

Retrieving implied financial networks from bank balance sheet and market data

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Outline

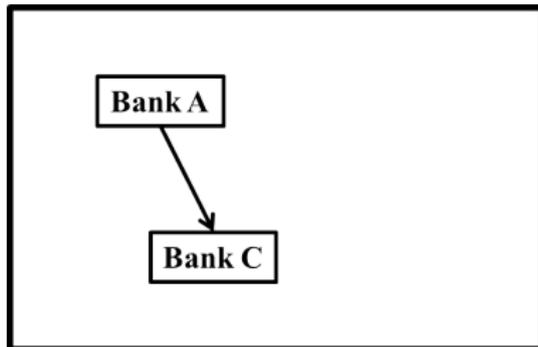
- 1 Motivation
- 2 Implied Networks
- 3 Simulations
- 4 Empirical Application

Motivation

- Interconnectedness is a structural vulnerability (Christensen, I. et al, 2015):
 - In normal times, makes the financial system more resilient by providing risk-sharing opportunities;
 - In times of stress, can allow for distress propagation.
- Lessons from the 2007–09 crisis:
 - Reserve primary fund “breaks the buck” due to its exposure to Lehman’s CP;
 - AIG bailout.
- Simulations used to assess the risk of contagion frequently employ a network of exposures (e.g., MFRAF):
 - MFRAF: Interbank and Major Exposures Return.

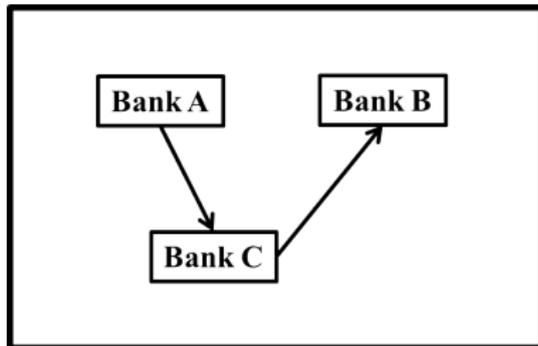
Motivation (2)

- Market participants only have a partial knowledge of these exposures.
 - Example: simple interbank loan



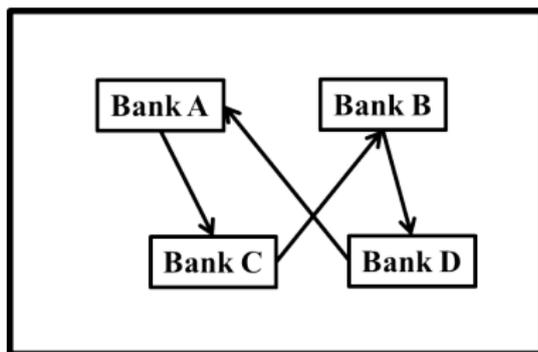
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“Knowing your ultimate counterparty risk then becomes like solving a high-dimension Sudoku puzzle” Haldane (2009).

Motivation (3)

- A motivating example:

	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	Total
<i>A</i>	0	?	?	?	50
<i>B</i>	?	0	?	?	5
<i>C</i>	?	?	0	?	20
<i>D</i>	?	?	?	0	20
Total	20	50	20	5	

? unknown;
 – known.

Motivation (4)

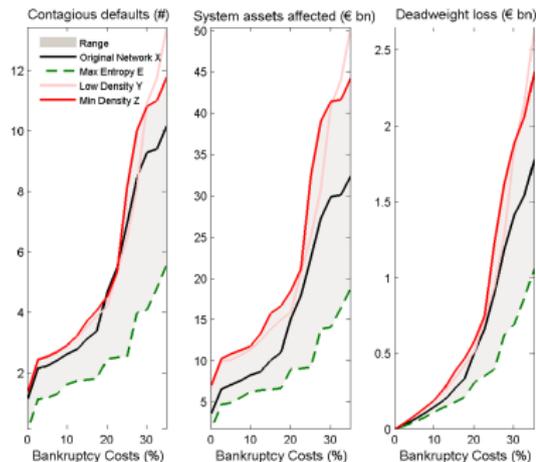
- Potential solutions:

