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
  $\Rightarrow$ 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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The Case Study: Intraday Liquidity in Payment System

- On average, in 2009, £700bn of transactions were settled every day across the two UK systems, CREST and CHAPS: the UK nominal GDP settled every two days.
- 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.

$\Rightarrow$ Let the data speak:

- Decompose risk into exogenous and network generated parts $\Rightarrow$ time varying network generates heteroskedastic liquidity.
- Construct Network Impulse-Response Functions to individual banks' shocks $\Rightarrow$ akin to variance decomposition.

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Outline

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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

Network Specification

- A directed and weighted network of n banks.

Network g : characterized by n-square adjacency matrix $\mathbf{G}$ 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.

$\Rightarrow$ $\mathbf{G}$ is a (right) stochastic matrix and is not symmetric

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

$$\mathbf{M}(\phi, \mathbf{G}) = \mathbf{I} + \phi\mathbf{G} + \phi^2\mathbf{G}^2 + \phi^3\mathbf{G}^3 + \ldots = \sum_{k=0}^{\infty} \phi^k \mathbf{G}^k.$$

Note: If $|\phi| < 1$, this converges to $(\mathbf{I} - \phi\mathbf{G})^{-1}$.

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Bank Objective Function

- Bank i decision variables:

q_i : liquidity level of bank i absent bilateral effects.

$$q_i = q_i(x) := \underbrace{\alpha_i}_{\text{fixed effect}} + \underbrace{\sum_{m=1}^{M} \beta_m x_i^m}_{\text{characteristics}} + \underbrace{\sum_{p=1}^{P} \beta_p x^p}_{\text{common factors}}$$

z_i : the network component of liquidity buffer stock.

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Bank Objective Function cont'd

- A quadratic payoff function for buffer stock liquidity

$$u_i(z_i|g) = \hat{\mu}_i \underbrace{\left(z_i + \psi \sum_j g_{ij} z_j\right)}_{\text{Accesible Liquidity}} - \frac{1}{2}\gamma \left(z_i + \psi \sum_{j \neq i} g_{ij} z_j\right)^2 + \underbrace{z_i \delta \sum_j g_{ij} z_j}_{\text{Collateralized Liquidity}}$$

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Eq.um : (Nash) If $|\phi| < 1$

$$z_i^* = \bar{\mu}_i + \phi \sum_{j=1}^{n} g_{i,j} z_j + v_i$$

$$\Rightarrow l_i^* = q_i(x) + z_i^* = q_i(x) + \{\mathbf{M}(\phi, \mathbf{G})\}_{i.}\, \mu$$

where $\mu := \gamma^{-1} [\hat{\mu}_1, ..., \hat{\mu}_n]'$, $\{\}_{i.}$ is the row operator, and

$$\phi := \frac{\delta}{\gamma} - \psi$$

Note:

If $\phi > 0$ complementarity (reciprocate/herding/leverage stacks e.g. Moore (2011)).

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$$\mathbf{1}'z^* = \underbrace{\mathbf{1}'\mathbf{M}(\phi, \mathbf{G})\,\bar{\mu}}_{\text{level effect}} + \underbrace{\mathbf{1}'\mathbf{M}(\phi, \mathbf{G})\,v}_{\text{risk effect}}$$

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 ϕ (for $\bar{\mu} > 0$).

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

$$\max_i \frac{\partial \mathbf{1}'z^*}{\partial v_i}\sigma_i = \max_i \mathbf{1}'\{\mathbf{M}(\phi, \mathbf{G})\}_{.i}\,\sigma_i \to \text{outdregree centrality}$$

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

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

indegree centrality + shock analogous − correct double counting

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indegree centrality + shock analogous − correct double counting

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Planner

A planner chooses $z_i, i = 1, , ...n$ 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:

$$z_i = \underbrace{\mu_i + \phi \sum_{j \neq i} g_{ij} z_j}_{\text{decentralized f.o.c.}} + \underbrace{\psi \sum_{j \neq i} g_{ji} \mu_j}_{\substack{\text{neighbors' idiosyncratic} \\ \text{valuations of own liquidity}}} + \underbrace{\phi \sum_{j \neq i} g_{ji} z_j}_{\substack{\text{neighbors' indegree} \\ \text{i.e. own outdegree}}} - \underbrace{\psi^2 \sum_{j \neq i} \sum_{m \neq j} g_{ji} g_{jm} z_m}_{\substack{\text{volatility of neighbors'} \\ \text{accessible network liquidity}}}$$

