Size and complexity in model financial systems

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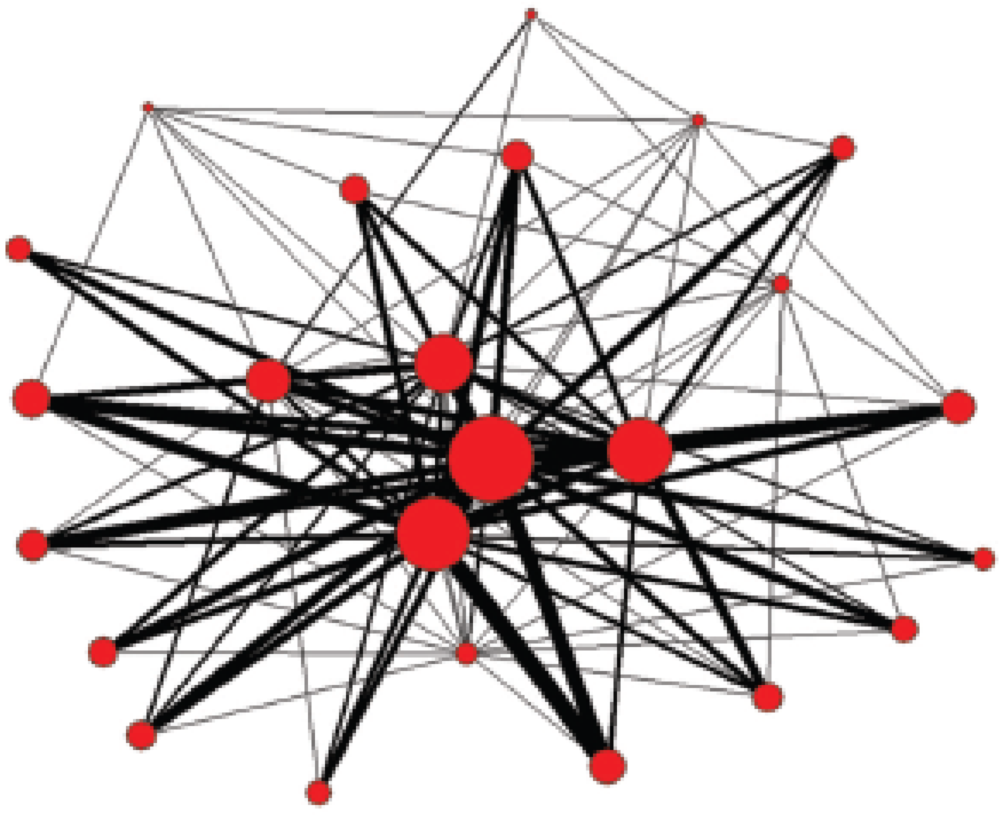
Complexity and Concentration in the Network

Network of large exposures[(a)] between UK banks[(b)(c)]



Source: FSA regulatory returns.

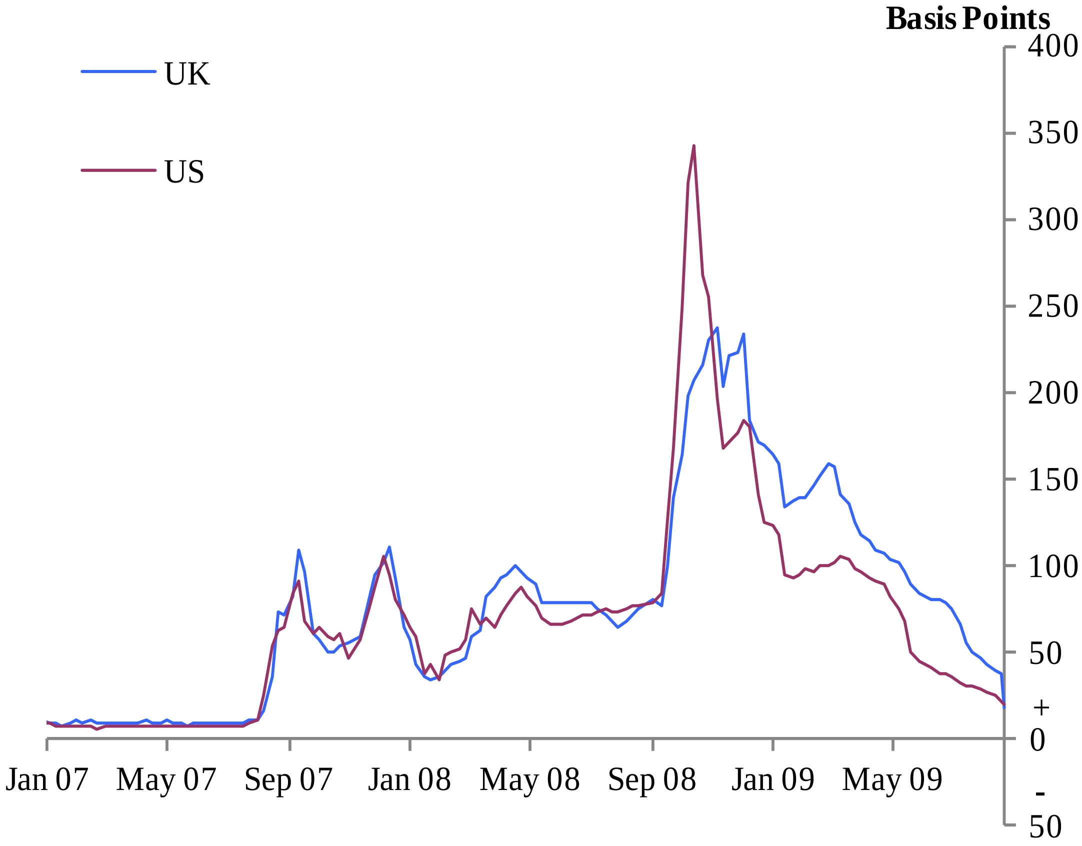
(a) A large exposure is one that exceeds 10% of a lending bank's eligible capital during a period. Eligible capital is defined as Tier 1 plus Tier 2 capital, minus regulatory deductions.

(b) Each node represents a bank in the United Kingdom. The size of each node is scaled in proportion to the sum of (1) the total value of exposures to a bank, and (2) the total value of exposures of the bank to others in the network. The thickness of a line is proportionate to the value of a single bilateral exposure.

(c) Based on 2006 Q4 data.

The Interbank Market Collapse

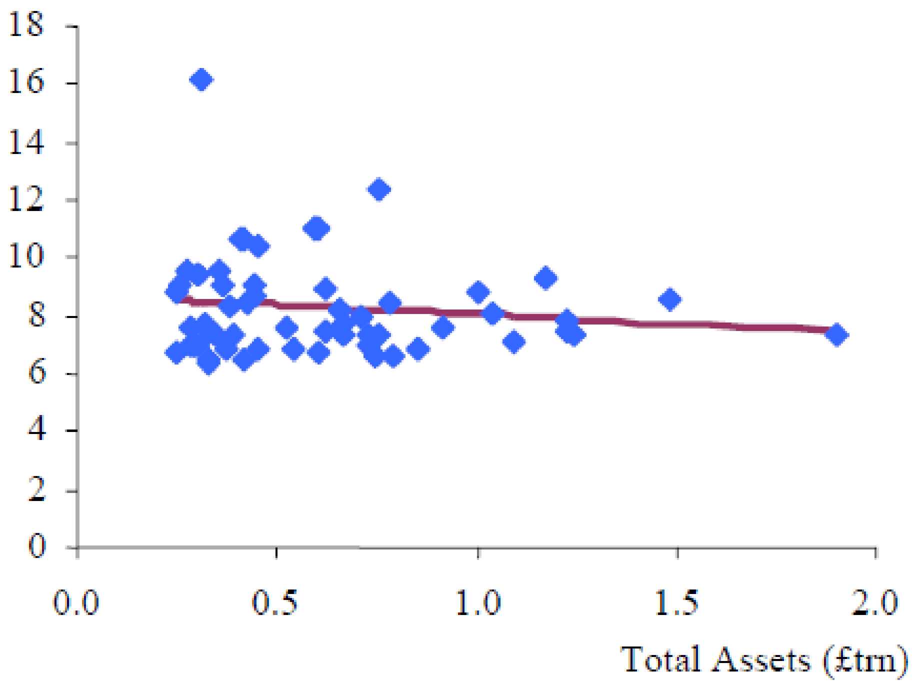
Three-month interbank rates relative to expected policy rates[a]



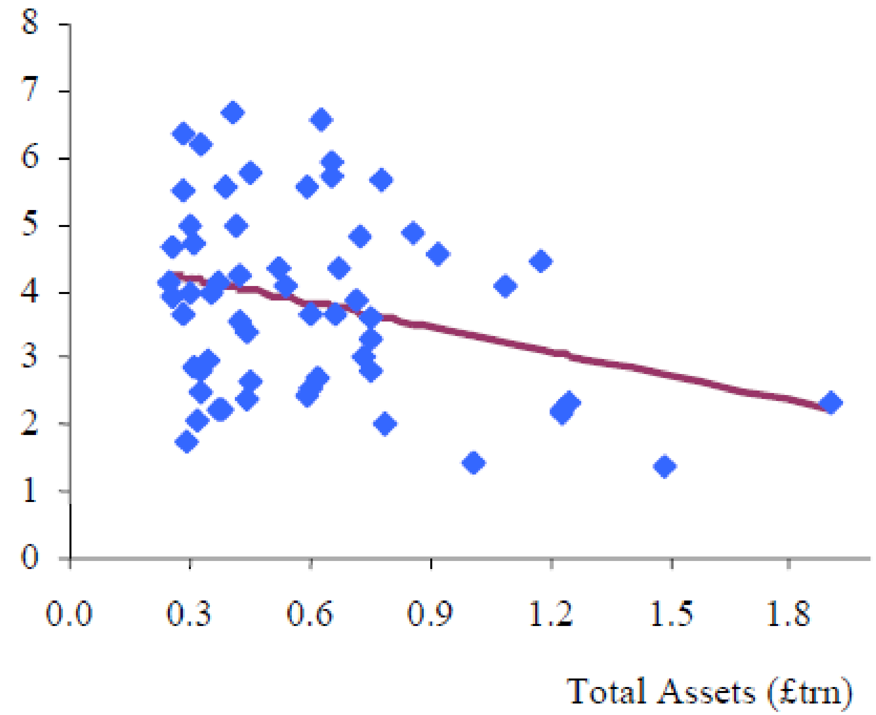
Sources: Bloomberg and Bank calculations.
(a) Spread of three-month Libor to three-month overnight index swap (OIS) rates.
Five-day moving average.