	A	B	C	D	Total
A	0	31	15	4	50
B	3	0	2	0	5
C	9	10	0	1	20
D	8	9	3	0	20
Total	20	50	20	5	

	A	B	C	D	Total
A	0	30	20	0	50
B	0	0	0	5	5
C	0	20	0	0	20
D	20	0	0	0	20
Total	20	50	20	5	

Motivation (5)

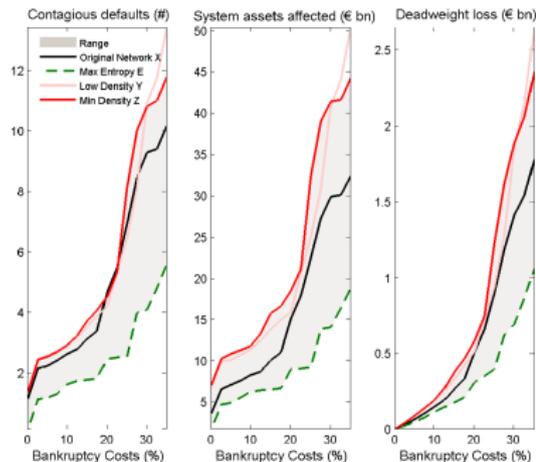
- Standard method: Maximum Entropy (ME) approach - divide exposures equally among counterparties.
- Limitations:
 - Not informed by market participants' beliefs w.r.t. the distribution of these exposures;
 - Real data shows that ME produces biased results.



Source: Fig 6., Anand et al. (2014)

Motivation (5)

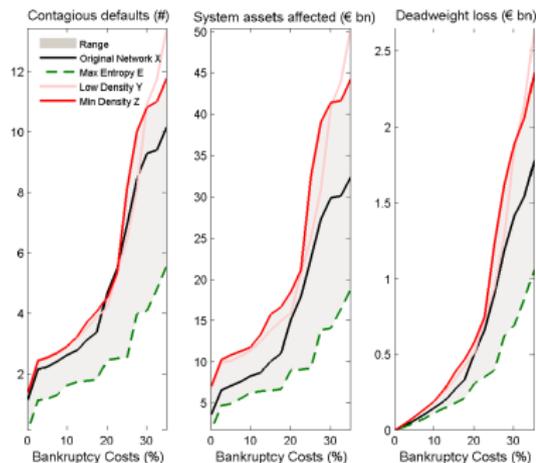
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Proposed Contribution

- Use market signals of network-dependent contingent claims to infer the implied network of exposures:
 - Pricing model that takes into account the network of exposures: implied price;
 - Data on market signals of contingent claims: observed prices;
 - Find the network(s) that is(are) consistent with the observed prices and aggregate exposures.

Literature Review

- Reconstructing networks from partial information: Anand et al. (2017)
- Uncertainty in financial networks: Caballero and Simsek (2013) and Li et al. (2016);
- Asset pricing in financial networks: Eisenberg and Noe (2001), Egloff et al. (2007), Gouriéroux et al. (2013) and Barucca et al. (2016), and Abbassi et al. (2017).

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The Pricing Model

- Consider a stylized balance sheet:

<i>Assets</i>	<i>Liabilities</i>
EA_i	EL_i
	IL_i
IA_i	EQ_i

EA - external assets; IA - internal assets; EL - external liabilities; IL - internal liabilities; EQ - equity.

The Pricing Model (2)

- Similar to the standard Merton (1974) model:
 - $\frac{dEA_i(t)}{EA_i} = \mu_i dt + \sigma_i dZ_i(t)$, where Z_i is a one-dimensional Brownian motion.
- Extension:
 - $IA_j(T) = \sum_{i=1}^n p_i^* m_{ij}$, where m_{ij} is the exposure of bank j to bank i and p_i^* is the fraction of the exposure borrower i is able to repay at maturity.