Outline

Empirical Model

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

$$l_{i,t} = \alpha_i + \sum_{m=1}^{M} \beta_m^{bank} x_{i,t}^m + \sum_{p=1}^{P} \beta_p^{time} x_t^p + z_{i,t}$$

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

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
   $\Rightarrow$ (average) Network Multiplier: $1/(1-\phi)$
2. Total liquidity, $L_t \equiv \mathbf{1}'[l_{1,t}, ..., l_{n,t}]$, is heteroskedastic:

$$Var_{t-1}(L_t) = \mathbf{1}'\mathbf{M}(\phi, \mathbf{G}_t)\,\text{diag}\left(\left\{\sigma_i^2\right\}_{i=1}^n\right)\mathbf{M}(\phi, \mathbf{G}_t)'\,\mathbf{1}.$$

3. Can perform Q-MLE (ϕ overidentified if $rank(\mathbf{M}(\phi, \mathbf{G}_t)) > 2$)

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Empirical Model: Specification Test

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)

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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 \\
&\quad + \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}
\end{aligned}
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Note: if $x_{i,j,t} := vec(x^m_{j \neq i,t})'$, $\psi = \phi$, $\theta = -\phi vec(\beta_m^{bank})$, $\gamma_p^{time} = (1-\phi)\beta_p^{time} \forall p \Rightarrow$ back to SEM

$\Rightarrow$ this more general spatial structure provides a specification test for our model.

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Network Impulse-Response Functions

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

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

NIRFs:

1. are pinned down by the outdegree centrality and

$$\text{Risk Key Player} \equiv \underset{i}{\text{argmax}}\ NIRF_i(\phi, \mathbf{G}_t, \sigma_i)$$

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

$$\mathbf{1}' \{\mathbf{M}(\phi, \mathbf{G}_t)\}_{.i} = \mathbf{1}' \{\mathbf{I} + \phi \mathbf{G}_t + \phi^2 \mathbf{G}_t^2 + \dots\}_{.i} = \mathbf{1}' \left\{\sum_{k=0}^{\infty} \phi^k \mathbf{G}_t^k\right\}_{.i}$$

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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

video clustering

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

$\Rightarrow g_{i,j,t}$ = the fraction of bank i's loans borrowed from bank j

Note: weights computed as monthly averages in previous month.

e-value

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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.

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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Estimation Results

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 ▸ Agg. Liq.

2. Rolling estimations with 6-month window $\Rightarrow$ allow ϕ to change at higher frequency.

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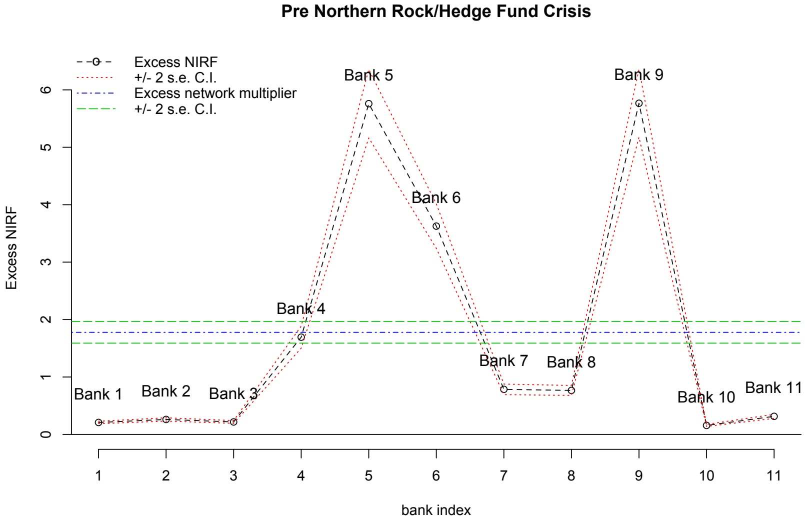
SEM Estimation

	Period 1	*Period 2*	*Period 3*
Network Effect: ϕ	0.640^* (52.44)	0.166^* (7.06)	-0.151^* (-6.45)
R^2	69.11%	89.71%	85.54%
(average) Network Multiplier	2.77^*	1.12^*	0.87^*

