Markose et. al. (2012a,b) Eigen Pair Analysis : *Endogenous to contractual financial obligations and not on external shocks etc*

- Stress Test and Systemic Risk Metrics
- Monitoring Systemic Risk : Is the financial system becoming more or less stable ?
- Monitor maximum Eigen-value of the ratio of net liabilities to Tier 1 capital matrix
- Cause for concern if max eigen value is greater than the fixed threshold/ratio of prefunded capital : Focus on policy relevant regulatory variable
- Advantages: Certifiable and transparent contractual obligations; I do not think a FI can be held culpable for pre existing macro conditions or for unknowable losses from fire sales.

Solvency Contagion and Stability of Matrix Θ' : Netted impact of *i* on *j* relative to *j*'s capital

$$\Theta = \begin{bmatrix} 0 & \frac{(x_{12}-x_{21})^+}{C_{2t}} & \frac{(x_{13}-x_{31})^+}{C_{3t}} & .0. & .... & 0 \\ 0 & 0 & \frac{(x_{23}-x_{32})^+}{C_{3t}} & .... & .... & \frac{(x_{3N}-x_{N3})^+}{C_{Nt}} \\ . & . & 0 & .... & .... & . \\ \frac{(x_{i1}-x_{1i})^+}{C_{1t}} & . & ... & 0 & ... & \frac{(x_{iN}-x_{Ni})}{C_{Nt}} \\ . & . & ... & ... & 0 & . \\ \frac{(x_{N1}-x_{1N})^+}{C_{1t}} & . & ... & \frac{(x_{Nj}-x_{jN})^+}{C_{jt}} & ... & 0 \end{bmatrix} \Big| (2$$

From Epidemiology : Failure of i at q+1 determined by the criteria that losses exceed a predetermined buffer ratio, ρ, of Tier 1 capital

- $u_{iq+1} = (1 - \rho)\, u_{iq} + \sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}}\, u^1_{jq} \qquad (2)$

(i)First term i's own survival probability given by the capital C_{iq} it has remaining at q relative to initial capital C_{i0} , ρ is common cure rate and (1 - ρ) is rate of not surviving in the worst case scenario .

(ii) The sum of 'infection rates'= sum of net liabilities of its j failed counterparties relative to its own capital is given by the term $\sum_j \frac{(x_{ji} - x_{ij})^+}{C_{i0}}$

Stability of the dynamical network system : Eigen Pair (λ_{max} , **v**)

λ_{max} is maximum eigenvalue of Θ

In matrix algebra dynamics of bank failures given by:

$$\mathbf{U}_{t+1} = [\Theta' + (1-\rho)I]\,\mathbf{U}_t = \mathbf{Q}\,\mathbf{U}_t \quad (3)$$

I is identity matrix and ρ is the % buffer

Stability Condition $\lambda_{max}(\mathbf{\Theta}') < \rho$ After q iterations

- The system stability of (2) will be evaluated on the basis of the power iteration of the matrix $\boldsymbol{Q}$=[(1-ρ)**I**+$\mathbf{\Theta}'$]. From (3), $\boldsymbol{U}_q$ takes the form:

- $\boldsymbol{U}_q = \boldsymbol{Q}^q \boldsymbol{U}_\mathbf{0}$

- ρ is the solvency threshold in terms of Tier 1 capital (care should be taken if criteria is specified in terms of Basel IIRWA Capital Ratio)

Basel II Criterion of Failure

- Stress Tests: Follow Furfine (2003) Algorithm

- Criteria of failure of a bank in the contagion analysis is based on the Basel rule that

$$(\text{Tier 1 capital} - \text{LGD}) / \text{RWA} < 0.06 = T_{RWA}.$$

- Here LGD is loss given default and the threshold for bank failure in terms of RWA is denoted as T_{RWA}.

- However, as the practical aspects of insolvency requires recapitalization, it is important to see the equivalence of the above Basel rule with a Tier 1 capital threshold criteria (T_c) for failure :

- $$T_c = 1 - T_{RWA} \frac{RWA}{Tier\ 1\ Capital}.$$

Role of Maximum Row Sum and Maximum Eigenvalue

$\lambda_{max} \leq ||\Theta'||_{\infty} = \max_{i} \sum_j \theta_{ji} = max_i \, S_i$.

