Network Risk and Key Players: A Structural Analysis of Interbank Liquidity

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England.
The Big Picture

- Recent crisis stressed the need of understanding **systemic risk** generation and exposure in the banking industry.
- Traditional regulatory tools focused on bank-specific variables (e.g. capital ratios) and risk (e.g. default probabilities).
- Macro-prudential regulation seeks tools to quantify the systemic implication of individual bank’s behavior ⇒ e.g. banks that generate more systemic risk could face more stringent requirements.

**Our paper**: develops such a tool using **network theory**.

- Using a linear quadratic model, we can identify:
  1. the amplification mechanism, or multiplier, of liquidity shocks;
  2. the liquidity **level** key players (for bailout?);
  3. the liquidity **risk** key players (to regulate?).

- We also have implications for the efficiency of monetary policy interventions, liquidity injections, and Quantitative Easing.
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Daily Gross Settlement requires large intraday liquidity buffers.

Almost all banks in CHAPS regularly have intraday liquidity exposures in excess of £1bn to individual counterparties. For larger banks these exposures are regularly greater than £3bn.

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Why the Network Might Matter?

Several possible network effects, e.g.:
- domino/contagion (e.g. Gai & Kapadia (2010));
- free riding/strategic substitution (e.g. Bhattacharya & Gale (1987));
- economies of scale/"leverage stacks" strategic complementarity (e.g. Katz & Shapiro (1985), Moore (2011));

Our paper: ex-ante agnostic about network role and relevance.
- Flexible parametrization allows different “directions” of network effects.
- Allow network role to change over time.
  ⇒ Let the data speak:
  - Decompose risk into exogenous and network generated parts
    ⇒ time varying network generates heteroskedastic liquidity.
  - Construct Network Impulse-Response Functions to individual banks’ shocks ⇒ akin to variance decomposition.
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1. Theoretical Framework
   - Network Specification
   - Bank Objective Function and Nash Equilibrium
   - Risk, and Level, Key Players

2. Empirical Analysis
   - Empirical Specification
   - Network and Data Description
   - Estimation Results

3. Related Literature

4. Conclusions

Appendix
Outline

1. Theoretical Framework
   - Network Specification
   - Bank Objective Function and Nash Equilibrium
   - Risk, and Level, Key Players

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> Appendix
Network Specification

- A directed and weighted network of \( n \) banks.

Network \( g \): characterized by \( n \)-square adjacency matrix \( G \) with elements \( g_{i,j} \), and \( g_{i,i} = 0 \).

\( g_{i,j \neq i} \): the fraction of borrowing by Bank \( i \) from Bank \( j \).

\( \Rightarrow \) \( G \) is a (right) stochastic matrix and is not symmetric

- A centrality metric (à la Katz-Bonacich) with decay \( \phi \)

\[
M(\phi, G) = I + \phi G + \phi^2 G^2 + \phi^3 G^3 + ... = \sum_{k=0}^{\infty} \phi^k G^k.
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Note: If \( |\phi| < 1 \), this converges to \( (I - \phi G)^{-1} \).
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Bank Objective Function

- **Bank \( i \) decision variables:**
  
  \[ q_i : \text{liquidity level of bank } i \text{ absent bilateral effects.} \]

  \[ q_i = q_i(x) := \alpha_i + \sum_{m=1}^{M} \beta_m x_i^m + \sum_{p=1}^{P} \beta_p x^p \]

  \[ z_i : \text{the network component of liquidity buffer stock.} \]

  \[ \Rightarrow l_i = q_i + z_i : \text{is the observable liquidity holding of bank } i. \]
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A quadratic payoff function for buffer stock liquidity

\[ u_i(z_i|g) = \hat{\mu}_i \left( z_i + \psi \sum_j g_{ij} z_j \right) - \frac{1}{2} \gamma \left( z_i + \psi \sum_{j \neq i} g_{ij} z_j \right)^2 + z_i \delta \sum_j g_{ij} z_j \]

\[ \hat{\mu}_i / \gamma = \bar{\mu}_i + \nu_i \sim i.i.d (0, \sigma_i^2) \]

bilateral network influence:

\[ \frac{\partial^2 u_i(z|g)}{\partial z_i \partial z_j} = (\delta - \gamma \psi) g_{ij} \]

Note: \( g \) predetermined at decision time (but can change over time).
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Bank Objective Function cont’d