Size and Pre-Crisis Capital Adequacy

End-2007 Global Banks' Size and Capital Ratios



End-2007 Global Banks' Size and Leverage Ratios



Contributions of the Paper

- Three key contagion channels in a unified framework

- Key role for liquidity hoarding and confidence effects
  - hoarding be driven by counterparty concerns, precautionary behaviour, or collapsing confidence in the system
  - two forms of hoarding
  - interplay between hoarding, fire sales, bank failure and system confidence

- Heterogeneity in bank size:
  - distinct classes of large banks and small banks:

Key Results

- Liquidity hoarding plays a central role to contagion dynamics

- Importance of large, well-connected banks in system stability scales more than proportionately with their size
  - effects more pronounced in more concentrated systems
  - continue to apply when allowing for diversification benefits of larger banks

- Imposing tougher capital requirements on larger banks than smaller ones can enhance resilience.

Outline

- Methodological approach and intuition
  - example from epidemiology
- Model
- Simulation results
- Conclusion: methodological and policy implications

Epidemiology: ‘Tipping Points’ and ‘Super-spreaders’

- When will a disease spread through a population?
- Suppose everyone spreads the disease to 1 in 10 of their friends:
  - If everyone has exactly 9 friends, the disease will die out
  - But if everyone has exactly 11 friends, it will go viral

Epidemiology: ‘Tipping Points’ and ‘Super-spreaders’

- In reality, some are better connected than others.
  - People with more friends spread the disease more widely.
  - But they are also more likely to catch it in the first place, since they have many friends to catch it from.

- So connectivity enters twice. A person with 10 friends is 10x10 = 100 times important in spreading the disease than someone with 1 friend.

- Highly connected ‘super-spreaders’ are key to the propagation of contagion.

- Policy response: target super-spreaders (eg vaccines, education programmes)

Epidemiology: Behavioural Responses

- ‘Flight’ or ‘Hide’
  - Memphis yellow fever outbreak, 1878
  - SARS and self-quarantining

Why Complex Networks for Finance?

- Examples highlight usefulness of approach:
  - Contagion
  - Nonlinearities (big effects from small shocks)
  - Seemingly Identical Shocks → Different Outcomes
  - Heterogeneity – role of key players (fat tails)
  - Dynamics and Path Dependence
  - Behavioural Feedbacks and Amplifiers

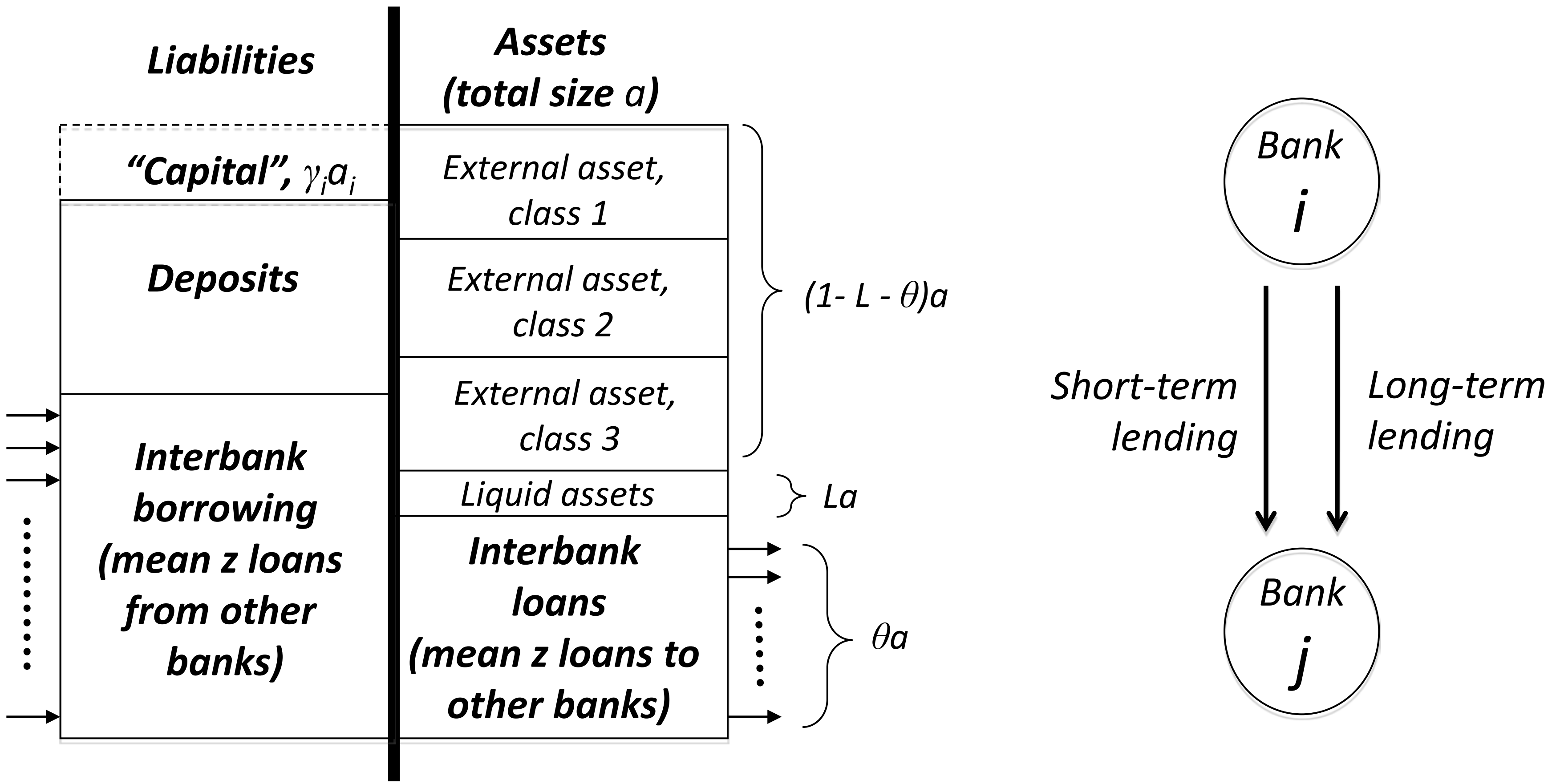
- All key dimensions of systemic risk

Epidemiology and Finance

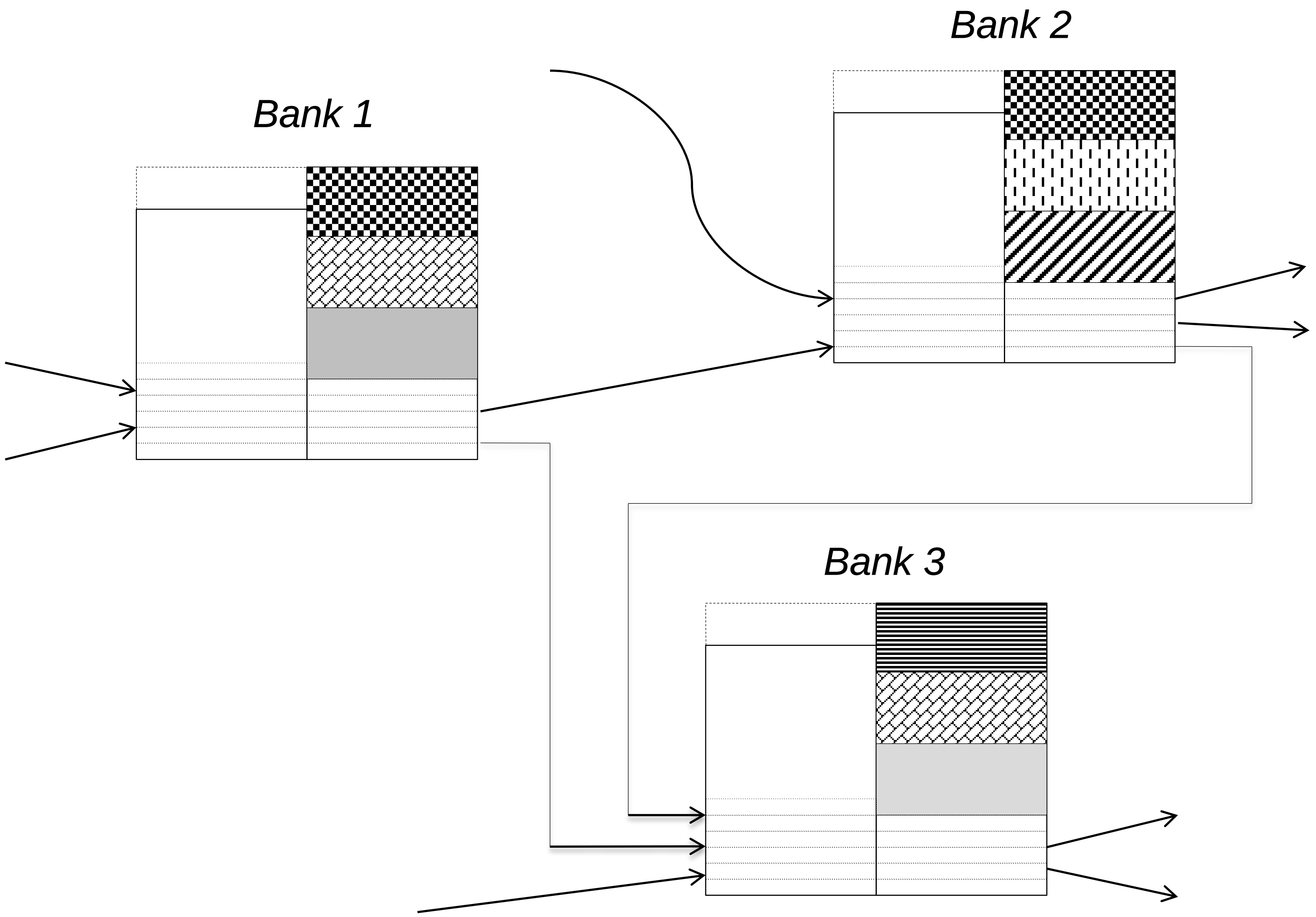
- Financial systems have particular features:
  - Balance sheets (more complex nodes)
  - Links which are directed and weighted
  - Possibility for risk sharing
  - Local dependence