- Here, $||\,.\,||_{\infty}$ stands for the infinity norm of a matrix, which is the maximum of row sums S_{i} where $S_{\mathrm{i}} = \sum_j \theta_{ji}$.
- Row sum in Θ'matrix

$S_i = \sum_j \theta_{ji} = \sum_j [\frac{1}{C_i}(x_{ji} - x_{ij})^+]$.

Eigenvector Centrality

A variant is used in the Page Ranking algorithm used by Google

Centrality: a measure of the relative importance of a node within a network

Eigenvector centrality

Based on the idea that the centrality v_i of a node should be proportional to the sum of the centralities of the neighbors

$$v_i = \frac{1}{\lambda} \sum_j \theta_{ij} v_j$$

λ is maximum eigenvalue of Θ

The vector v, containing centrality values of all nodes is obtained by solving the eigenvalue equation $\Theta \, \widetilde{\boldsymbol{v_1}} = \lambda_{max} \widetilde{\boldsymbol{v_1}}$.

λ_{max} is a real positive number and the eigenvector $\widetilde{\boldsymbol{v_1}}$ associated with the largest eigenvalue has non-negative components by the Perron-Frobenius theorem (see Meyer (2000))

Right Eigenvector Centrality : Systemic Risk Index

Left Eigenvector centrality Leads to vulnerability Index

Mitigation of Systemic Risk Impact of Network Central Banks: How to stabilize ?

To date the problem of how to have banks internalize their systemic risk costs to others (and tax payer) from failure has not been adequately solved

In particular, penalty for being *too interconnected* has not been dealt with from direct bilateral network data

There are 5 ways in which stability of the financial network can be achieved

(i)Constrain the bilateral exposure of financial intermediaries (Ad hoc constraints do not work) Serafin Martinez implemented these in Mexico