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Eq. \( ^{um} \) : (Nash) If \(|\phi| < 1\)

\[
\begin{align*}
    z_i^* &= \bar{\mu}_i + \phi \sum_{j=1}^{n} g_{i,j} z_j + v_i \\
    \Rightarrow l_i^* &= q_i(x) + z_i^* = q_i(x) + \{ M(\phi, G) \}_i. \mu \\

    \text{where } \mu := \gamma^{-1} [\hat{\mu}_1, ..., \hat{\mu}_n]', \{ \} _i. \text{ is the row operator, and}
    \\
    \phi := \frac{\delta}{\gamma} - \psi
\end{align*}
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Note:
If \( \phi > 0 \) complementarity (reciprocate/herding/leverage stacks e.g. Moore (2011)).
If \( \phi < 0 \) substitutability (free ride à la Bhattacharya and Gale (1987)).
(Decentralized) Equilibrium Outcome

\[ \text{Eq.}^{um} : \text{(Nash) If } |\phi| < 1 \]

\[ z_i^* = \mu_i + \phi \sum_{j=1}^{n} g_{i,j} z_j + \nu_i \]

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The total liquidity originating from the network externalities is

$$1'z^* = 1'M(\phi, G)\bar{\mu} + 1'M(\phi, G)v$$

where $z^* \equiv [z_1^*, ..., z_n^*]'$, $\bar{\mu} \equiv [\bar{\mu}_1, ..., \bar{\mu}_n]'$, $v \equiv [v_1, ..., v_n]'$

$\Rightarrow$ tradeoff: both terms increasing in $\phi$ (for $\bar{\mu} > 0$).

**Risk Key Player:** (the one to worry about...)

$$\max_i \frac{\partial 1'z^*}{\partial v_i}\sigma_i = \max_i 1'\{M(\phi, G)\}_i \sigma_i \rightarrow \text{outdegree centrality}$$

**Level Key Player:** (the one you might want to bailout...)

$$\max_i E[1'z^* - 1'z_i^*] = \max_i \{M(\phi, G)\}_i \bar{\mu} + 1'\{M(\phi, G)\}_i \bar{\mu}_i - m_{i,i} \bar{\mu}_i$$

indegree centrality + shock analogous – correct double counting
The total liquidity originating from the network externalities is

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Key Players

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where \( z^* \equiv [z_1^*, ..., z_n^*]' \), \( \bar{\mu} \equiv [\bar{\mu}_1, ..., \bar{\mu}_n]' \), \( v \equiv [v_1, ..., v_n]' \)

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**Risk Key Player:** (the one to worry about...)

\[ \max_i \frac{\partial 1'z^*}{\partial v_i} \sigma_i = \max_i 1' \{M(\phi, G)\}_i \sigma_i \rightarrow \text{outdegree centrality} \]

**Level Key Player:** (the one you might want to bailout...)

\[ \max_i E[1'z^* - 1'z_i^*] = \max_i \{M(\phi, G)_i, \bar{\mu} + 1' \{M(\phi, G)\}_i \bar{\mu}_i - m_{i,i}\bar{\mu}_i \]

indegree centrality + shock analogous − correct double counting
Key Players

The total liquidity originating from the network externalities is

\[ 1'z^* = 1'M(\phi, G)\bar{\mu} + 1'M(\phi, G)v \]

where \( z^* \equiv [z^*_1, \ldots, z^*_n]' \), \( \bar{\mu} \equiv [\bar{\mu}_1, \ldots, \bar{\mu}_n]' \), \( v \equiv [v_1, \ldots, v_n]' \)

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level effect risk effect

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$$\max_i E \left[1'z^* - 1'z^*_{\setminus i}\right] = \max_i \{M(\phi, G)\}_i \bar{\mu} + 1' \{M(\phi, G)\}_i \bar{\mu}_i - m_{i,i} \bar{\mu}_i$$

indegree centrality + shock analogous − correct double counting
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\]

indegree centrality + shock analogous - correct double counting
A planner chooses \( z_i, i = 1, \ldots, n \) to maximize the total

\[
\max_{z_1, \ldots, z_i, \ldots, z_n} \sum_i \left[ \hat{\mu}_i \left( z_i + \psi \sum_j g_{ij} z_j \right) + z_i \delta \sum_j g_{ij} z_j - \frac{1}{2} \gamma \left( z_i + \psi \sum_{j \neq i} g_{ij} z_j \right)^2 \right].
\]