Assumption

EL_i have the same priority in liquidation as IL_i .

The Pricing Model (3)

- Find the clearing payment vector:

$$p^* = \min \left\{ \mathbf{1}, \max \left[(\mathbf{M}' p^* + \mathbf{e}) \odot \left(\frac{1}{d_1}, \dots, \frac{1}{d_n} \right), 0 \right] \right\},$$

where

$\mathbf{e} = EA(T)$; \mathbf{M} is the liabilities matrix (or network);

$d_i = \sum_j m_{ij} + EL_i$ and \odot is the Hadamard product.

Assumption

Limited liability

Assumption

Proportional repayment

The Pricing Model (4)

- Example (revisited)

	A	B	C	D	Total
A	0	30	20	0	50
B	0	0	0	5	5
C	0	20	0	0	20
D	20	0	0	0	20
Total	20	50	20	5	

- Eisenberg and Noe (2001) propose an algorithm to find p^* .
- A owes \$30 to B and \$20 to C, but D owes \$20 to A.
- If $e_A = \$20$, then, assuming D is solvent, A only has \$40 to pay B and C.
- Thus, A can only pay 80 cents on the dollar owed (fundamental default).
- If $e_C = 0$, then C will also only be able to pay 80 cents on the dollar (default by contagion).

The Pricing Model (5)

- I allow for bankruptcy costs as in Rogers and Veraart (2013):
 - Failed banks' external assets lose α of their value.
- Price contingent claims by Monte Carlo simulation since a closed form solution does not exist:
 - 1 Sample a random path for EA_i in a risk-neutral world;
 - 2 Find p^* for each sample path;
 - 3 Repeat steps 1. and 2. K times;
 - 4 Given p^* find the payoff of the contingent claim for each sample path and then compute the average payoff;
 - 5 Discount the expected payoff using the risk-free rate to obtain the theoretical price.

Implied Networks

- Example of a zero-coupon bond with \$1 face value:
 - Set of implied networks:

$$\text{IN} := \underset{\tilde{\mathbf{M}} \in \mathbb{F}}{\text{argmin}} \left\{ \Xi \left(\tilde{\mathbf{M}} \mid \theta \right) \right\},$$

where

$$\Xi \left(\tilde{\mathbf{M}} \mid \theta \right) := \frac{1}{n} \left[\begin{array}{c} p_t^{\text{obs}} - e^{-r_f \tau} E_t^Q \left(\mathbf{p}^* \left(\tilde{\mathbf{M}} \mid \theta \right) \right) \\ p_t^{\text{obs}} - e^{-r_f \tau} E_t^Q \left(\mathbf{p}^* \left(\tilde{\mathbf{M}} \mid \theta \right) \right) \end{array} \right]' W,$$