(ii) Ad hocly increase the threshold rho in (11),

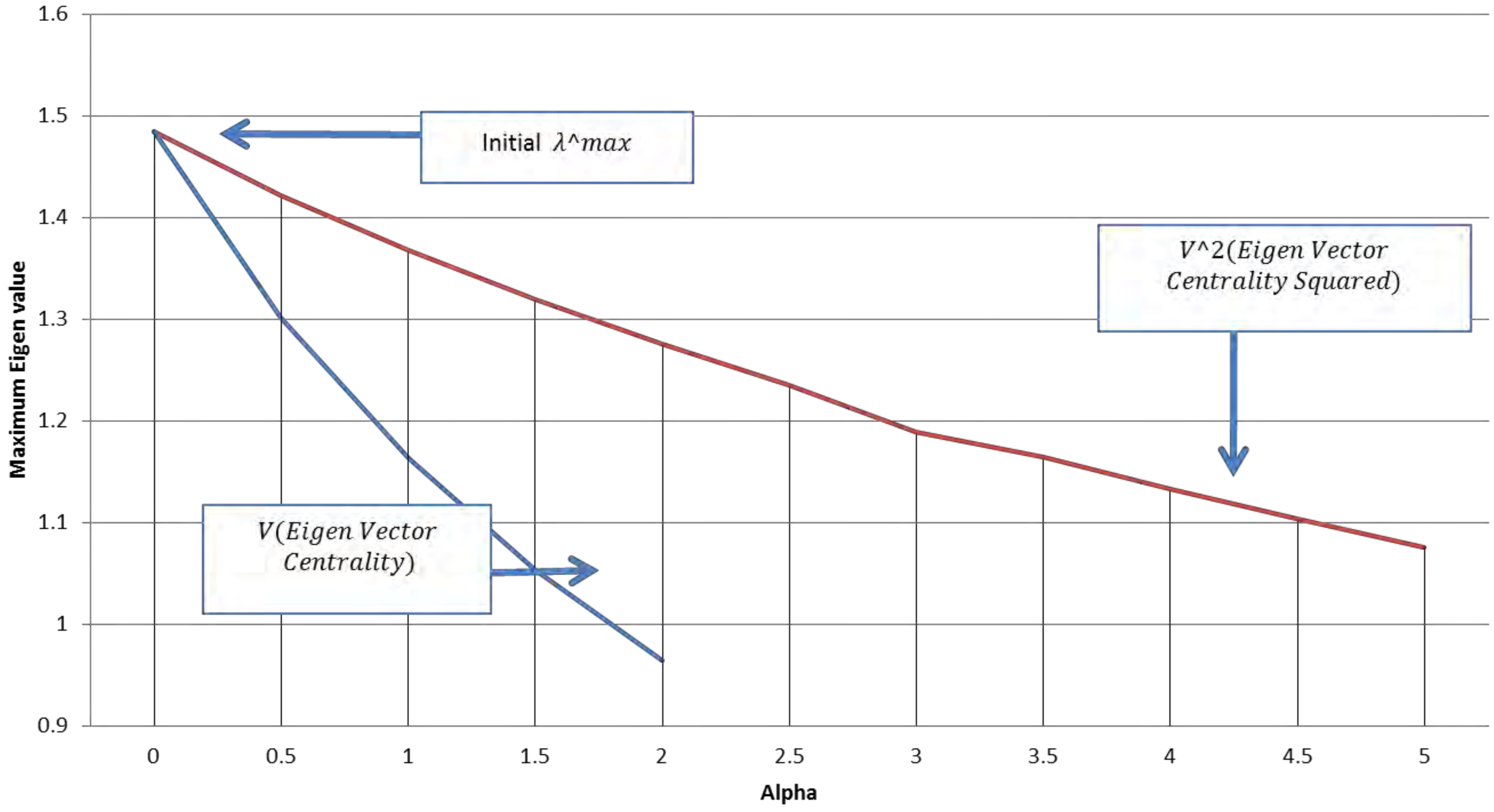
(iii) Change the topology of the network

(iv) Directly deduct a eigenvector centrality based **prefunded buffer** in matrix