Period 1: $NIRF^e(\phi, \bar{\mathbf{G}}, 1)$ – Risk Key Players



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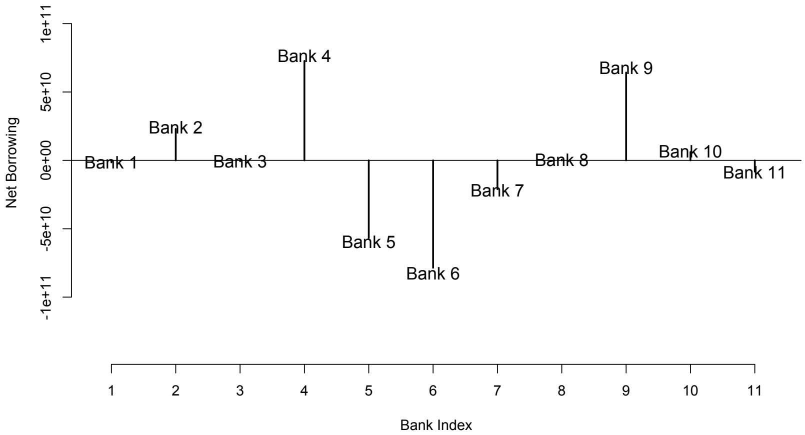
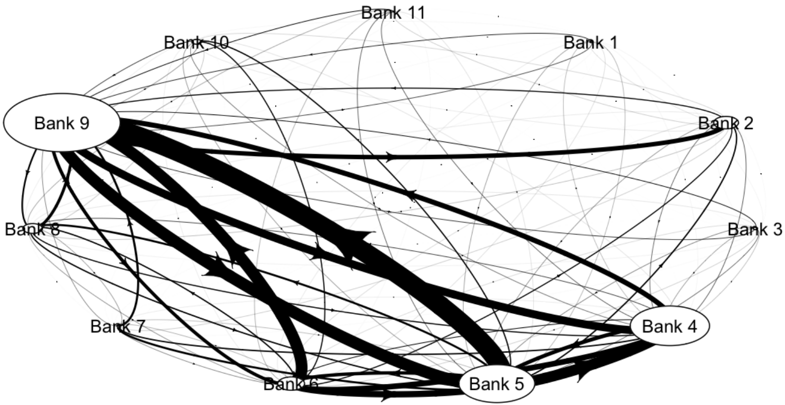
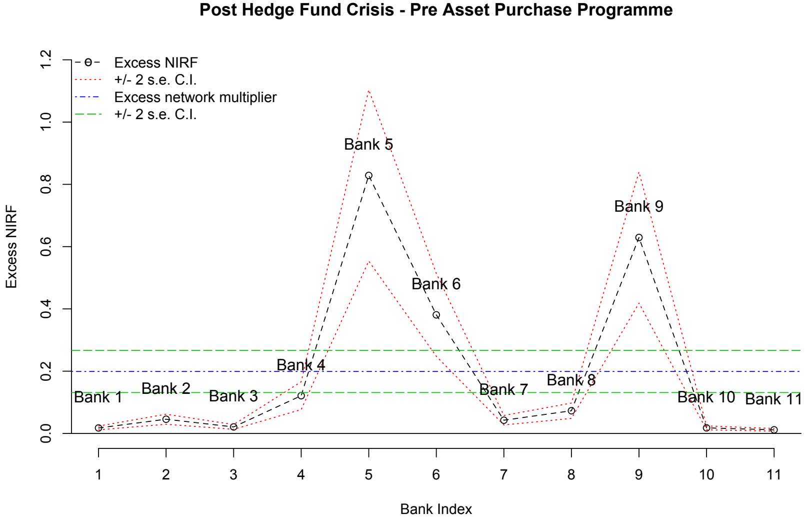