FOC:

\[
z_i = \mu_i + \phi \sum_{j \neq i} g_{ij} z_j + \psi \sum_{j \neq i} g_{ji} \mu_j + \\
\phi \sum_{j \neq i} g_{ji} z_j - \psi^2 \sum_{j \neq i} \sum_m g_{ji} g_{jm} z_m
\]

- decentralized f.o.c.
- neighbors' idiosyncratic valuations of own liquidity
- neighbors' indegree i.e. own outdegree
- volatility of neighbors' accessible network liquidity
1. Theoretical Framework
   - Network Specification
   - Bank Objective Function and Nash Equilibrium
   - Risk, and Level, Key Players

2. Empirical Analysis
   - Empirical Specification
   - Network and Data Description
   - Estimation Results

3. Related Literature

4. Conclusions

Appendix
Theoretical Framework
Empirical Analysis
Conclusions

Empirical Specification
Network and Data Description
Estimation Results

Empirical Model

**SEM:** the theoretical framework is matched by a **Spatial Error Model**

\[ l_{i,t} = \alpha_i + \sum_{m=1}^{M} \beta_{m}^{\text{bank}} x_{i,t}^{m} + \sum_{p=1}^{P} \beta_{p}^{\text{time}} x_{t}^{p} + z_{i,t} \]

\[ z_{i,t} = \bar{\mu}_i + \phi \sum_{j=1}^{n} g_{i,j,t} z_{j,t} + \nu_{i,t}, \quad \nu_{i,t} \sim iid \left( 0, \sigma_i^2 \right), \]

where \( g_{i,j,t}, x_{i,t}^{m} \) and \( x_{t}^{p} \) are predetermined at time \( t \).

**Note:**
1. Network as a shock propagation mechanism
   \( \Rightarrow (\text{average}) \) Network Multiplier: \( 1 / (1 - \phi) \)
2. Total liquidity, \( L_t \equiv 1'[l_{1,t}, \ldots, l_{n,t}] \), is heteroskedastic:
   \[ Var_{t-1} (L_t) = 1' M (\phi, G_t) \text{ diag } \left( \{ \sigma_i^2 \}_{i=1}^{n} \right) M (\phi, G_t)' 1. \]
3. Can perform Q-MLE (\( \phi \) overidentified if \( rank \left( M (\phi, G_t) \right) > 2 \))
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I_{i,t} = \alpha_i + \sum_{m=1}^{M} \beta_{m}^{bank} x_{i,t}^m + \sum_{p=1}^{P} \beta_{p}^{time} x_{t}^p + z_{i,t}
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SDM: For robustness, we also consider a direct network effect of banks observable characteristic, liquidity decisions, and possible match specific control variables, $x_{i,j,t}$ (Spatial Durbin Model)

$$l_{i,t} = \bar{\alpha}_i + \sum_{m=1}^{M} \beta_m^{bank} x_{i,t}^m + \sum_{p=1}^{P} \gamma_p^{time} x_{t}^p + \psi \sum_{j=1}^{n} g_{i,j,t} l_{j,t} + \sum_{j=1}^{n} g_{i,j,t} x_{i,j,t} \theta + v_{i,t}$$

Note: if $x_{i,j,t} := \text{vec}(x_{j\neq i,t}^m)'$, $\psi = \phi$, $\theta = -\phi \text{vec}(\beta_m^{bank})$, $\gamma_p^{time} = (1 - \phi) \beta_p^{time} \forall p \Rightarrow$ back to SEM

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Empirical Model: Specification Test

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The network impulse-response of total liquidity, $L_t$, to a one standard deviation shock to bank $i$ is

$$NIRF_i (\phi, G_t, \sigma_i) \equiv \frac{\partial L_t}{\partial \nu_{i,t}} \sigma_i = 1' \{ M (\phi, G_t) \}.i \sigma_i$$

NIRFs:

1. are pinned down by the outdegree centrality and

   $$\text{Risk Key Player} \equiv \arg\max_i NIRF_i (\phi, G_t, \sigma_i)$$

2. account for all direct and indirect links among banks since

   $$1' \{ M (\phi, G_t) \}.i = 1' \{ I + \phi G_t + \phi^2 G_t^2 + \ldots \}.i = 1' \left\{ \sum_{k=0}^{\infty} \phi^k G_k^k \right\}.i$$

3. are a natural decomposition of total liquidity variance

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Network Impulse-Response Functions

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Network Description

Network Banks: all CHAPS members in 2006-2010

- Bank of Scotland
- Barclays
- Citibank
- Clydesdale
- Co-operative Bank
- Deutsche Bank
- HSBC
- Lloyds TSB
- NatWest/RBS
- Santander
- Standard Chartered

Note: non CHAPS members have to channel their payments through these banks.