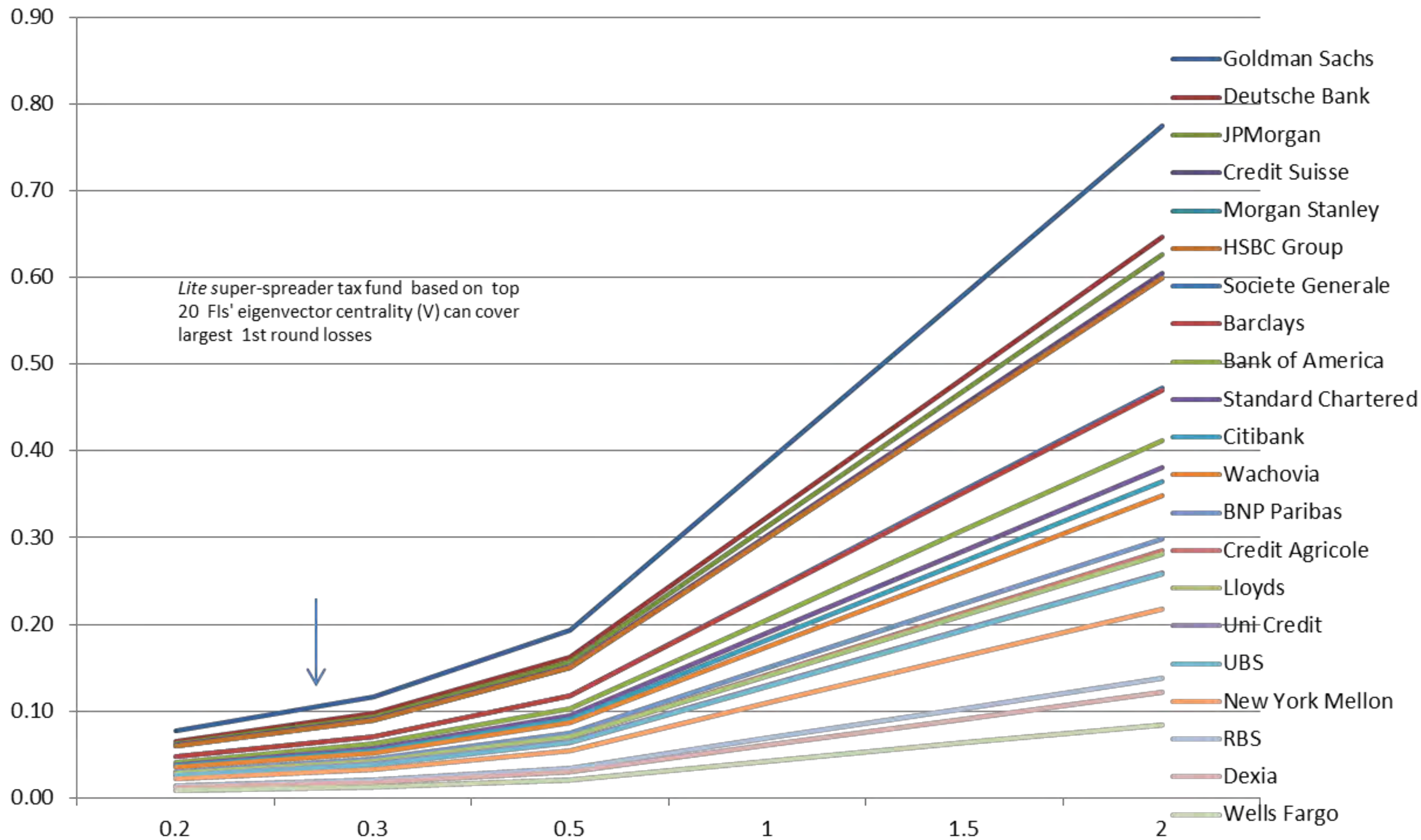
$S_i{}^{\#} = \sum_j \theta_{ji}{}^{\#} = \left[\frac{1}{C_i}\left(\sum_j (x_{ji} - x_{ij})^+ - \tau\,(\mathrm{v_i}) C_i\right)\right].$

(i) & (ii) do not price in negative externalities and systemic risk of failure of highly network central nodes. Network topologies emerge endogenously and are hard to manipulate exogenously

How to stabilize: Superspreader tax quantified : tax using Eigen Vector Centrality of each bank v_i or v_i^2 to reduce max eigenvalue of matrix to 6%



Superspreader tax rate



Super-Spreader Tax Raised From Top 20 SIFIs (All columns other than EVC \$bns) (2012 Global Derivatives)

Note EVC is Eigenvector Centrality ; Tax % = EVC x alpha; Tax\$s= Tax Rate x Tier 1 Capital

- Super-spreader fund works like an escrow account; amounts escrowed as in a CCP or by regulator to be used to recapitalize when default occurs
- Super Spreader Fund *lite* : Secure funds to cover max losses of 1st tier (q=1) from any trigger bank failure
- Full stabilization for $\lambda_{max} < \rho$, costly implies tax rates of 77% of Tier 1 capital of Goldman Sachs etc