Period 1: Network Borrowing/Lending Flows



Period 2: $NIRF^e\left(\phi, \bar{\mathbf{G}}, 1\right)$ – Risk Key Players



Note: network risk reduction despite increased borrowing & lending

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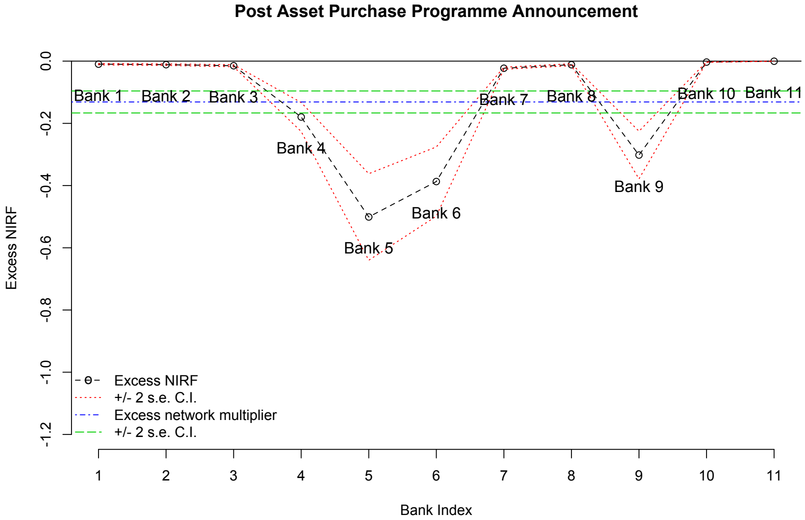
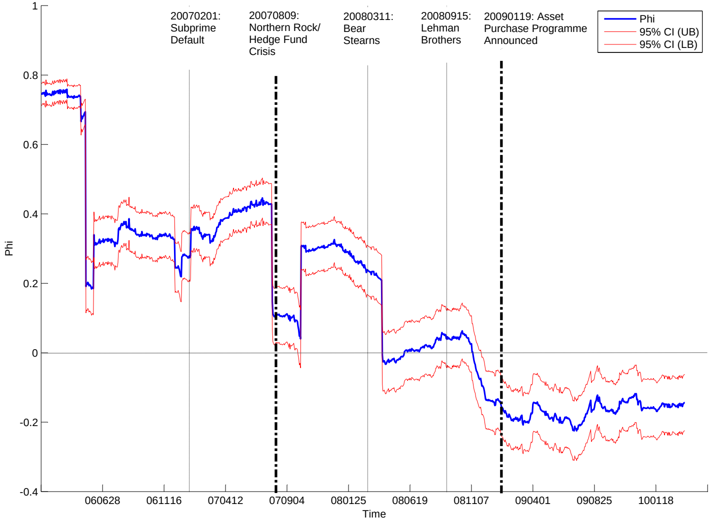
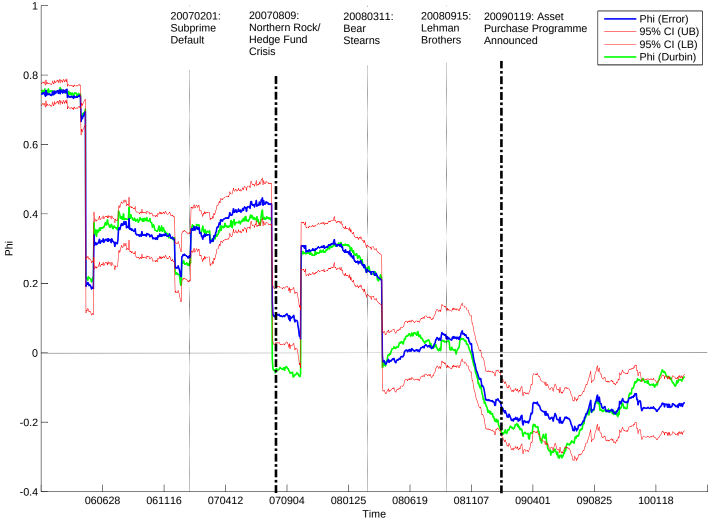


$\hat{\phi}$: SEM Rolling Estimation (6-month window)



$\hat{\phi}$ and $\hat{\psi}$: SEM and SDM Rolling Estimation (6-month window)



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▸ Appendix

Related Literature

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
- Acharya & Merrouche (2010) and Ashcraft, McAndrews & Skeie (2010): liquidity hoarding
- 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

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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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5. Additional Data Info
   - Second Largest Eigenvalue of $\mathbf{G}_t$
   - 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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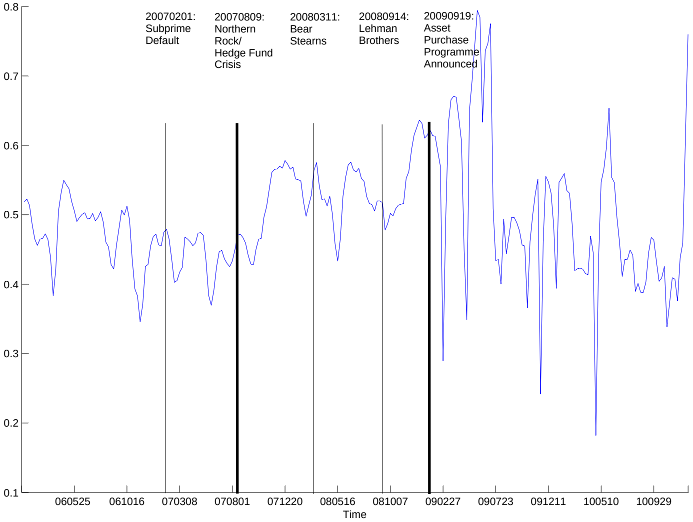
The Second Largest Eigenvalue of $\mathbf{G}_t$



Cohesiveness

Q: How cohesive is this network?