Network Proxy:

proxy the intensity of network links using the interbank borrowing relations

\[ g_{i,j,t} = \text{the fraction of bank } i \text{'s loans borrowed from bank } j \]

Note: weights computed as monthly averages in previous month.
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Other Data Description

**Sample:** from Feb 2006 to Sept 2010, daily data.  
**Dependent Variable:** liquidity available at the beginning of the day (account balance plus posting of collateral)

**Macro Controls:** (aggregate risk proxies, lagged)
- LIBOR; Interbank Rate; Intraday Volatility of Liquidity Available; Turnover Rate in Payment System; Right Kurtosis of Aggregate Payment Time; time trend.

**Banks Characteristics:** (lagged)
- Interest Rate (weighted average); Right Kurtosis of Payment (Out) Time; Right Kurtosis of Payment (In) Time; Intraday Volatility of Liquidity Available; Total Intraday Payments; Liquidity Used; (Benos, Garratt and Zimmerman, 2010); Repo liability to Total Asset Ratio; Cumulative Change in Retail Deposit to Total Asset Ratio; Total Lending and Borrowing in Interbank Market; Stock Return; CDS.
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Other Data Description

**Sample:** from Feb 2006 to Sept 2010, daily data.

**Dependent Variable:** liquidity available at the beginning of the day (account balance plus posting of collateral)

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Two types of estimation:

1. **Subsample estimations:**
   - (good times) Pre Hedge Fund Crisis/ Northern Rock
   - (fin. crisis) Hedge Fund Crisis – Asset Purchase Program Announcement
   - (Q.E.) Post Asset Purchase Program Announcement

2. Rolling estimations with 6-month window $\Rightarrow$ allow $\phi$ to change at higher frequency.
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2. **Rolling estimations with 6-month window** ⇒ allow $\phi$ to change at higher frequency.
### SEM Estimation

<table>
<thead>
<tr>
<th></th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Network Effect:</strong> ( \phi )</td>
<td>0.640*</td>
<td>0.166*</td>
<td>-0.151*</td>
</tr>
<tr>
<td></td>
<td>(52.44)</td>
<td>(7.06)</td>
<td>(-6.45)</td>
</tr>
<tr>
<td><strong>( R^2 )</strong></td>
<td>69.11%</td>
<td>89.71%</td>
<td>85.54%</td>
</tr>
<tr>
<td><strong>(average) Network Multiplier</strong></td>
<td>2.77*</td>
<td>1.12*</td>
<td>0.87*</td>
</tr>
</tbody>
</table>
Period 1: \( NIRQ^e(\phi, \bar{G}, 1) \) – Risk Key Players

Pre Northern Rock/Hedge Fund Crisis

Excess NIRF

+/- 2 s.e. C.I.

Excess network multiplier

+/- 2 s.e. C.I.

Bank 1

Bank 2

Bank 3

Bank 4

Bank 5

Bank 6

Bank 7

Bank 8

Bank 9

Bank 10

Bank 11

bank index
**Period 1: Net Borrowing**

- Bank 1: 1e+11
- Bank 2: -5e+10
- Bank 3: 0e+00
- Bank 4: 5e+10
- Bank 5: 1e+11
- Bank 6: -1e+11
- Bank 7: 5e+10
- Bank 8: 1e+11
- Bank 9: -5e+10
- Bank 10: 0e+00
- Bank 11: 1e+11
Period 1: Network Borrowing/Lending Flows
Period 2: $NIRF^e(\phi, \bar{G}, 1)$ – Risk Key Players

Post Hedge Fund Crisis - Pre Asset Purchase Programme

Note: network risk reduction despite increased borrowing & lending
Period 3: $NIRF^e(\phi, \bar{G}, 1)$ – Risk Key Players