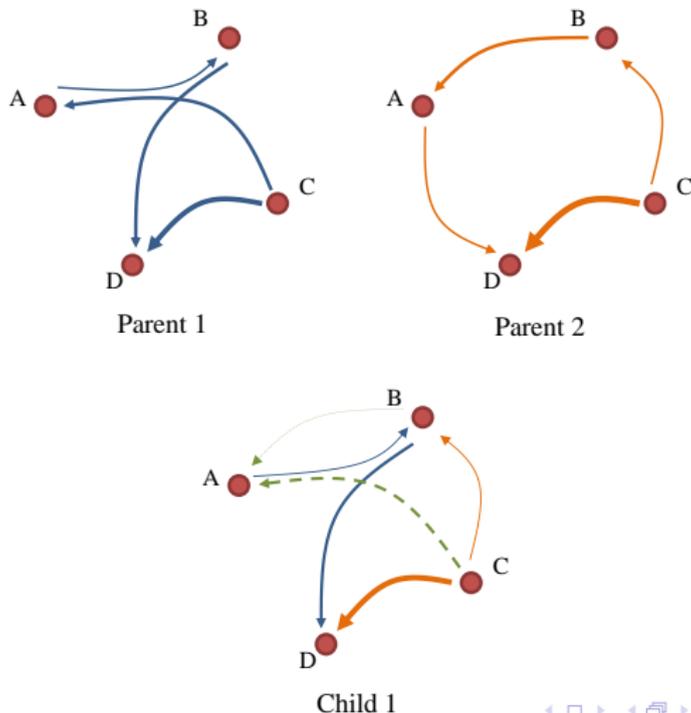
with

$$W = \left[\begin{array}{cccc} \frac{TA_1}{\sum_{j=1}^n TA_j} & 0 & \dots & 0 \\ 0 & \frac{TA_2}{\sum_{j=1}^n TA_j} & \dots & 0 \\ \dots & \dots & \dots & 0 \\ 0 & 0 & 0 & \frac{TA_n}{\sum_{j=1}^n TA_j} \end{array} \right], \theta = (TA, \Sigma).$$

Heuristic approach to network optimization

- 1 Use the ME network as a starting point;
- 2 Generate $ngen$ “mutations” of the ME matrix. This set of matrices is referred to as the children set;
- 3 Evaluate the fitness, i.e., of all matrices generated in 2.;
- 4 Preserve the $npar$ matrices with the lowest weighed mean squared error. This set of matrices is referred to as the set of parents;
- 5 Create $ngen$ “mutations” based on the matrices identified in 4. and proceed as in 3.;
- 6 Repeat steps 4 and 5 until the fitness measure shows a high enough improvement over the fitness measure obtained under ME.

Heuristic approach to network optimization (2)



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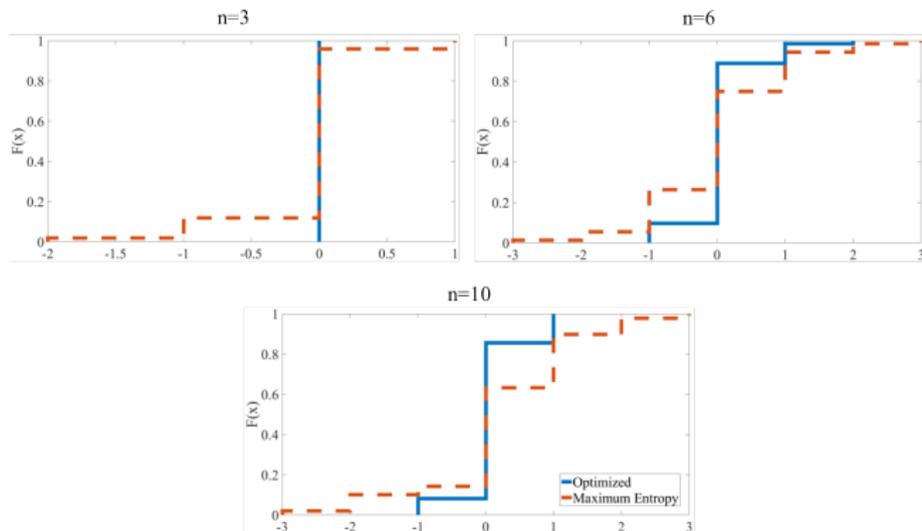
Simulation Results

- Simulate the “true” network implied by market prices:
 - Based on the total exposures: obtain the ME network;
 - Based on the implied price: obtain the optimized/implied network.

Simulation Results (2)

Setup: bankruptcy costs = 5% (i.e., $\alpha = 0.95$).