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

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

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

where n is the number of members in the network and $n_i(\mathbf{G})$ 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

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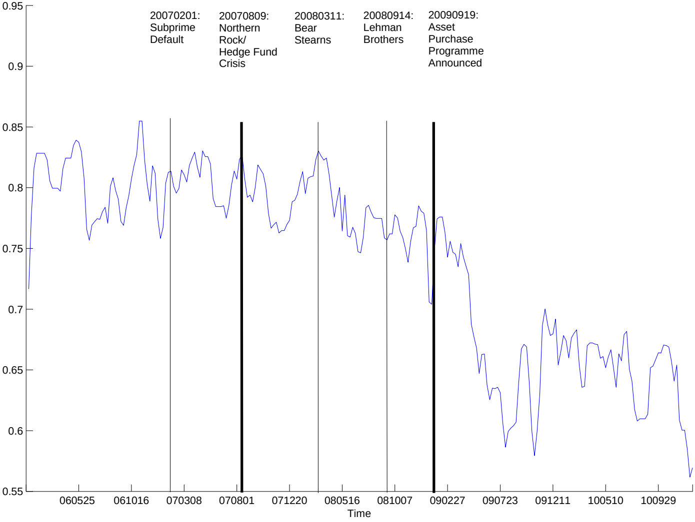
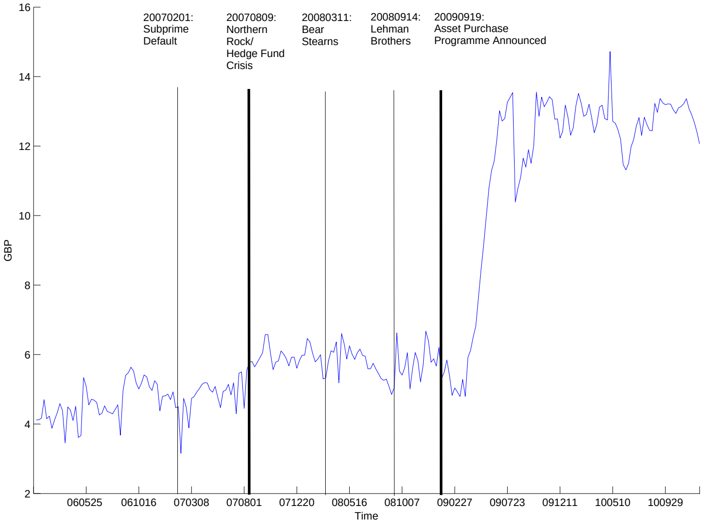
Average Clustering Coefficient of the Network