- Behavioural responses key
  - But may be analogies to ‘hide’ and ‘flight’

Balance Sheets



Schematic characterisation of networks



Structure of the System

- Two networks: (i) interbank lending; (ii) shared exposures to a set of external assets.
- Two sizes of banks: big and small.
  - Big banks λ times 'larger' than small but λ times fewer.
- Links are all the same size and drawn randomly in a Poisson way but:
  - banks can have multiple links between them (aggregation)
  - big banks have systematically more links than little ones.
- Interbank loans: half short-term; half long-term

Liquidity Hoarding Behaviour (1)

- **Individual bank health:** $h_i = c_i m_i$

  where c_i is bank capital as a proportion of its initial level, and:

$$m_i = \min\left[1, \frac{A_i^{ST} + l_i}{L_i^{ST}}\right]$$

- **System confidence**: $C = EA$

  E – proportion of interbank loans not withdrawn

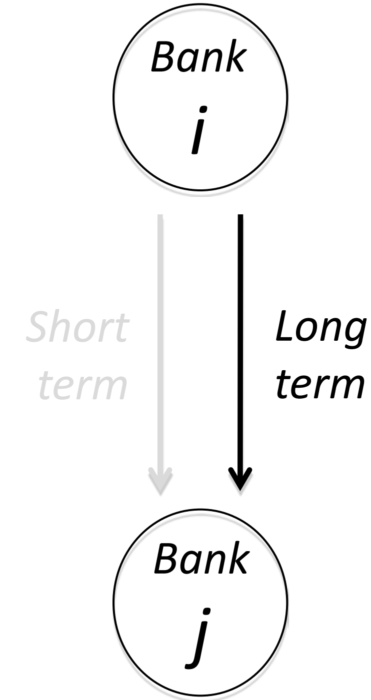
  A – total value of all remaining assets in the system (at current market price) as a proportion of its initial level

Liquidity Hoarding Behaviour (2)

- Banks shorten the maturity of their long-term IB loans if:

$$h_i\, h_j < (1 - C)$$

- This improves their own health at the expense of the system



Liquidity Hoarding Behaviour (3)

- Banks shorten the maturity of their long-term IB loans if:

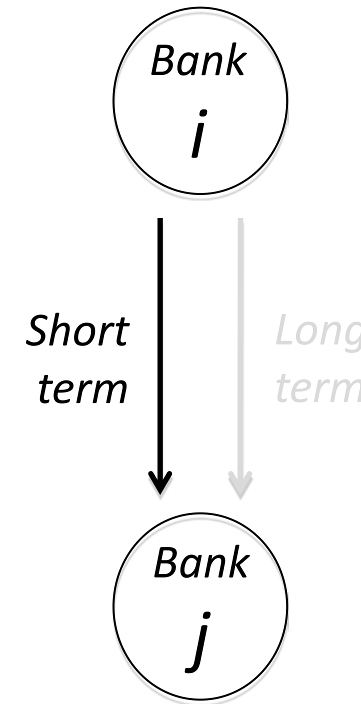
$$h_i \, h_j < (1 - C)$$

- This improves their own health at the expense of the system

- Banks withdraw loans altogether if either:

$$h_i \, h_j < (1 - C)^2$$

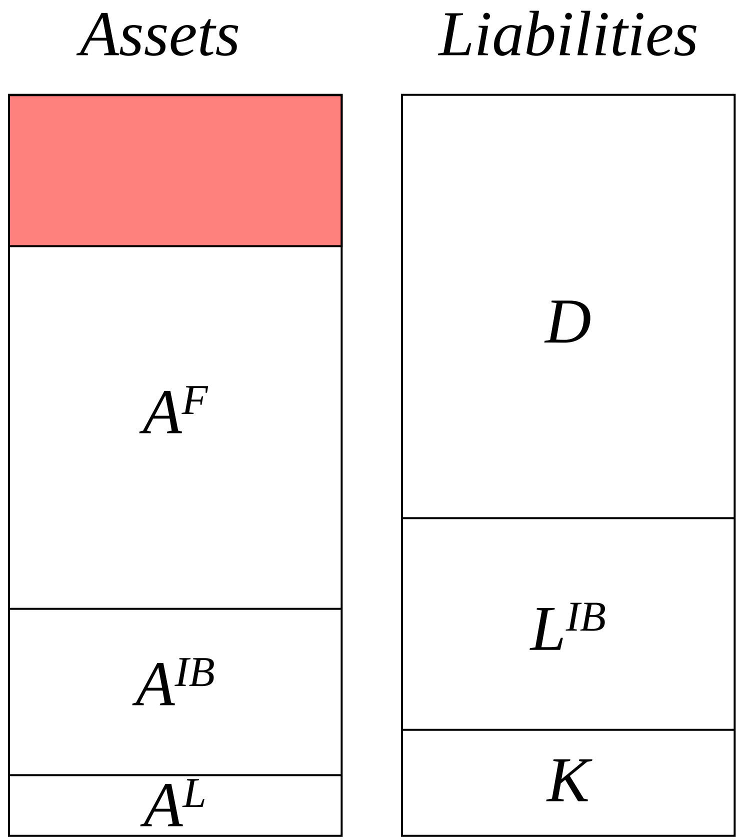
  or if they are forced to because they do not have sufficient liquid assets to meet funding withdrawals by other banks (as in Gai *et al*, 2011)



Default contagion and fire sales

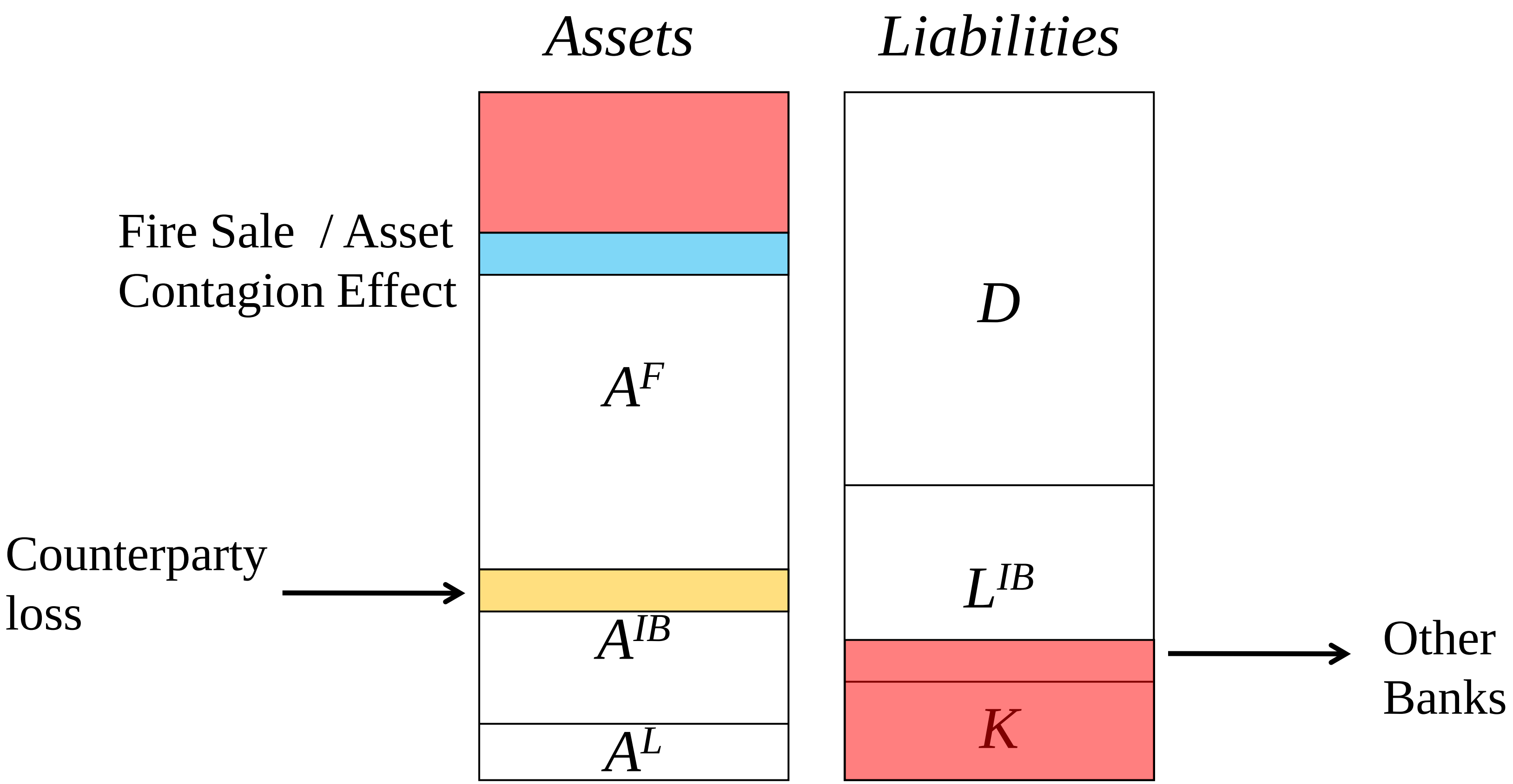
Default contagion – simulations: Nier *et al* (2007)