Figure: CDF of the deviations in the number of defaults vis-a-vis the "true" network

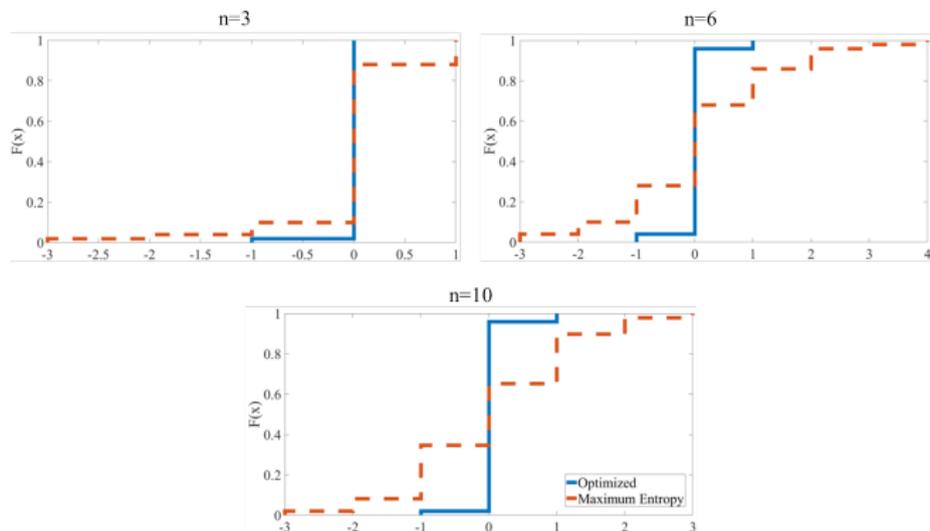


of defaults in excess of the ones obtained under the "true" network, in all states of nature

Simulation Results (3)

Setup: bankruptcy costs = 15% (i.e., $\alpha = 0.85$).

Figure: CDF of the deviations in the number of defaults vis-a-vis the "true" network

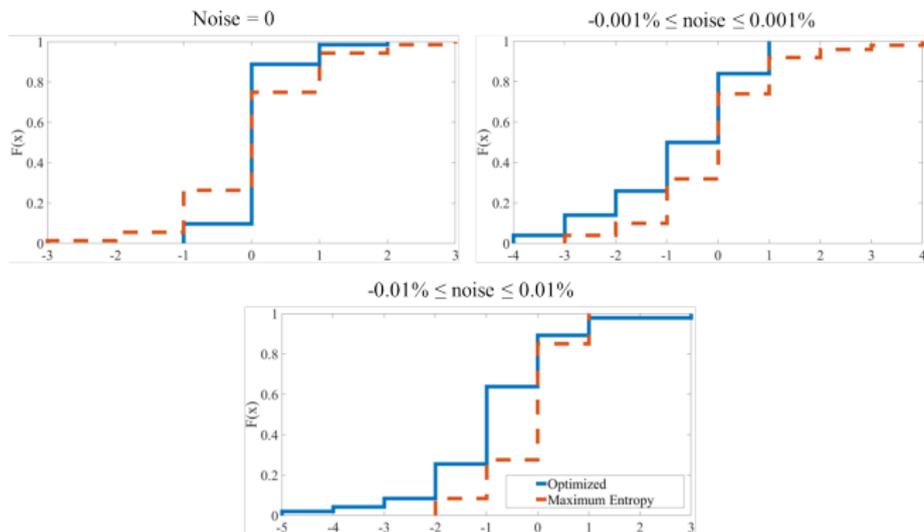


of defaults in excess of the ones obtained under the "true" network in all states of nature

Simulation Results (4)

Setup: noisy prices for $n = 6$ and $\alpha = 0.95$.

Figure: CDF of the deviations in the number of defaults vis-a-vis the "true" network



of defaults in excess of the ones obtained under the "true" network in all states of nature