![Diagram showing excess NIRF and network multipliers for various banks post Asset Purchase Programme Announcement.](image-url)
Theoretical Framework
Empirical Analysis
Conclusions

Empirical Specification
Network and Data Description
Estimation Results

\( \hat{\phi} \): SEM Rolling Estimation (6-month window)

\[ \hat{\phi} \text{ : SEM Rolling Estimation (6-month window)} \]

\( \hat{\phi} \) vs Time

- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
- 20080311: Bear Stearns
- 20080915: Lehman Brothers
- 20090119: Asset Purchase Programme Announced

Network Risk and Key Players
\( \hat{\phi} \) and \( \hat{\psi} \): SEM and SDM Rolling Estimation (6-month window)
1 Theoretical Framework
   - Network Specification
   - Bank Objective Function and Nash Equilibrium
   - Risk, and Level, Key Players

2 Empirical Analysis
   - Empirical Specification
   - Network and Data Description
   - Estimation Results

3 Related Literature

4 Conclusions
Theoretical models on liquidity provision in banking systems: coinsurance, counterparty & liquidity risk, hoarding, free-riding, leverage stacks …

- Allen & Gale (2000); Freixas, Parigi & Rochet (2000); Allen, Carletti & Gale (2008); Bhattacharya & Gale (1987), Moore (2011)

Empirical work

Liquidity provision in payment systems

- Furfine (2000): Fed fund rate is related to payment flows
- Benos, Garratt, & Zimmerman (2010): banks make payments at a slower pace after the Lehman failure
- Ball, Dendee, Manning & Wetherilt (2011): intraday liquidity

Overnight loan networks in recent financial crises

- Afonso, Kovner & Schoar (2010): counter-party risk plays a role in the interbank lending market during the 2008 crisis.
- Wetherilt, Zimmerman, & Sormaki (2010): document the network characteristics during the recent crisis
Outline

1. Theoretical Framework
   - Network Specification
   - Bank Objective Function and Nash Equilibrium
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2. Empirical Analysis
   - Empirical Specification
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3. Related Literature

4. Conclusions

Appendix
Conclusions

We provide:

- an implementable approach to assess interbank network risk:
  1. network shocks multiplier
  2. risk, and level, key players identification
  3. network impulse-response functions

Empirical Findings:

1. First estimation of network risk multiplier ⇒ a significant shock propagation mechanism for liquidity
2. The network multiplier and risk:
   - vary significantly over time, and can be very large.
   - implies complementarity (and high risk) before the crisis.
   - it’s basically zero post Bearn Stearns ⇒ rational reaction.
   - indicates free riding on the liquidity provided by the Quantitative Easing.
3. most of the systemic risk is generated by a small subset of key players (and not necessarily the obvious ones).
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Appendix

5 Additional Data Info
- Second Largest Eigenvalue of $G_t$
- Average Clustering Coefficient
- Other Variables

6 Additional Estimation Result
- Full SEM Results

7 Network Evolution
- Net Borrowing
- Network Borrowing/Lending Flows
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The Second Largest Eigenvalue of $G_t$

The graph shows the second largest eigenvalue of the weight matrix over time, with significant spikes occurring during certain events:
- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
- 20080311: Bear Stearns
- 20080914: Lehman Brothers
- 20090919: Asset Purchase Programme Announced

The events are marked on the time axis, with the corresponding eigenvalue values plotted over time.
Cohesiveness

**Q:** How cohesive is this network?

**A:** Average Clustering Coefficient (Watts and Strogatz, 1998)

\[
ACC = \frac{1}{n} \sum_{i=1}^{n} CL_i(G),
\]

\[
CL_i(G) = \frac{\#\{jk \in G \mid k \neq j, j \in n_i(G), k \in n_i(G)\}}{\#\{jk \mid k \neq j, j \in n_i(G), k \in n_i(G)\}}
\]

where \(n\) is the number of members in the network and \(n_i(G)\) is the set of players between whom and player \(i\) there is an edge.