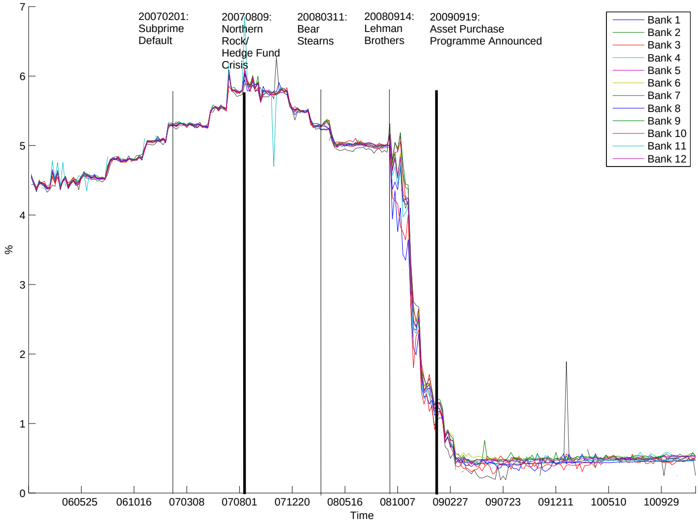


Aggregate Liquidity Available at the Beginning of a Day

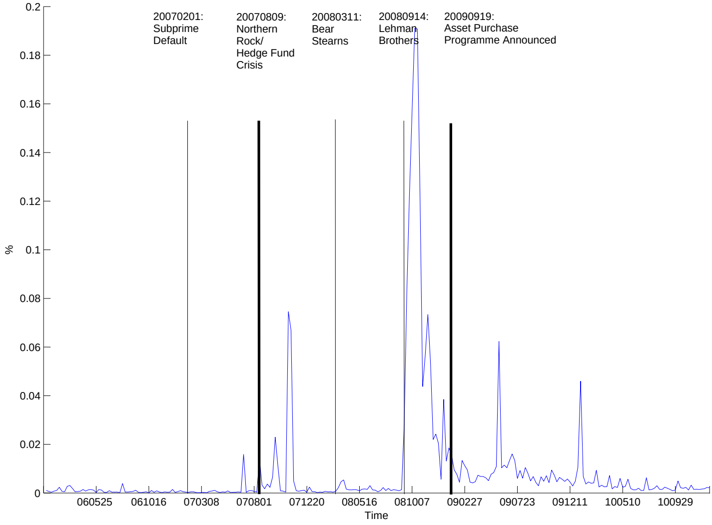


estimation

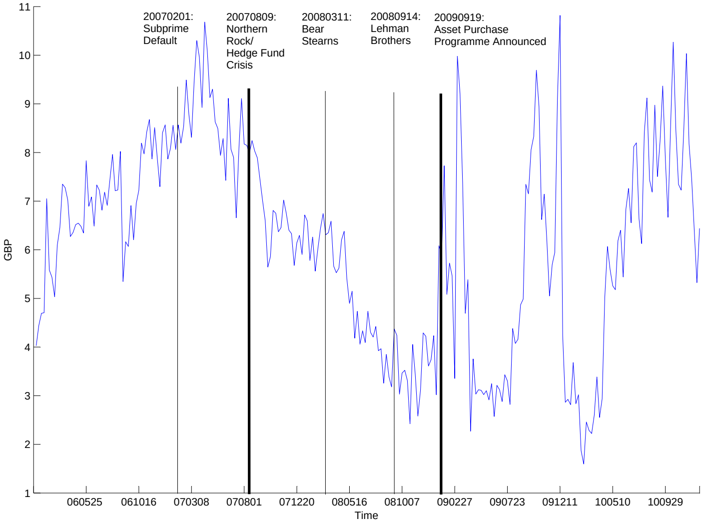
Interest Rate in Interbank Market



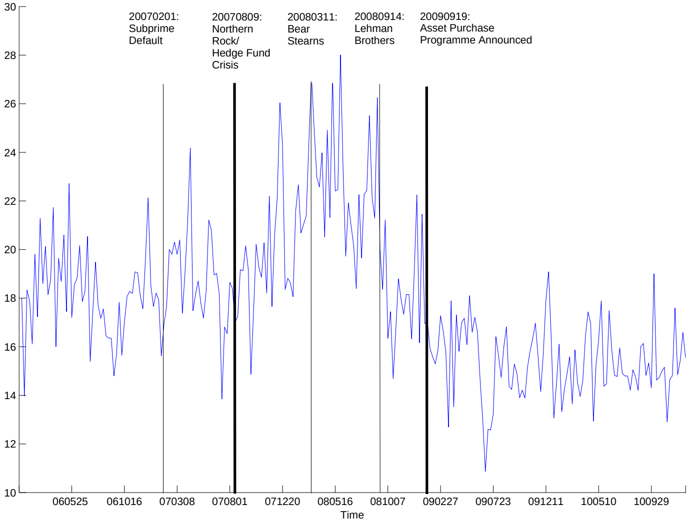
Cross-Sectional Dispersion of Interbank Rate



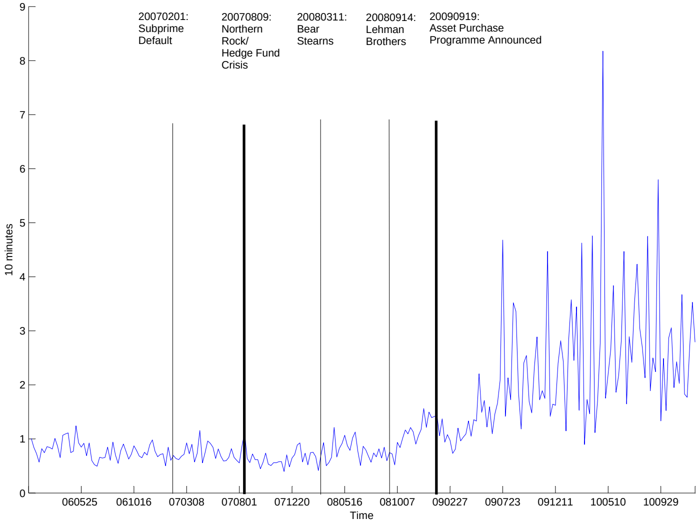
Intraday Volatility of Aggregate Liquidity Available