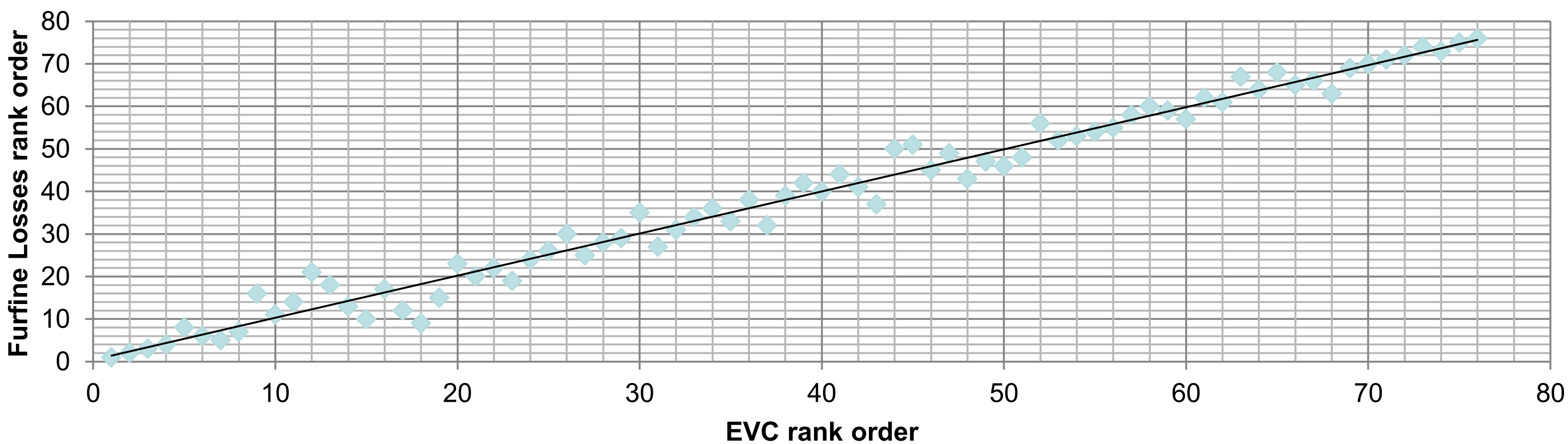
			Alpha											
			0.2		0.3		0.5		1.00		1.5		2	
Bank Name	Tier 1 Capital	EVC	Tax%	Tax $s	Tax %	Tax $s	Tax%	Tax $s	Tax%	Tax $s	Tax%	Tax $s	Tax%	Tax
Goldman Sachs	17.15	0.39	0.08	1.33	0.12	1.99	0.19	3.32	0.39	6.64	0.58	9.96	0.77	13.28
Deutsche Bank	49.42	0.32	0.06	3.20	0.10	4.80	0.16	7.99	0.32	15.99	0.49	23.98	0.65	31.98
JPMorgan	96.37	0.31	0.06	6.04	0.09	9.06	0.16	15.09	0.31	30.19	0.47	45.28	0.63	60.37
Credit Suisse	39.49	0.30	0.06	2.39	0.09	3.58	0.15	5.97	0.30	11.94	0.45	17.91	0.60	23.87
Morgan Stanley	46.67	0.30	0.06	2.80	0.09	4.20	0.15	7.00	0.30	14.00	0.45	21.00	0.60	28.00
HSBC Group	35.48	0.30	0.06	2.13	0.09	3.19	0.15	5.32	0.30	10.63	0.45	15.95	0.60	21.26
Societe Generale	34.69	0.24	0.05	1.64	0.07	2.46	0.12	4.10	0.24	8.20	0.35	12.30	0.47	16.41
Barclays	77.56	0.23	0.05	3.64	0.07	5.46	0.12	9.10	0.23	18.20	0.35	27.29	0.47	36.39
Bank of America	111.92	0.21	0.04	4.61	0.06	6.92	0.10	11.53	0.21	23.05	0.31	34.58	0.41	46.11
Standard Chartered	24.58	0.19	0.04	0.94	0.06	1.40	0.10	2.34	0.19	4.68	0.29	7.02	0.38	9.36
Citibank	96.83	0.18	0.04	3.52	0.05	5.29	0.09	8.81	0.18	17.62	0.27	26.43	0.36	35.25
Wachovia	39.79	0.17	0.03	1.38	0.05	2.08	0.09	3.46	0.17	6.92	0.26	10.38	0.35	13.84
BNP Paribas	90.37	0.15	0.03	2.70	0.04	4.06	0.07	6.76	0.15	13.52	0.22	20.28	0.30	27.03
Credit Agricole	44.53	0.14	0.03	1.27	0.04	1.90	0.07	3.17	0.14	6.34	0.21	9.50	0.28	12.67
Lloyds	74.27	0.14	0.03	2.09	0.04	3.14	0.07	5.23	0.14	10.45	0.21	15.68	0.28	20.90
Uni Credit	56.07	0.13	0.03	1.45	0.04	2.18	0.06	3.63	0.13	7.26	0.19	10.89	0.26	14.52
UBS	42.32	0.13	0.03	1.09	0.04	1.63	0.06	2.72	0.13	5.45	0.19	8.17	0.26	10.90
New York Mellon	10.15	0.11	0.02	0.22	0.03	0.33	0.05	0.55	0.11	1.11	0.16	1.66	0.22	2.21
RBS	98.28	0.07	0.01	1.35	0.02	2.03	0.03	3.39	0.07	6.77	0.10	10.16	0.14	13.54
Dexia	25.24	0.06	0.01	0.31	0.02	0.46	0.03	0.76	0.06	1.53	0.09	2.29	0.12	3.06
		Superspreader fund		44.10		66.14		110.24		220.48		330.72		440.9

