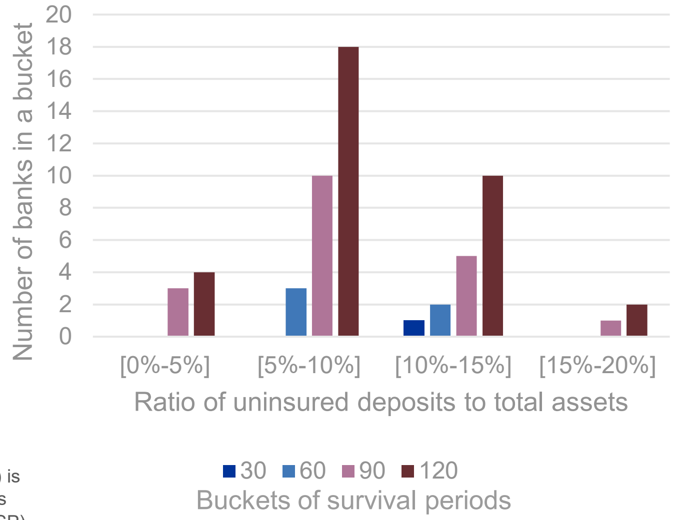
Funding stress and valuation losses – market participants' behavior or "can SVB-like case happen in Europe?"

- Unrealised losses on euro area banks' held-to-maturity bond portfolios are contained
- …and substantial liquidity buffers mean low probability of liquidation needs

Additional losses on amortised cost portfolios under the adverse scenario (EUR billion)



Liquidity stress survival period and reliance on uninsured deposits (Q2 2023)

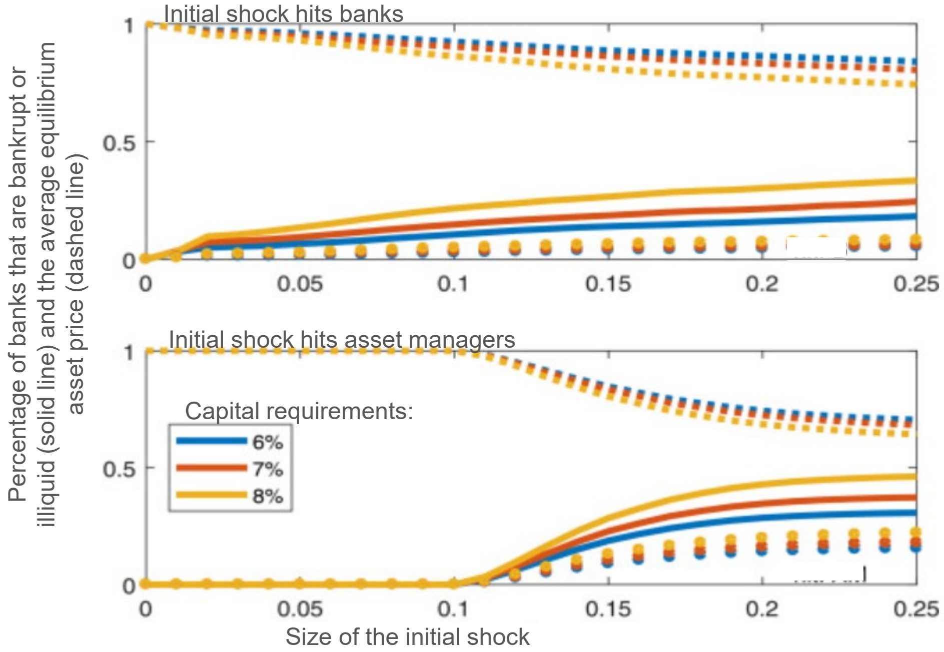


Source: ECB, ITS data (COREP 68) and ECB calculations.
Notes: LHS chart – ad hoc data collection in the context of EBA/SSM 2023 stress test. RHS chart - The 'survival period' (SP) is derived using the SSM's liquidity stress test tool and corresponds to the first day in which the net liquidity position (NLP) turns negative (i.e. when a bank would have no further available liquidity to counter the simulated net outflows). Survival Periods (SP) above 6 months are trimmed at 180 days.

How do difference in objectives of market players impact contagion spreading?

- **Question:** How do **different financial entities manage their balance sheet** structure, e.g., maximizing return on assets while limiting risk, while facing various business and regulatory constraints, influence the relationship structure?
- **Solution:** An agent-based model that considers return and risk, and the decisions of other entities with diverse objective functions, and **only banks** with capital constraints

- **Significance:** Using scenario analysis, demonstrating how different objective functions of banks and investment funds can destabilize the financial market; assessing the impact of capital requirements



The financial system is more resilient to small shocks when they affect investment funds, but the negative effects of large shocks on financial stability are less severe when banks are affected by the initial shock.
Source: Calimani, Hałaj & Żochowski (2022), JBF

What have we learned?

- **Multiplicity of the shock transmission channels in networks that determine the origin and magnitude of systemic risk**
- **Simulation methods, of agent-based-model type, are a practical tool to get insights on how systemic risk may depend on behaviors of the agents in the system, and to trace shock propagation in the system**