Turnover Rate in the Payment System



Right Kurtosis of Aggregate Payment Time



Outline

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SEM Estimation

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R^2	69.11%	89.71%	85.54%
Network Effect: ϕ	0.6400* (52.44)	0.1660* (7.06)	−0.1510* (−6.45)
Macro Controls			
Aggregate Liquidity (log)	−0.0020 (−0.04)	0.3324* (4.59)	0.5974* (14.73)
Right Kurtosis of Payments	−0.1654* (−2.39)	0.0265 (1.12)	0.0031 (1.01)
Volatility of Liquidity (log)	0.1750 (1.37)	0.1935* (7.15)	0.0075 (0.52)
Turnover Rate	0.0097 (1.51)	0.0055* (2.87)	0.0049* (2.07)
LIBOR	0.6456* (2.16)	0.3216* (6.48)	−0.1633 (−1.12)
Interbank Rate Premium	1.9305* (2.75)	−0.0505 (−0.61)	0.9514* (2.86)
Constant	16.0761* (5.14)	10.7165* (5.66)	11.7844* (9.70)

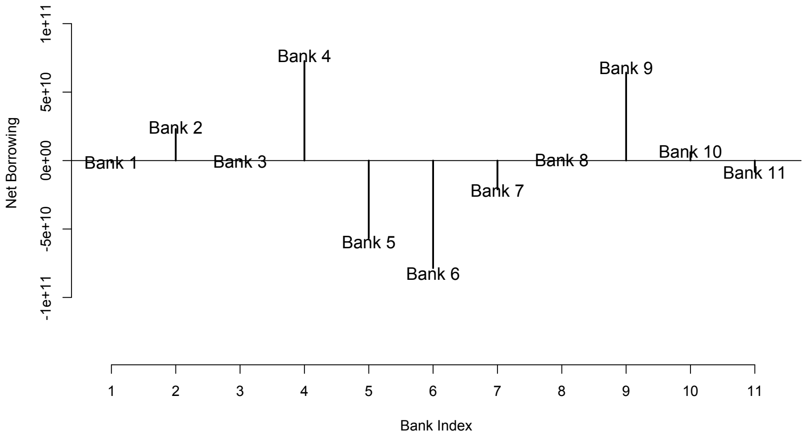
SEM Estimation cont'd

Bank Characteristics			
Interbank Rate	-0.5096	-0.2977^{*}	0.1414
	(-1.72)	(-6.02)	(1.0428)
Intraday Payment Level (log)	-0.1558^{*}	-0.1595^{*}	0.0478^{*}
	(-5.73)	(-8.87)	(2.51)
Right Kurtosis of Payment In	0.0359	-0.0045	-0.0395^{*}
	(1.90)	(-0.26)	(-3.39)
Right Kurtosis of Payment Out	0.1416^{*}	0.1742^{*}	0.0426^{*}
	(8.17)	(15.89)	(4.16)
Vol of Liquidity Available (log)	0.0558^{*}	0.0524^{*}	0.0417^{*}
	(39.72)	(50.23)	(36.73)
Liquidity Used (log)	0.0303^{*}	-0.0023	0.0052
	(3.00)	(-0.34)	(0.68)
Top 4 Bank in Payment Activity	1.3374^{*}	1.6815^{*}	2.3738^{*}
	(26.97)	(46.31)	(57.18)
Repo Liability / Assets	-0.7721	0.7401^{*}	0.0575
	(-0.92)	(14.46)	(0.64)
Change in Deposit / Assets	0.5050	-1.3275^{*}	-1.2503^{*}
	(0.68)	(-6.65)	(-3.70)
Total Lending and Borrowing (log)	0.1209^{*}	0.0249	-0.3231^{*}
	(3.56)	(0.99)	(-23.70)
CDS (log)	-0.0652	-0.0274^{*}	0.0514^{*}
	(-1.49)	(-3.17)	(4.55)
CDS Missing Dummy	-2.1893^{*}	-2.2618^{*}	-0.8502^{*}
	(-11.38)	(-32.04)	(-8.37)