How Useful is the Eigen Vector Centrality Rank Order As a Proxy for Furfine Losses of Capital ?

Pearson Correlation in the Rank Order of Eigen vector centrality of bank and that of Furfine Capital Losses when bank fails as a

2011	Q1	Q2	Q3	Q4
Pearson Correlation	0.948	0.980	0.989	0.930

Scatter Plot of Pearson Correlation of 0.98993 in the Rank Order of Eigenvector centrality (EVC) and that of Furfine Losses (1 being the highest and 76 is lowest) Q3 2011



Results of Systemic Risk Monitoring Q1- Q4 2011 for Real World Banking Sector

Can a Northern Rock Situation Be Detected by EVC method ? A Bank xxx which was Eigenvector centrality rank of 6 in June 2010 increases to rank1 by Q3 2011; it was winning bank of year awards but it was aggressively borrowing on inter bank markets and systemic risk of network jumped up !

In previous years high EVC banks led to 6%-14% of total Furfine capital losses; now this almost doubled

Is Basel II criteria far too lenient as solvency threshold ? *It has become fashionable to say that there is no direct contagion : Check the failure/loss threshold (Markose experience as academic advisor on FSB MAGD Report on OTC Reforms where no G-SIB causes contagion by failing !)*

- For a real financial system, the Basel criteria implies that the median T_c is around 40%
- On average percentage Tier 1 capital they can lose before declared a failed bank is 46%.
- Every national regulator should check out what the capital adequacy criterion wrt Risk Weighted Assets means in terms of an absolute Tier 1 capital constraint for their system
- Then check this with the maximum eigenvalue of the Tier 1 capital adjusted net liabilities bilateral matrix a la Markose eigen pair systemic risk analytics
- Can a network of subset of total financial assets be given the same failure/loss threshold as a network for all assets ?

Conclusion : Regulators and Systemic Risk Researchers must face up to limits of data mining market price data for early warning signals and instead mandate structural bilateral financial data and digitally map the macro-financial network system

- *Too interconnected to fail* addressed only if systemic risk from individual banks can be rectified with a price or tax reflecting the negative externalities of their connectivity
- Lessons to be learnt : Disease Transmission in scale free networks (May and Lloyd (1998), Barthelemy et. al : With higher probabilities that a node is connected to highly connected nodes means disease spread follows a hierarchical order. *Knowledge of financial interconnectivity essential for targeted interventions*
- Highly connected nodes become infected first and epidemic dying out fast and often contained in first two tiers
- Innoculate a few rather than whole population; Strengthen hub; Reduce variance of node strength in maximum eigenvalue formula

Other Concluding Remarks

- Changes in eigenvector centrality of FIs can give early warning of instability causing banks
- EVC basis of Bail in Escrow fund/Capital Surcharge
- *These high EVC banks will, like Northern Rock, be winning bank of the year awards ; however potentially destabilizing from macro-prudential perspective*
  Capital for CCPs to secure system stability can use same calculations
- Beware gross aggregation and netting across product classes for which there is no multi-lateral clearing ; more systemic risk and hence more, capital/collateral needed for stabilization
- Single network v multi-layer networks