Default contagion and asset fire sales – theory and simulations: Gai and Kapadia (2010); May and Arinaminpathy (2010)



Default contagion and fire sales

Strength of asset price contagion effects depend on system confidence, *C*

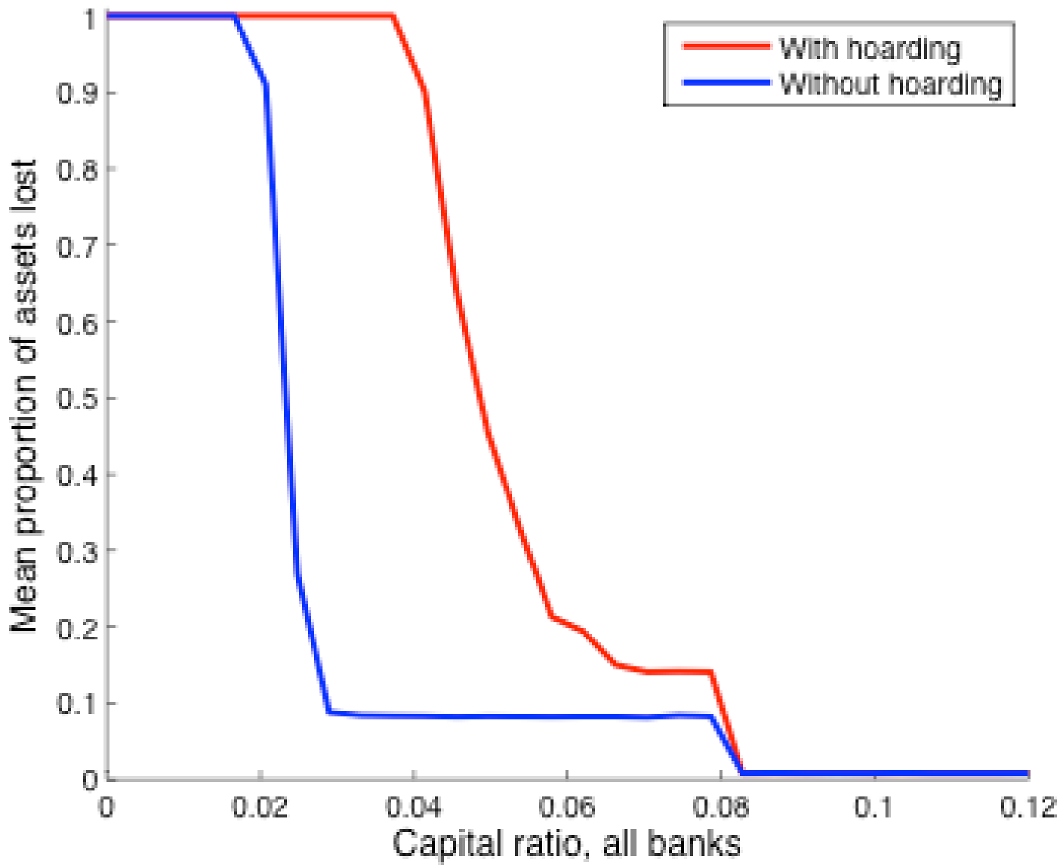


Shocks and Failure Conditions

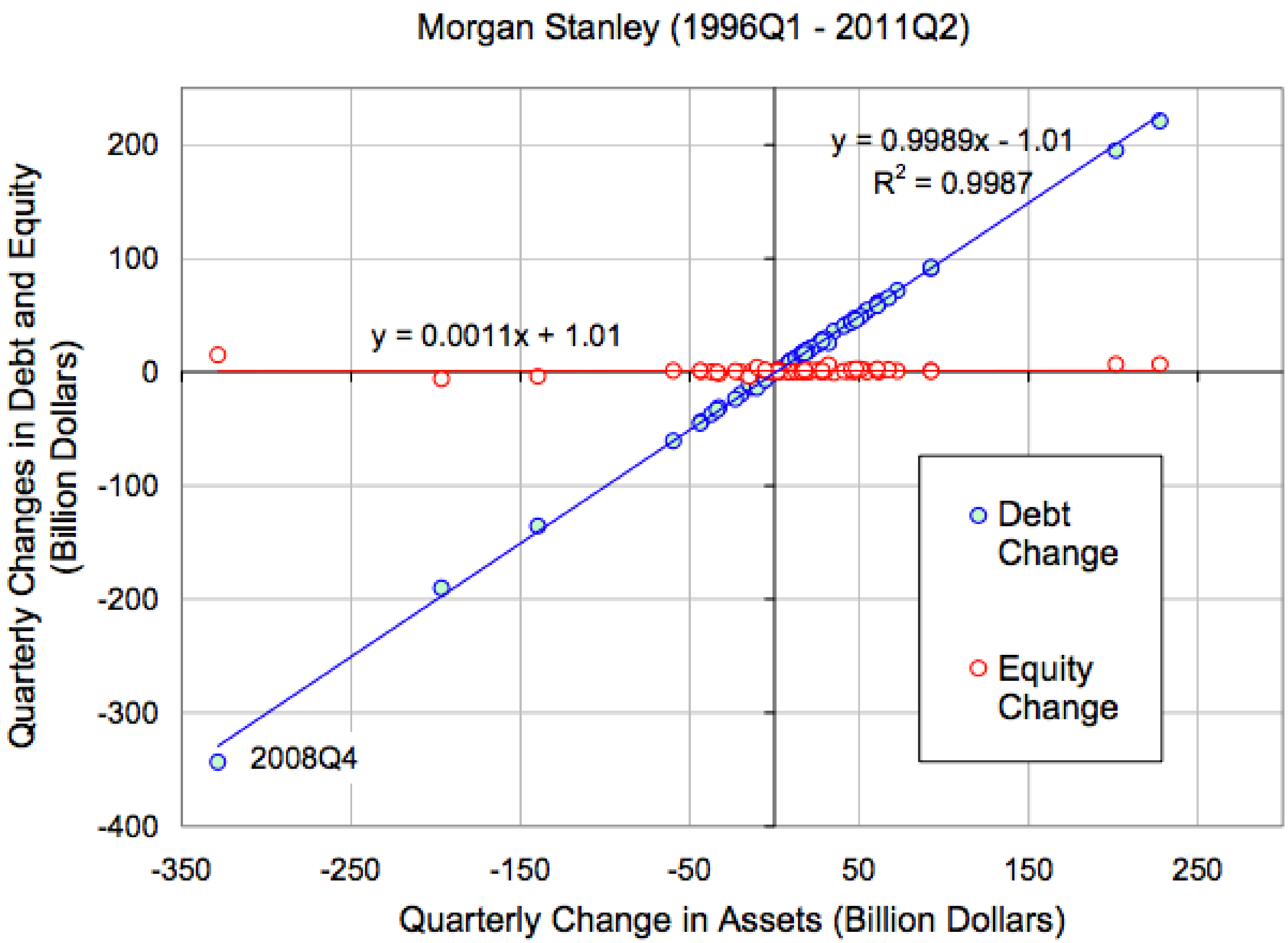
- Banks can fail for either:
  - capital reasons
  - liquidity reasons

- Initiating shock is either:
  - forced capital default of an individual bank
  - exogenous shock to a particular asset class