**Numerator:** # of pairs of banks linked to \(i\) that are also linked to each other

**Denominator:** # of pairs of banks linked to \(i\)
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Denominator: \# of pairs of banks linked to \( i \)
Average Clustering Coefficient of the Network

The graph shows the average clustering coefficient of the network over time, with key events marked along the x-axis:
- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
- 20080311: Bear Stearns
- 20080914: Lehman Brothers
- 20090919: Asset Purchase Programme Announced

The y-axis represents the clustering coefficient, ranging from 0.55 to 0.95.
Aggregate Liquidity Available at the Beginning of a Day

- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
- 20080311: Bear Stearns
- 20080914: Lehman Brothers
- 20090919: Asset Purchase Programme Announced

Time (GBP):
- 060525
- 061016
- 070308
- 070801
- 071220
- 080516
- 081007
- 090227
- 090723
- 091211
- 100510
- 100929

Network Risk and Key Players
Interest Rate in Interbank Market

- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
- 20080311: Bear Stearns
- 20080914: Lehman Brothers
- 20090919: Asset Purchase Programme Announced

Graph showing changes in interest rate over time with key events marked on the timeline.
Cross-Sectional Dispersion of Interbank Rate

- 20070201: Subprime Default
- 20070809: Bear Stearns
- 20080311: Northern Rock/Hedge Fund Crisis
- 20080814: Lehman Brothers
- 20090919: Asset Purchase Programme Announced
Intraday Volatility of Aggregate Liquidity Available

- 20070201: Subprime Default
- 20070809: Northern Rock/Hedge Fund Crisis
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Right Kurtosis of Aggregate Payment Time

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▶ Appendix
### SEM Estimation

**R²**

<table>
<thead>
<tr>
<th></th>
<th>Period 1</th>
<th>Period 2</th>
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<tbody>
<tr>
<td><strong>69.11%</strong></td>
<td><strong>89.71%</strong></td>
<td><strong>85.54%</strong></td>
<td></td>
</tr>
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</table>

**Network Effect: φ**

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<th></th>
<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.6400*</td>
<td>0.1660*</td>
<td>−0.1510*</td>
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<tr>
<td>(52.44)</td>
<td>(7.06)</td>
<td>(−6.45)</td>
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</table>

### Macro Controls

<table>
<thead>
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<th>Period 1</th>
<th>Period 2</th>
<th>Period 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Aggregate Liquidity (log)</strong></td>
<td>−0.0020</td>
<td>0.3324*</td>
<td>0.5974*</td>
</tr>
<tr>
<td></td>
<td>(−0.04)</td>
<td>(4.59)</td>
<td>(14.73)</td>
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<tr>
<td><strong>Right Kurtosis of Payments</strong></td>
<td>−0.1654*</td>
<td>0.0265</td>
<td>0.0031</td>
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<tr>
<td></td>
<td>(−2.39)</td>
<td>(1.12)</td>
<td>(1.01)</td>
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<tr>
<td><strong>Volatility of Liquidity (log)</strong></td>
<td>0.1750</td>
<td>0.1935*</td>
<td>0.0075</td>
</tr>
<tr>
<td></td>
<td>(1.37)</td>
<td>(7.15)</td>
<td>(0.52)</td>
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<tr>
<td><strong>Turnover Rate</strong></td>
<td>0.0097</td>
<td>0.0055*</td>
<td>0.0049*</td>
</tr>
<tr>
<td></td>
<td>(1.51)</td>
<td>(2.87)</td>
<td>(2.07)</td>
</tr>
<tr>
<td><strong>LIBOR</strong></td>
<td>0.6456*</td>
<td>0.3216*</td>
<td>−0.1633</td>
</tr>
<tr>
<td></td>
<td>(2.16)</td>
<td>(6.48)</td>
<td>(−1.12)</td>
</tr>
<tr>
<td><strong>Interbank Rate Premium</strong></td>
<td>1.9305*</td>
<td>−0.0505</td>
<td>0.9514*</td>
</tr>
<tr>
<td></td>
<td>(2.75)</td>
<td>(−0.61)</td>
<td>(2.86)</td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>16.0761*</td>
<td>10.7165*</td>
<td>11.7844*</td>
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<tr>
<td></td>
<td>(5.14)</td>
<td>(5.66)</td>
<td>(9.70)</td>
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### Bank Characteristics