References:
(1) Markose, S.M (2013) "Systemic Risk Analytics: A Data Driven Multi-Agent Financial Network (MAFN) Approach", *Journal of Banking Regulation* , Vol.14, 3/4, p.285-305, Special Issue on Regulatory Data and Systemic Risk Analytics.
(2) *Markose, S. (2012) "Systemic Risk From Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation With Super-Spreader Tax",* November, IMF Working Paper No. 12/282,
(3) Markose, S., S. Giansante, and A. Shaghaghi, (2012), "Too Interconnected To Fail Financial Network of U.S. CDS Market: Topological Fragility and Systemic Risk", ***Journal of Economic Behavior and Organization****,* Volume 83, Issue 3, August 2012, P627-646
http://www.sciencedirect.com/science/article/pii/S0167268112001254
(3)Multi-Agent Financial Network (MAFN) Model of US Collateralized Debt Obligations (CDO): Regulatory Capital Arbitrage, Negative CDS Carry Trade and Systemic Risk Analysis, Sheri M. Markose, Bewaji Oluwasegun and Simone Giansante, Chapter in *Simulation in Computational Finance and Economics: Tools and Emerging Applications* ***Editor(s):*** *Alexandrova-Kabadjova B., S. Martinez-Jaramillo, A. L. Garcia-Almanza, E. Tsang,* IGI Global, August 2012.
http://www.acefinmod.com/CDS1.html

More Readings

Borio, C and M. Drehmann (2009a), "Towards an operational framework for financial stability: 'fuzzy' measurement and its consequences", in Banco Central de Chile (ed), *Financial stability, monetary policy and central banking;* also available as *BIS Working Papers,* no 284.

Craig, B and von Peter, G. (2010) "Interbank Tiering and Money Center banks", BIS Working Paper No. 322.

Fricke, D. And T. Lux (2012) "Identifying a Core-Periphery Structure in the Italian Interbank Market",Kiel Institute for the World Economy, Mimeo.

Haldane Andrew G (April 2009), "Rethinking the financial network", Speech delivered at th Financial Student Association, Amsterdam.

Minski, H. (1982) "The Financial-Instability hypothesis: Capitalist processes and the behavior of the economy", 1982, in Kindleberger and Laffargue, editors, *Financial Crises*.
http://www.acefinmod.com/CDS1.html

NEW MSc Computational Economics, Financial Markets and Policy – at University of Essex Econ Dept, Oct 2013
To train students with new computational and complexity approach with financial network and agent based models for policy and mark design

University of Essex

MSc Computational Economics, Financial Markets and Policy

Starting in October 2013

Our new MSc Computational Economics, Financial Markets and Policy offers a revolutionary and interdisciplinary study of macro-economics and financial regulation. It should interest those looking for careers in regulatory institutions, financial modelling, the civil service, real-world problem solving or undertaking further research.

The financial crisis and global recession have triggered a search for new perspectives to deal with highly interconnected, global financial and industrial organisations. Our new course assists such search, with a strong policy orientation and operational content, including a special module to undertake a cutting-edge project with leading experts and practitioners.

MSc Computational Economics, Financial Markets and Policy provides a rigorous training in:

- economics, finance and policy design;
- multi-agent computational and simulation modelling approach to complement statistics and econometrics;
- lab-based instruction to build a range of computational models that include systemic risk analysis;
- financial networks and market micro-structure of stock markets; and
- the use of serious games and complexity economics for policy

Our Department of Economics has an international reputation for outstanding research and graduate training, being ranked third in the UK in the most recent Research Assessment Exercise (RAE, December 2008)

Entry requirements

Upper Second Class degree (or equivalent) in economics, finance, econometrics or business, or any quantitative/computational degree, such as physics, engineering, mathematics and computer science.

If English is not your first language, then we require IELTS 6.5, or equivalent.

Scholarships are available.

For more information, please contact us.

Department of Economics
University of Essex
Wivenhoe Park
Colchester CO4 3SQ
UK

T 01206 872647
E scher@essex.ac.uk or dhall@essex.ac.uk
▸ www.essex.ac.uk/economics