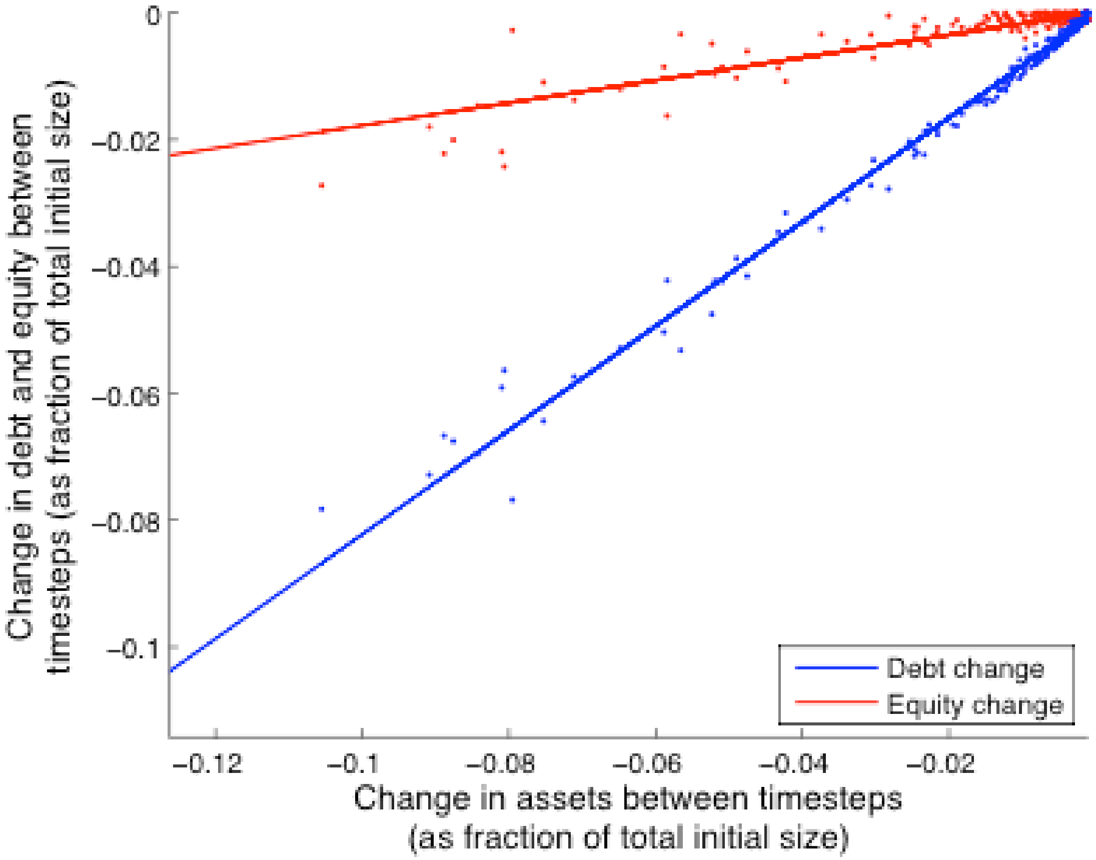
The effect of liquidity hoarding



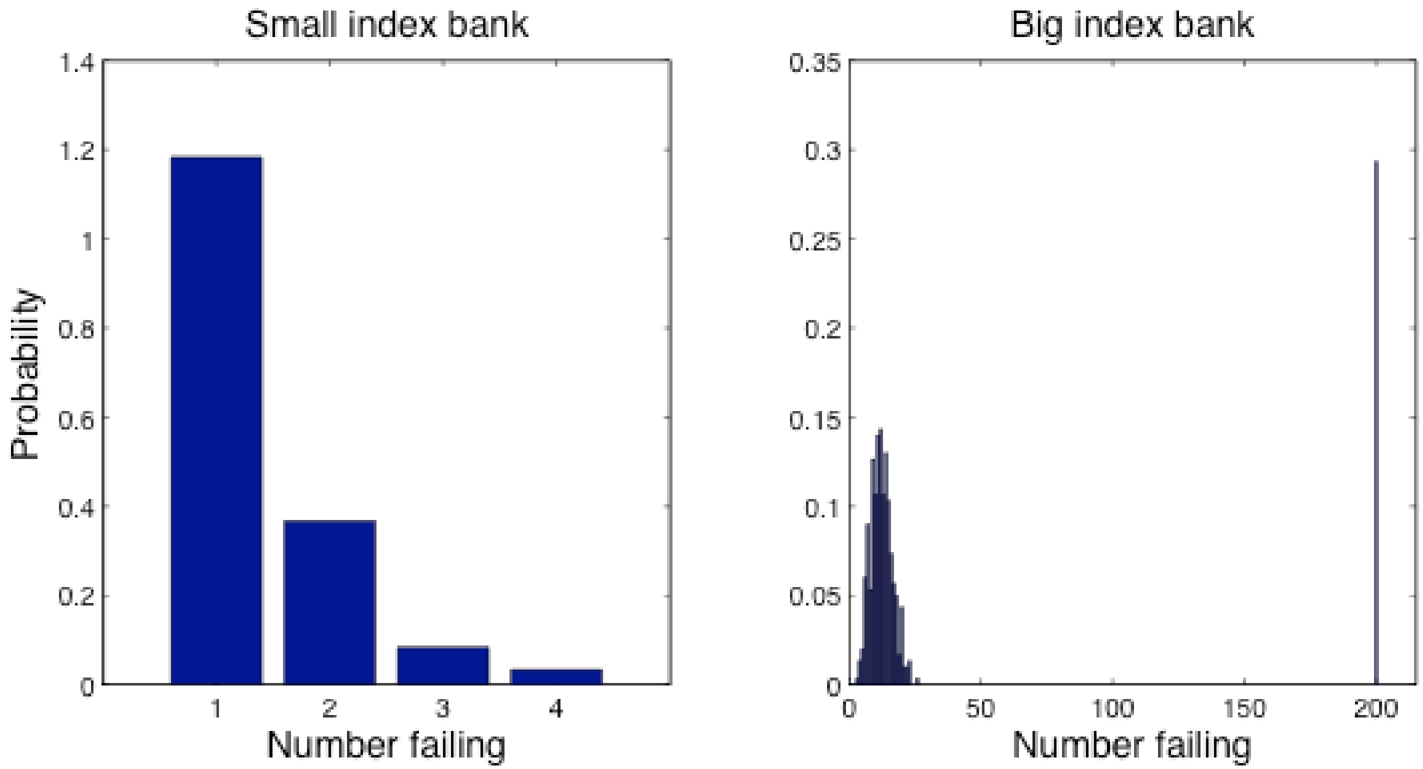
Procyclicality in leverage in the data… (Shin, 2012)



...and in the model

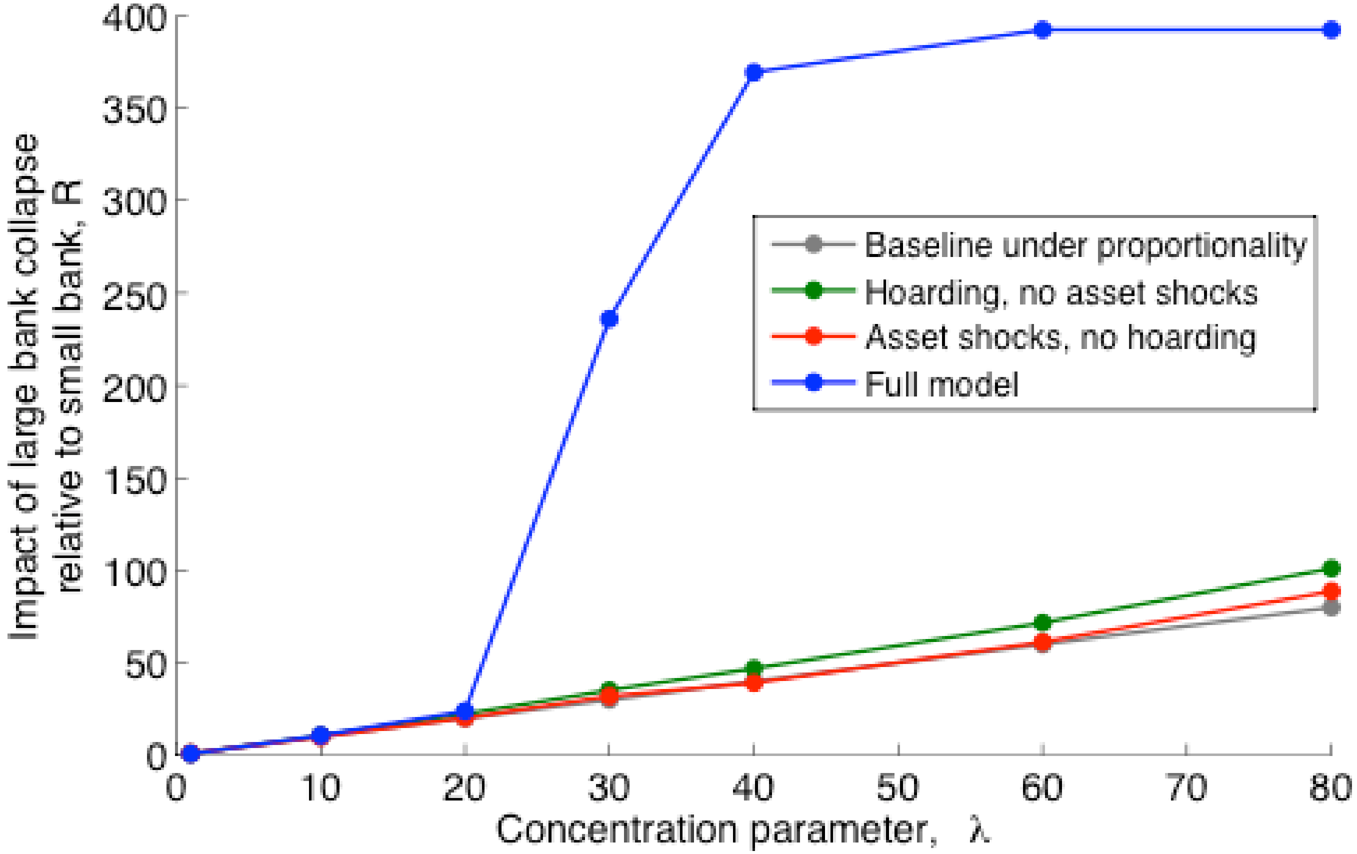


Effects of small and big bank collapse (1)