Outline

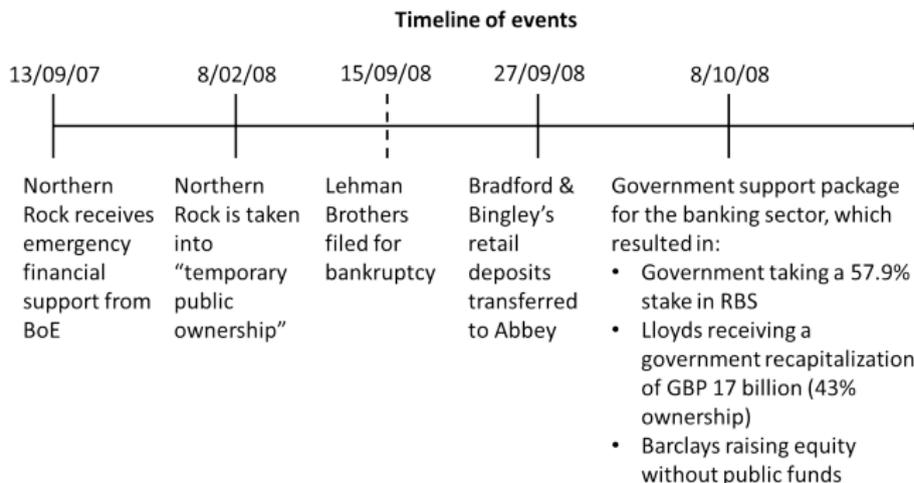
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Data

- 4 most systemic UK banks (part of the G-SIB list) - HSBC, RBS, BARC and STAN.
- Data on aggregate exposures referring to the 2007–09 crisis period:
 - Internal assets - “Loans and advances to banks”;
 - Internal liabilities - “Deposits by banks”.
- Market signals: 5-year Credit Default Swap (CDS) spreads;
- Calibration: following Chatterjee (2013) bankruptcy costs set at 10%.

Data (2)

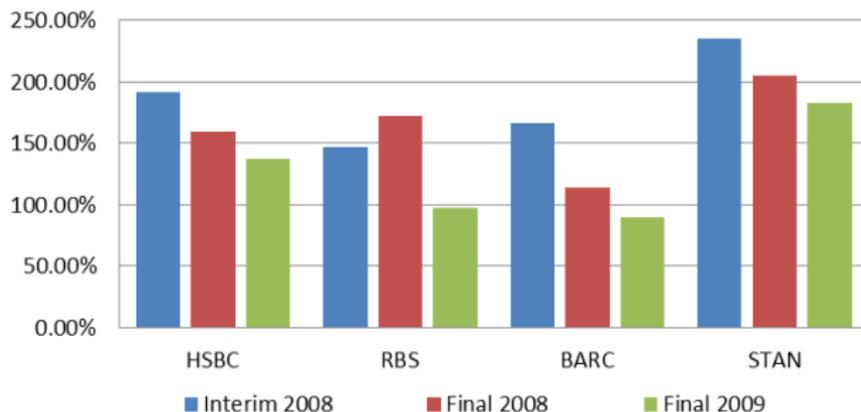
Timeline of the financial crisis in the UK



Source: author's summary based on House of Commons (2009).

Data (3)

Ratio of internal (interbank) assets to equity (book values)

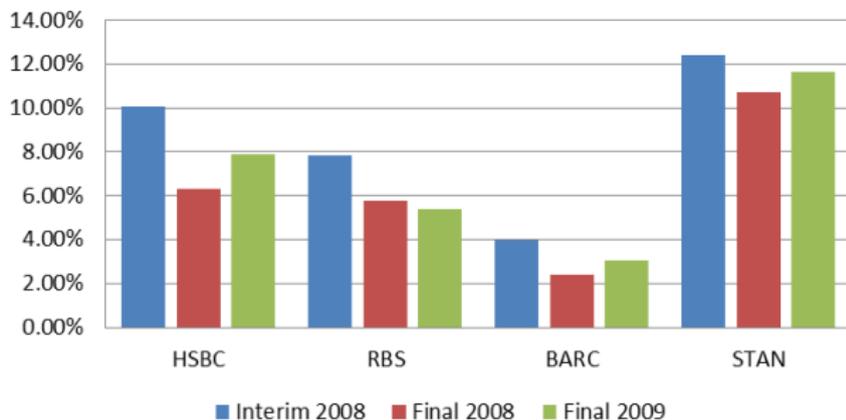


Source: Banks' annual reports.

- Interbank assets/book-value equity between 90 and 230%.