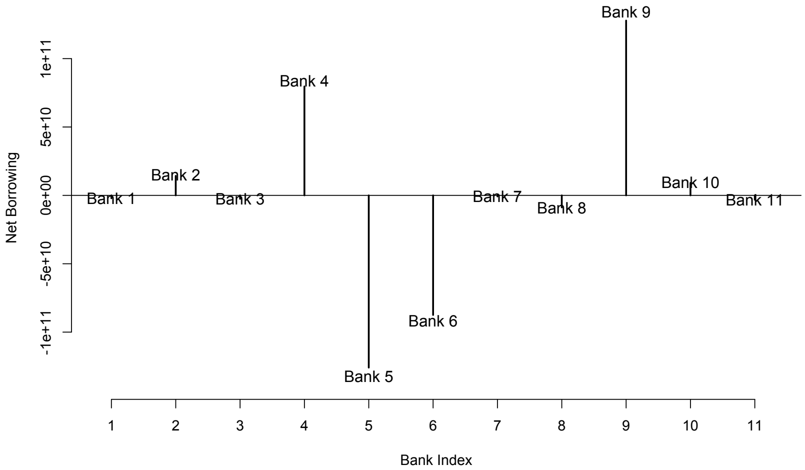
Outline

Appendix

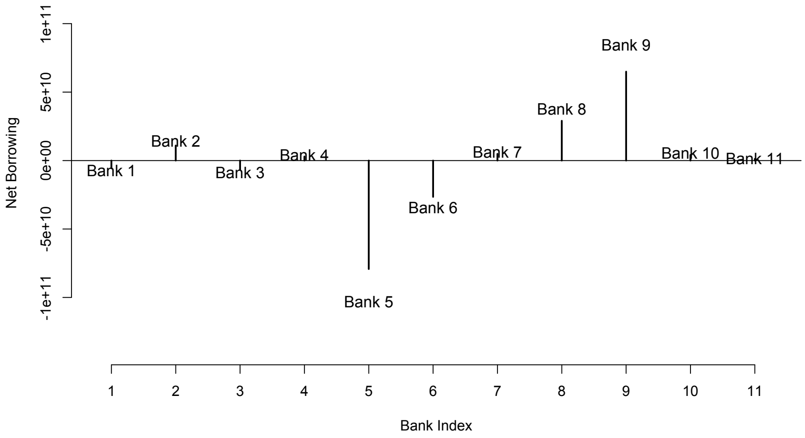
Period 1: Net Borrowing



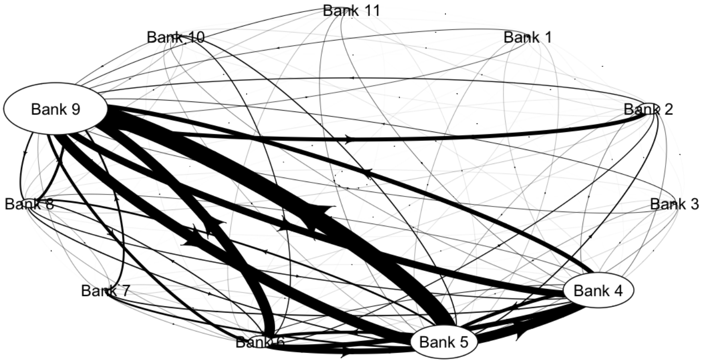
Period 2: Net Borrowing



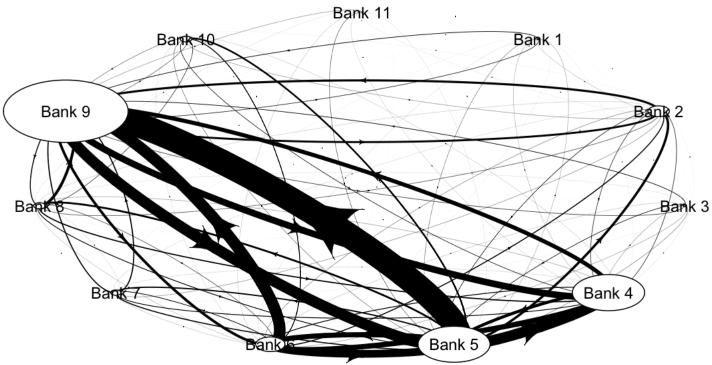
Period 3: Net Borrowing



Period 1: Network Borrowing/Lending Flows



Period 2: Network Borrowing/Lending Flows



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