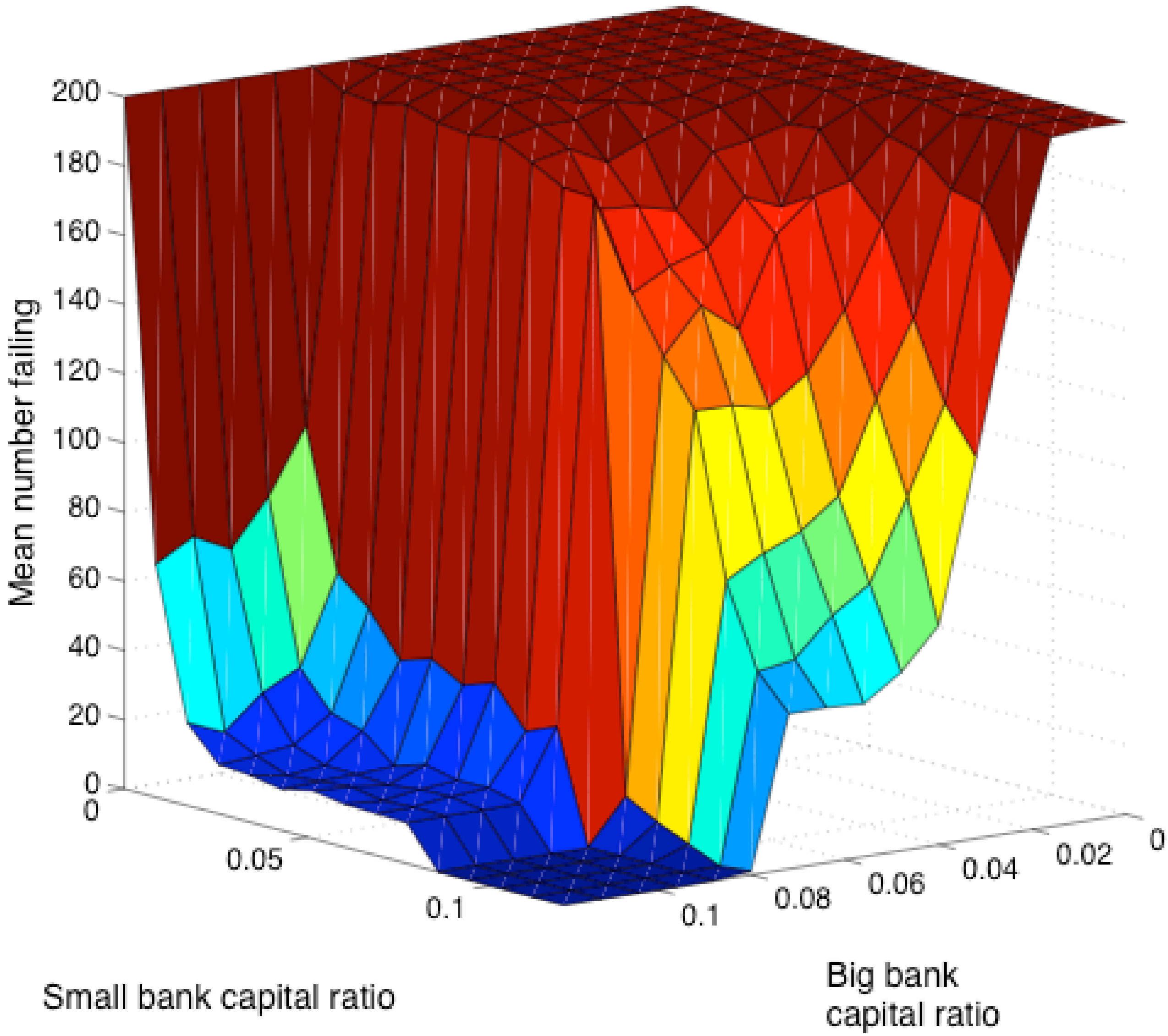


- Tipping point property evident

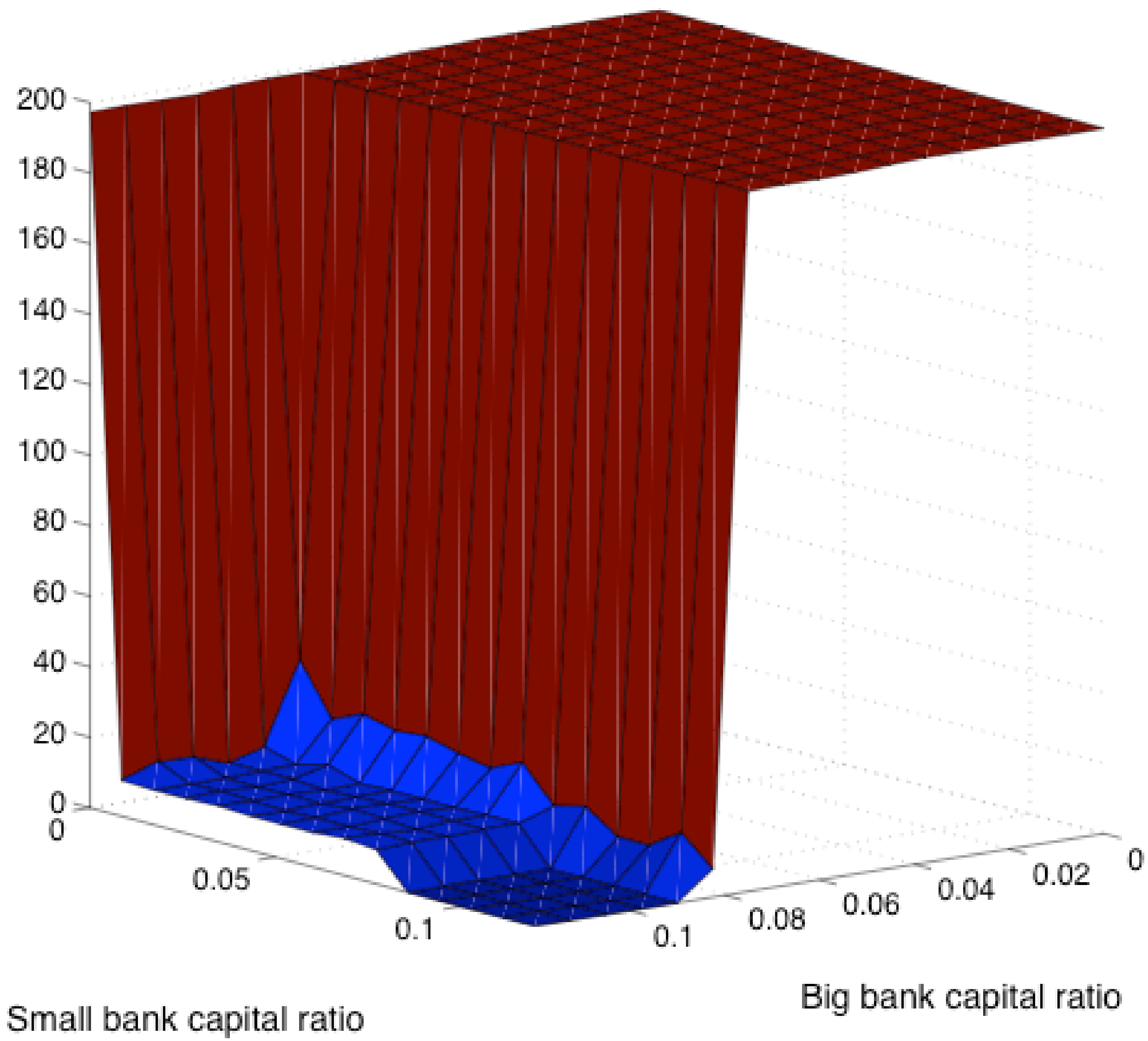
Effects of big and small bank collapse (2)



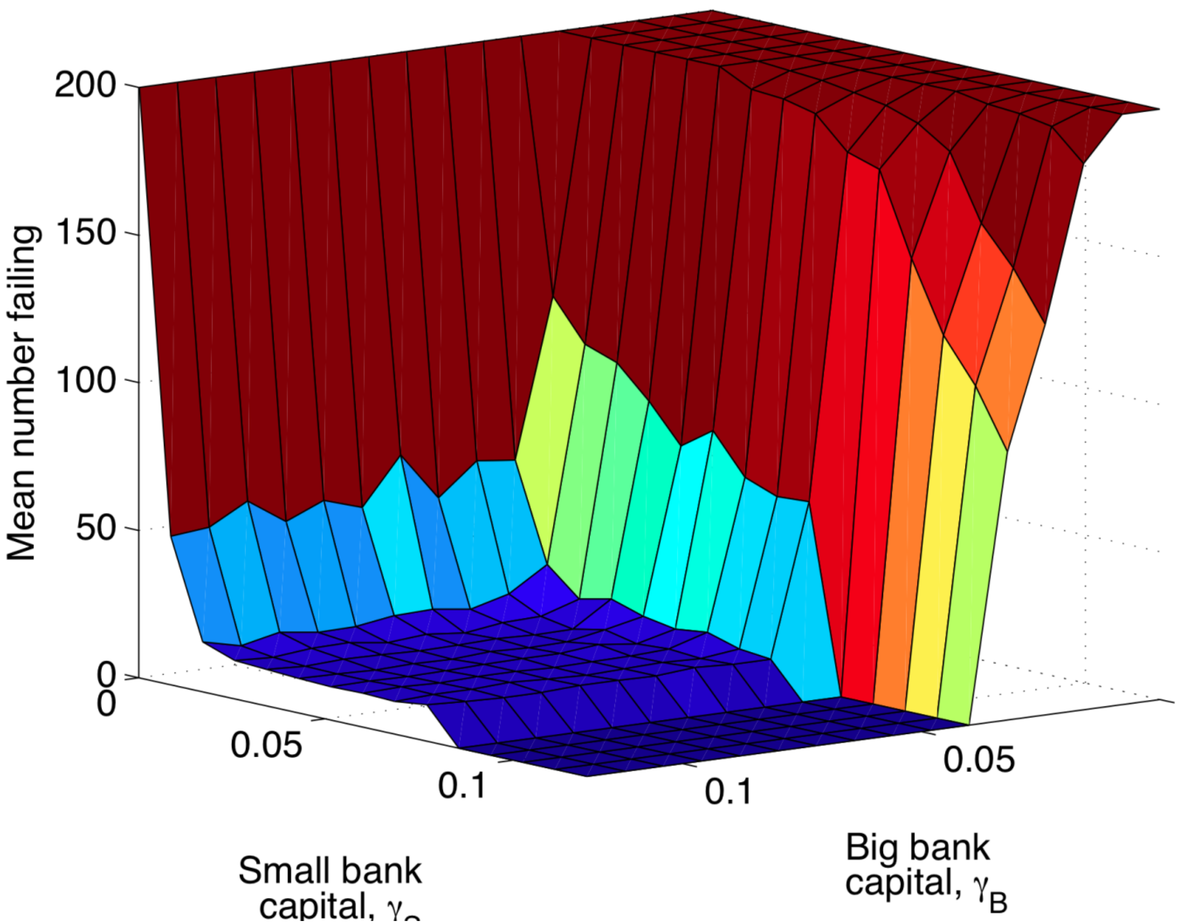
Capital ratios and systemic risk: baseline