Data (4)

Ratio of internal (interbank) assets to total assets (book values)

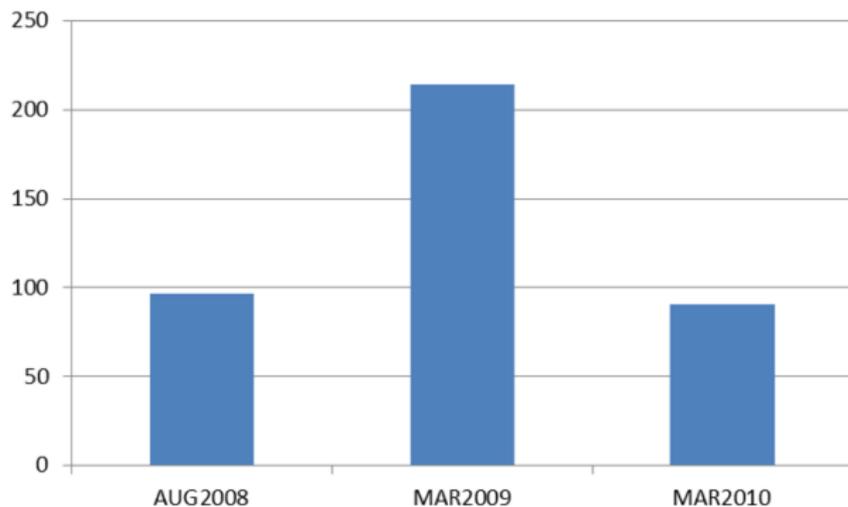


Source: Banks' annual reports.

- Interbank assets/book value assets between 3 and 12%.

Data (5)

5-Year CDS spreads (in bps)



Source: Bloomberg.

Estimation

- External assets stochastic processes' parameters estimated by Maximum Likelihood as in Duan (1994), Duan (2000).
- Consistency among total, external and internal assets obtained via a numerical fixed-point approach.

Results

Note: Edges' width represent the log of exposures. $A \rightarrow B$ represents exposure of A to B. [Appendix](#)

Results (2)

Relative differences expressed in percentage terms of the ME exposures

AUG2008	HSBC	RBS	BARC	STAN	Liabilities	DEC2008	HSBC	RBS	BARC	STAN
HSBC		-18	28	221		HSBC		19	2	48
RBS	-8		-18	-83		RBS	-19		8	-42
BARC	8.6	17		-87		BARC	27	-33		-9
STAN	15	-3	-6			STAN	-33	71	-80	

DEC2009	HSBC	RBS	BARC	STAN	Liabilities
HSBC		7	6	-68	
RBS	-22		-1	66	
BARC	29	4		-9	
STAN	-15	-58	-27		

Results (3)

- The network structure seems to be relevant for the pricing of risk:
 - (Roughly) 40% reduction in the weighted mean squared error under implied/optimized network in comparison to ME in some of the time slices;
 - Consistent with market participants having more information than simply aggregate exposures.

Results (4)

- Improvement over ME varies over time:
 - 40% improvement when looking at the AUG2008 and DEC2009 time slices, but declines to 25% improvement for the DEC2008 time slice;
 - Potential explanation: when the overall riskiness of banks increases so does the inability to distinguish bilateral exposures.
 - Argument consistent with CDS spreads (highest for the DEC2008 slice).

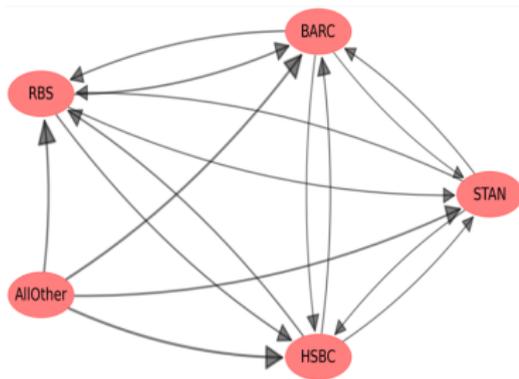
Summary

- Proposed a method to retrieve the set of implied networks from market data:
 - Value-added: Inform re: beliefs and behavioral reactions of market participants towards an institution.
- Increases in overall riskiness may play a role in market participants' ability to discern bilateral exposures.
- Limitations:
 - Partial identification;
 - Only as good as the underlying pricing model;
 - Only as good as the market data reflect counterparty risk.