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<tr>
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<th>Coefficient 1</th>
<th>Coefficient 2</th>
<th>Coefficient 3</th>
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<tr>
<td>Interbank Rate</td>
<td>-0.5096</td>
<td>-0.2977*</td>
<td>0.1414</td>
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<td>(-1.72)</td>
<td>(-6.02)</td>
<td>(1.0428)</td>
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<td>Intraday Payment Level (log)</td>
<td>-0.1558*</td>
<td>-0.1595*</td>
<td>0.0478*</td>
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<td>(-5.73)</td>
<td>(-8.87)</td>
<td>(2.51)</td>
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<td>Right Kurtosis of Payment In</td>
<td>0.0359</td>
<td>-0.0045</td>
<td>-0.0395*</td>
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<td>(1.90)</td>
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<td>(-3.39)</td>
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<td>Right Kurtosis of Payment Out</td>
<td>0.1416*</td>
<td>0.1742*</td>
<td>0.0426*</td>
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<td></td>
<td>(8.17)</td>
<td>(15.89)</td>
<td>(4.16)</td>
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<td>Vol of Liquidity Available (log)</td>
<td>0.0558*</td>
<td>0.0524*</td>
<td>0.0417*</td>
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<td></td>
<td>(39.72)</td>
<td>(50.23)</td>
<td>(36.73)</td>
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<td>Liquidity Used (log)</td>
<td>0.0303*</td>
<td>-0.0023</td>
<td>0.0052</td>
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<tr>
<td></td>
<td>(3.00)</td>
<td>(-0.34)</td>
<td>(0.68)</td>
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<tr>
<td>Top 4 Bank in Payment Activity</td>
<td>1.3374*</td>
<td>1.6815*</td>
<td>2.3738*</td>
</tr>
<tr>
<td></td>
<td>(26.97)</td>
<td>(46.31)</td>
<td>(57.18)</td>
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<tr>
<td>Repo Liability / Assets</td>
<td>-0.7721</td>
<td>0.7401*</td>
<td>0.0575</td>
</tr>
<tr>
<td></td>
<td>(-0.92)</td>
<td>(14.46)</td>
<td>(0.64)</td>
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<tr>
<td>Change in Deposit / Assets</td>
<td>0.5050</td>
<td>-1.3275*</td>
<td>-1.2503*</td>
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<tr>
<td></td>
<td>(0.68)</td>
<td>(-6.65)</td>
<td>(-3.70)</td>
</tr>
<tr>
<td>Total Lending and Borrowing (log)</td>
<td>0.1209*</td>
<td>0.0249</td>
<td>-0.3231*</td>
</tr>
<tr>
<td></td>
<td>(3.56)</td>
<td>(0.99)</td>
<td>(-23.70)</td>
</tr>
<tr>
<td>CDS (log)</td>
<td>-0.0652</td>
<td>-0.0274*</td>
<td>0.0514*</td>
</tr>
<tr>
<td></td>
<td>(-1.49)</td>
<td>(-3.17)</td>
<td>(4.55)</td>
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<td>CDS Missing Dummy</td>
<td>-2.1893*</td>
<td>-2.2618*</td>
<td>-0.8502*</td>
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<tr>
<td></td>
<td>(-11.38)</td>
<td>(-32.04)</td>
<td>(-8.37)</td>
</tr>
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Appendix
Period 1: Net Borrowing

Net Borrowing

Bank Index

Bank 1
Bank 2
Bank 3
Bank 4
Bank 5
Bank 6
Bank 7
Bank 8
Bank 9
Bank 10
Bank 11

Net Borrowing

-1e+11 -5e+10 0e+00 5e+10 1e+11

1 2 3 4 5 6 7 8 9 10 11

Network Risk and Key Players
Period 2: Net Borrowing

Net Borrowing

Bank Index

Net Borrowing

Bank 1
Bank 2
Bank 3
Bank 4
Bank 5
Bank 6
Bank 7
Bank 8
Bank 9
Bank 10
Bank 11

Bank Index
Period 3: Net Borrowing

The diagram illustrates the net borrowing for different banks across period 3. Each bank is represented by a vertical line on the graph, indicating its net borrowing amount. The x-axis represents the bank index, from Bank 1 to Bank 11, while the y-axis shows the net borrowing values ranging from $-1 \times 10^{11}$ to $1 \times 10^{11}$.
Period 1: Network Borrowing/Lending Flows
**Period 2: Network Borrowing/Lending Flows**

[Diagram showing network connections between different banks including Bank 9, Bank 10, Bank 11, Bank 1, Bank 2, Bank 3, Bank 4, Bank 5, Bank 6, and Bank 7.]
Period 3: Network Borrowing/Lending Flows