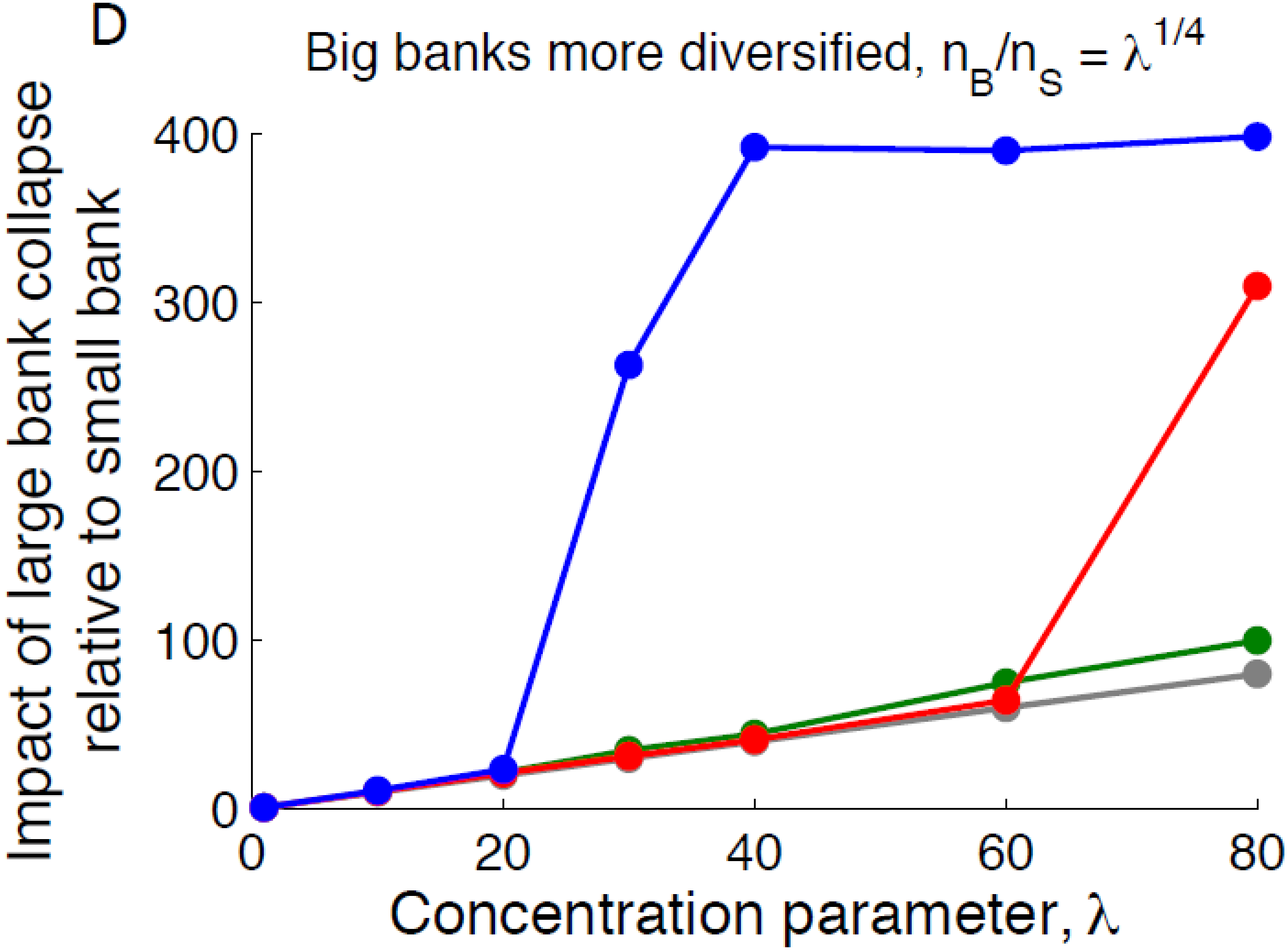
Capital ratios and systemic risk: more concentration



Allowing for diversification (1)



Allowing for diversification (2)



Methodological and Policy Implications

- Network approaches can parsimoniously capture key features of financial systems and contagion.
  - liquidity hoarding and confidence effects key

- Capital and liquidity surcharges for SIFIs
  - aim to make key nodes more resilient
  - incentivise banks to become less systemically important

- Broader policy implications:
  - Better Data and Greater Transparency (cf real-time management and mapping of SARS)
  - Netting and Central Clearing (simplicity and modularity)

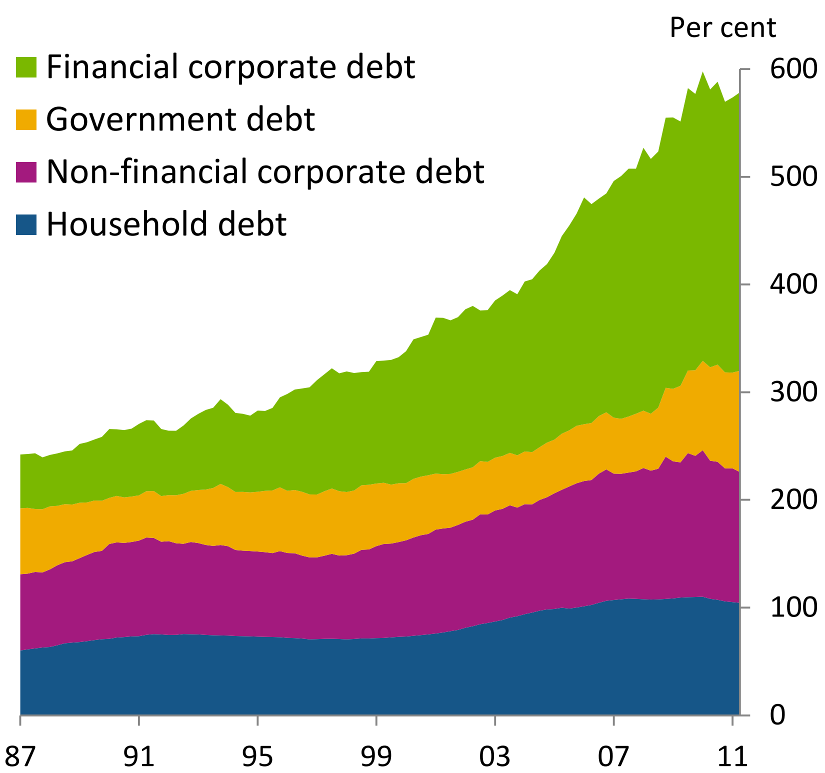
Challenges and Future Work

- Liquidity shocks and policies
- Stronger / more developed role for behavioural considerations (eg for the formation of links)
- Stronger role for uncertainty
- Procyclicality and endogenous shocks
- Integration into DSGE or agent-based models
- Greater empricism