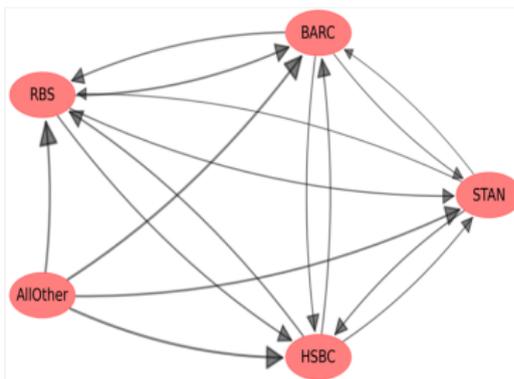
Appendix

August 2008

Maximum Entropy



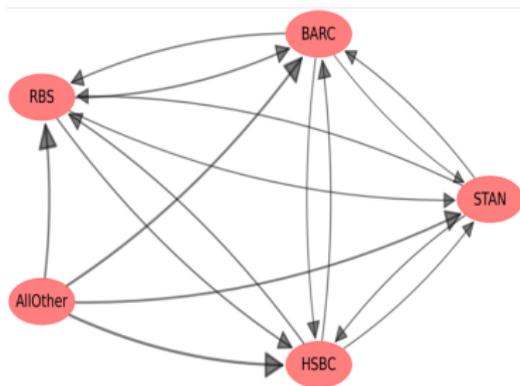
Implied Network



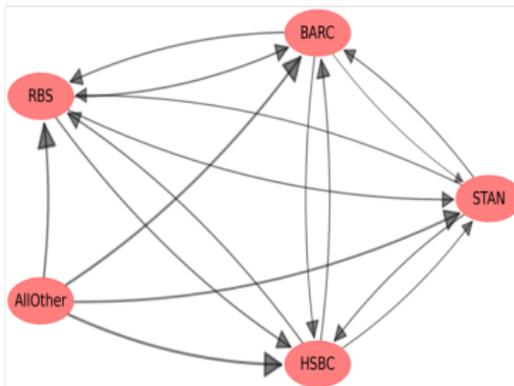
Appendix

December 2008

Maximum Entropy



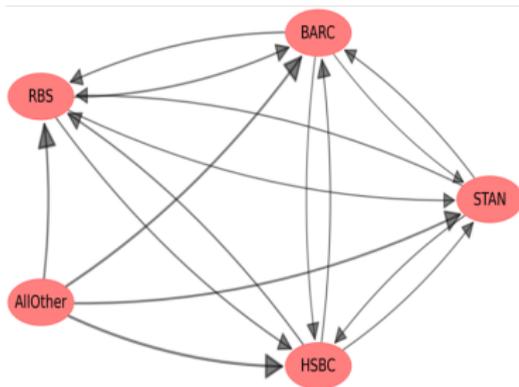
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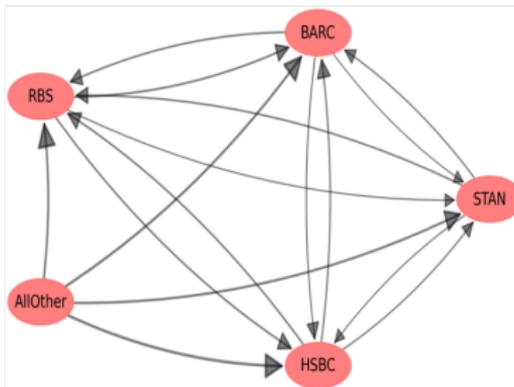
Appendix

December 2009

Maximum Entropy



Implied Network



Return