Size and complexity in model financial systems

Sujit Kapadia, Bank of England

Co-authors: Nimalan Arinaminpathy (Princeton)  
Robert May (Oxford)

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This paper represents the views of the authors and should not be thought to represent those of the Bank of England or Financial Policy Committee members.
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 $10 \times 10 = 100$ 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 $\Rightarrow$ 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

#### Liabilities

- "Capital", $\gamma a_i$
- **Deposits**
  - External asset, class 1
  - External asset, class 2
  - External asset, class 3
  - Liquid assets
  - **Interbank borrowing (mean z loans from other banks)**

#### Assets

**Assets (total size $a$)**

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#### Short-term lending

- Bank $i$ to Bank $j$

#### Long-term lending

- Bank $i$ to Bank $j$
Schematic characterisation of networks

Bank 1

Bank 2

Bank 3
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 $\lambda$ times ‘larger’ than small but $\lambda$ 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:

\[ h_i \cdot h_j < (1 - C) \]

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

- Banks withdraw loans altogether if either:

\[ h_i \cdot h_j < (1 - C)^2 \]

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 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

![Graph showing the effect of liquidity hoarding on mean proportion of assets lost versus capital ratio. The graph compares 'With hoarding' and 'Without hoarding' scenarios.]
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)

Big banks more diversified, $n_B/n_S = \lambda^{1/4}$

D

Impact of large bank collapse relative to small bank

Concentration parameter, $\lambda$

0  20  40  60  80

0  100  200  300  400
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 empiricism
Reserve Slides
Profile of Intra-financial System Activity

Sectoral breakdown of UK debt, proportion of GDP

- Financial corporate debt
- Government debt
- Non-financial corporate debt
- Household debt

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

- Primary dealer repos and financial open market paper
- Net repos and financial open market paper

Per cent
Diversity and Systemic Risk

![Graph](image)

- Blue line: \( \lambda = 24 \)
- Green line: \( \lambda = 250, N_B = 3 \)

Mean number of banks failing vs. Number of banks holding each asset, \( g \)
Figure S2

A) Alternative C expression

B) Mean proportion of assets lost vs. capital ratio, all banks

C) Assortative: \( P = 0.25 \)

D) Disassortative: \( P = 0.75 \)
**Figure S3**

![Graph showing the relationship between log10(y) and log10(x) with the equation log10(y) = -0.83 log10(x) + 6.5. The graph plots the proportion of banks larger than x against bank assets (x) in USD.](image)

Index bank size relative to system
Figure S4

A

B

C

bank failure

- Blue: Baseline model
- Green: Allowing pre-failure firesales
- Red: Taking $\alpha = 0.1$