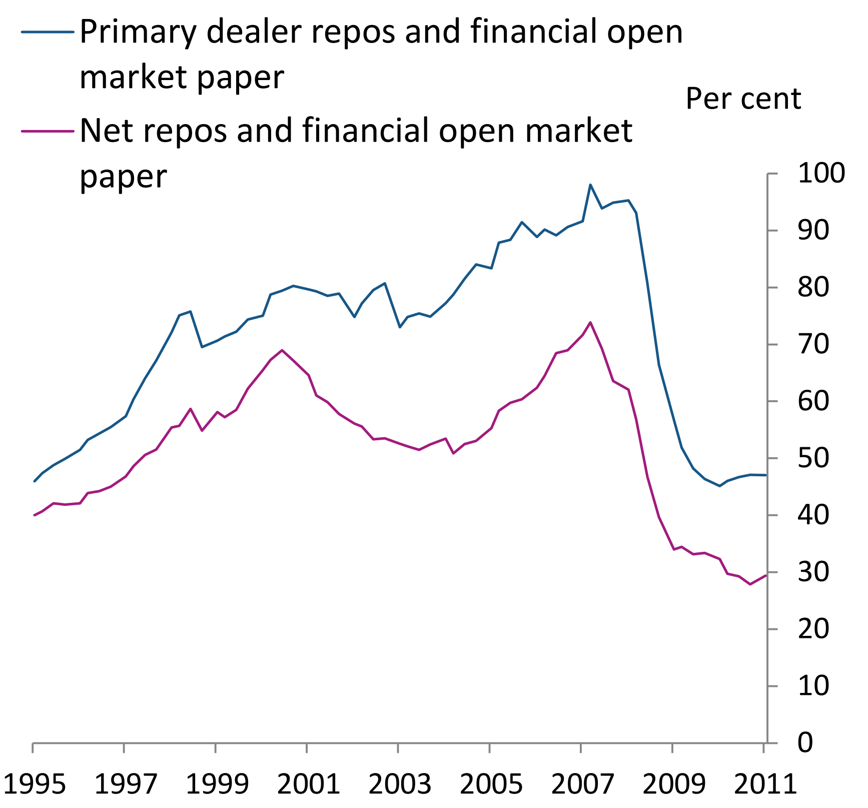
Reserve Slides

Profile of Intra-financial System Activity

Sectoral breakdown of UK debt, proportion of GDP



Repos & financial market open paper as a % of retail deposits in the US



Diversity and Systemic Risk

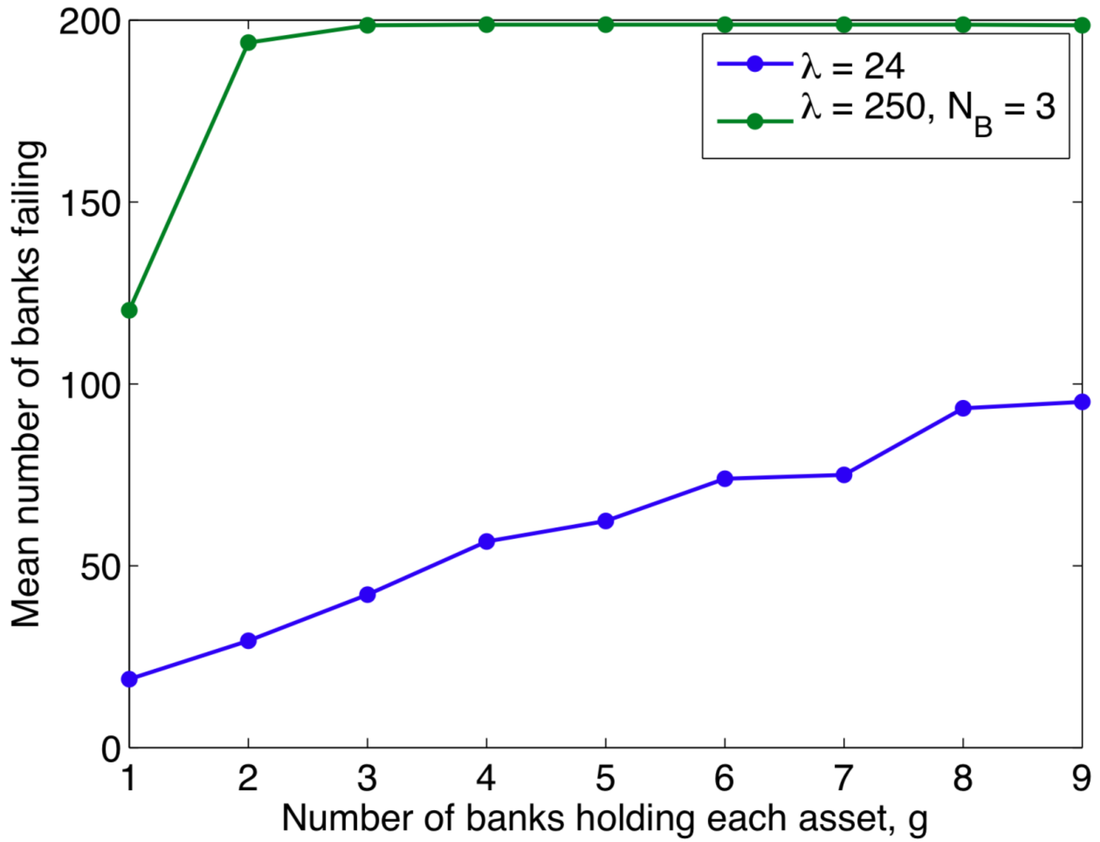


Figure S2

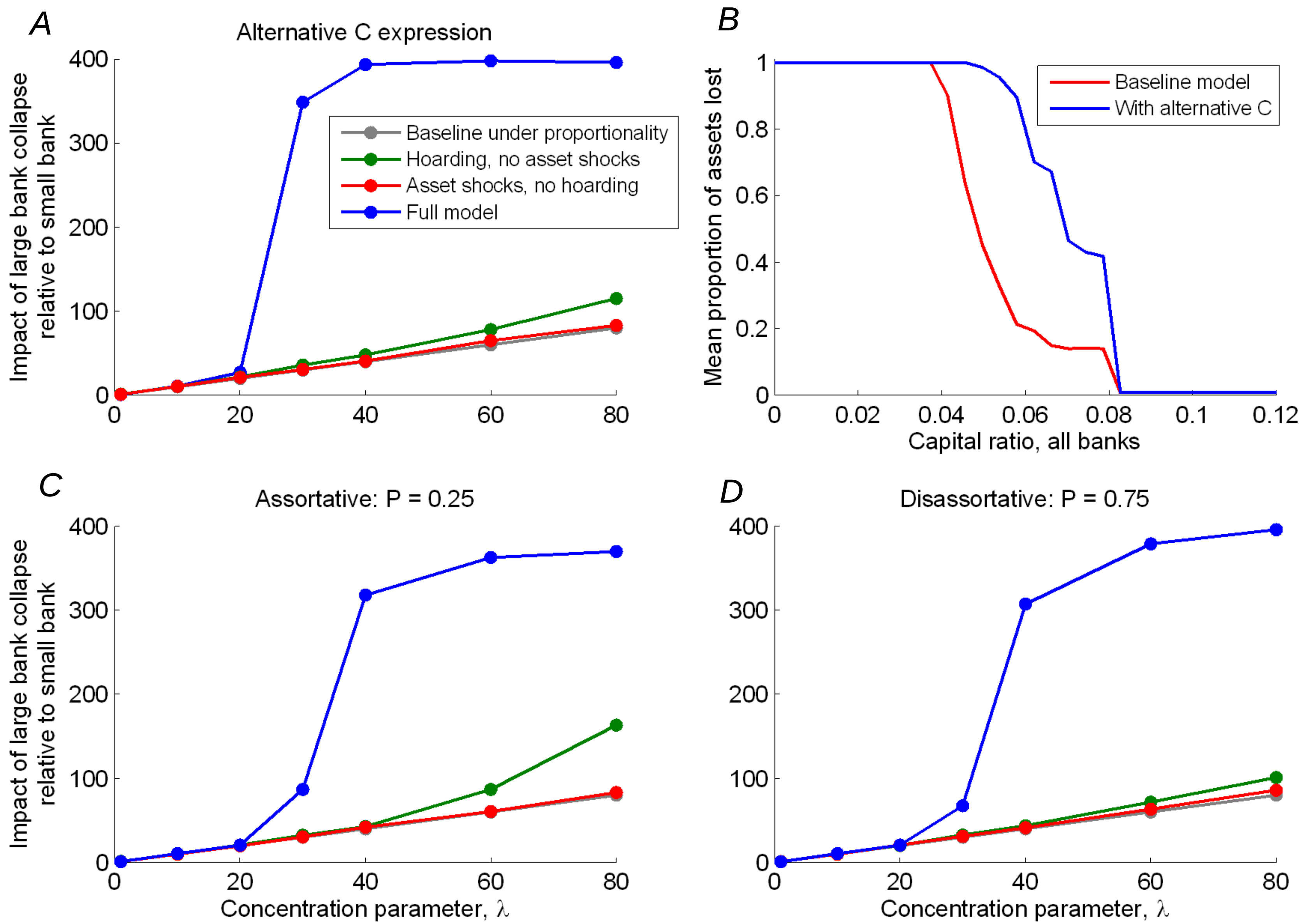
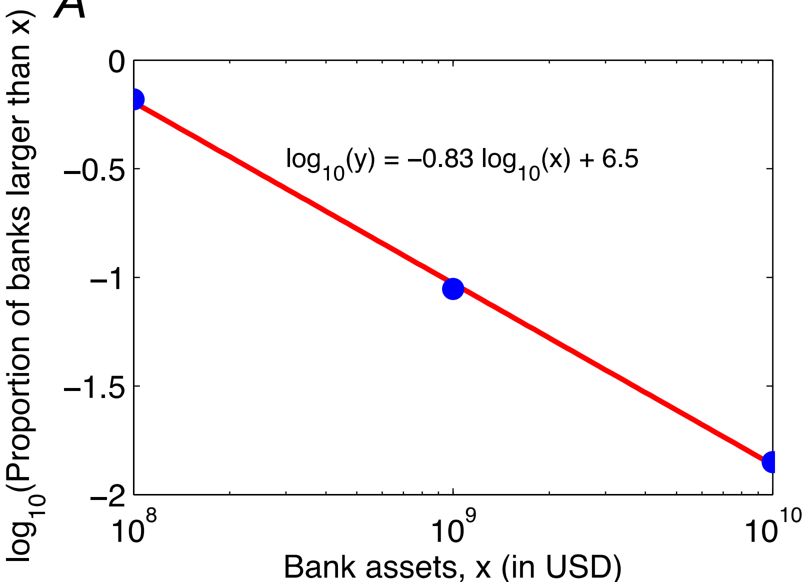

A
Alternative C expression
Impact of large bank collapse relative to small bank
400
300
200
100
0
0
20
40
60
80
Baseline under proportionality
Hoarding, no asset shocks
Asset shocks, no hoarding
Full model
B
Mean proportion of assets lost
1
0.8
0.6
0.4
0.2
0
0
0.02
0.04
0.06
0.08
0.1
0.12
Capital ratio, all banks
Baseline model
With alternative C
C
Assortative: P = 0.25
Concentration parameter, λ
D
Disassortative: P = 0.75
Concentration parameter, λ

Figure S3

A



B

C

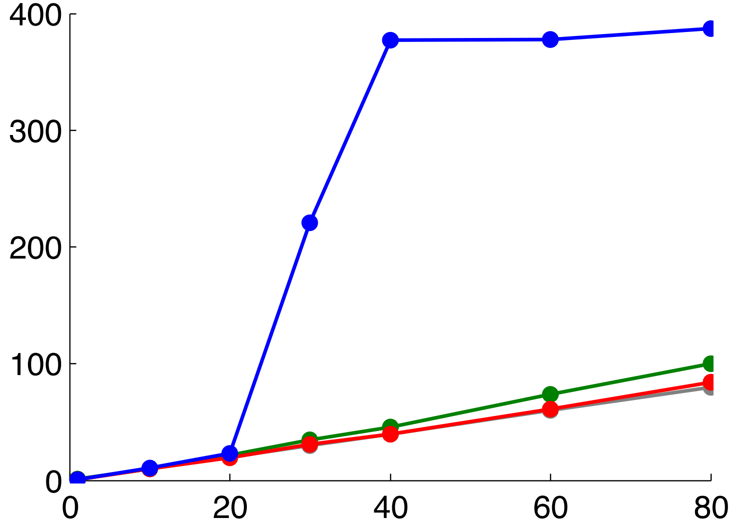
D

cks

Index bank size relative to system

Figure S4

A



B

C

bank failure