University of Essex
Economics Department

TOWARDS A SUSTAINABLE FINANCIAL SYSTEM
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Multi-Agent Financial Network Models And Global Macro-net Models: New Tools for Macro-Prudential Policy

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The software used in network modelling was developed by Sheri Markose with Simone Giansante and Ali Rais Shaghaghi

PART 1 OF 2

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Roadmap 1 : Why ACE : Agent-based Computational Economics ?

- Agents are computer programs with varying degrees of computational intelligence and can interact with one another;

- Computational intelligence varies from fixed rules (good to test out perverse incentives from policy, eg have all agents follow same rule eg Basel synthetic securitization incentive to reduce capital using CDS for RMBS, Markose et al 2012) to more adaptive learning using simple reinforcement learning a la Erev-Roth or Genetic Algorithms

- Dynamics not pre-specified by equations → ACE does not run into Lucas Critique in that structure changes are brought about by strategic interactions.

- ICT data base driven multi-agent financial networks: glorified data visualizations → Andrew Haldane/ John Buchanan *Star Trek Vision*

- Vintage Santa Fe Institute Artificial Stock Market Model : Self-Reflexivity of Prices and Contrarian Payoff Structure in stock market game impossibility of homogeneity and of **homogenous Rational Expectations**
- Brian Arthur's genius intuition: Why it is rational to be contrarian and anti-herd creating endogenous boom and bust. However, logical and neurophysiological source of heterogeneity, proteanism (viz novelty/innovation production) and non-computability not understood by most economists/agent based modellers , See Markose (2005) *Economic Journal "Markets as complex adaptive systems, Steve Spear , 1989.* "Learning *Rational Expectations* under *Computability Constraints,*" Econometrica

Roadmap 2 : Why MAFNs/Macro-Nets for Macro-prudential policy ?

- **Two methodological problems of financial contagion and systemic risk : (i)Paradox of Volatility and the pitfalls of market price data based systemic risk measures hence structural bilateral data based networks modeling needed (ii) Non- trivial Negative Externalities problem → the need for holistic visualization**

- **Two applications used: Systemic Risk From Global Financial Derivatives Modelled Using Network Analysis of Contagion and Its Mitigation With Super-Spreader Tax**

- **Global Macro-nets integrated with Real Side Sectoral Flow of Funds to assess extent of economic imbalance from financialization**

- **Some insights from Indian Financial System and Bilateral Data based Network Modeling: Pioneering first full bilateral digital map of financial system (Brazil and Mexico also mandating bilateral data)**

Roadmap 3*: Systemic Risk Analytics*

- **Stability of Networks and Eigen-Pair Analysis: Markose et. al. (2012)**
- **3 main questions of macro-prudential regulation :**

(i)Is financial system more or less stable?

(ii)Who contributes to Systemic Risk ?

(iii)How to internalize costs of systemic risk of 'super-spreaders' using Pigou tax based on eigenvector centrality: Management of moral hazard, Bail in vs Bail out : How to Stabilize system using EIG Algorithm ?

- **Superspreader *Lite* Escrow Fund**
- **Generalization to multi-layer networks**
  - **Conclusions**

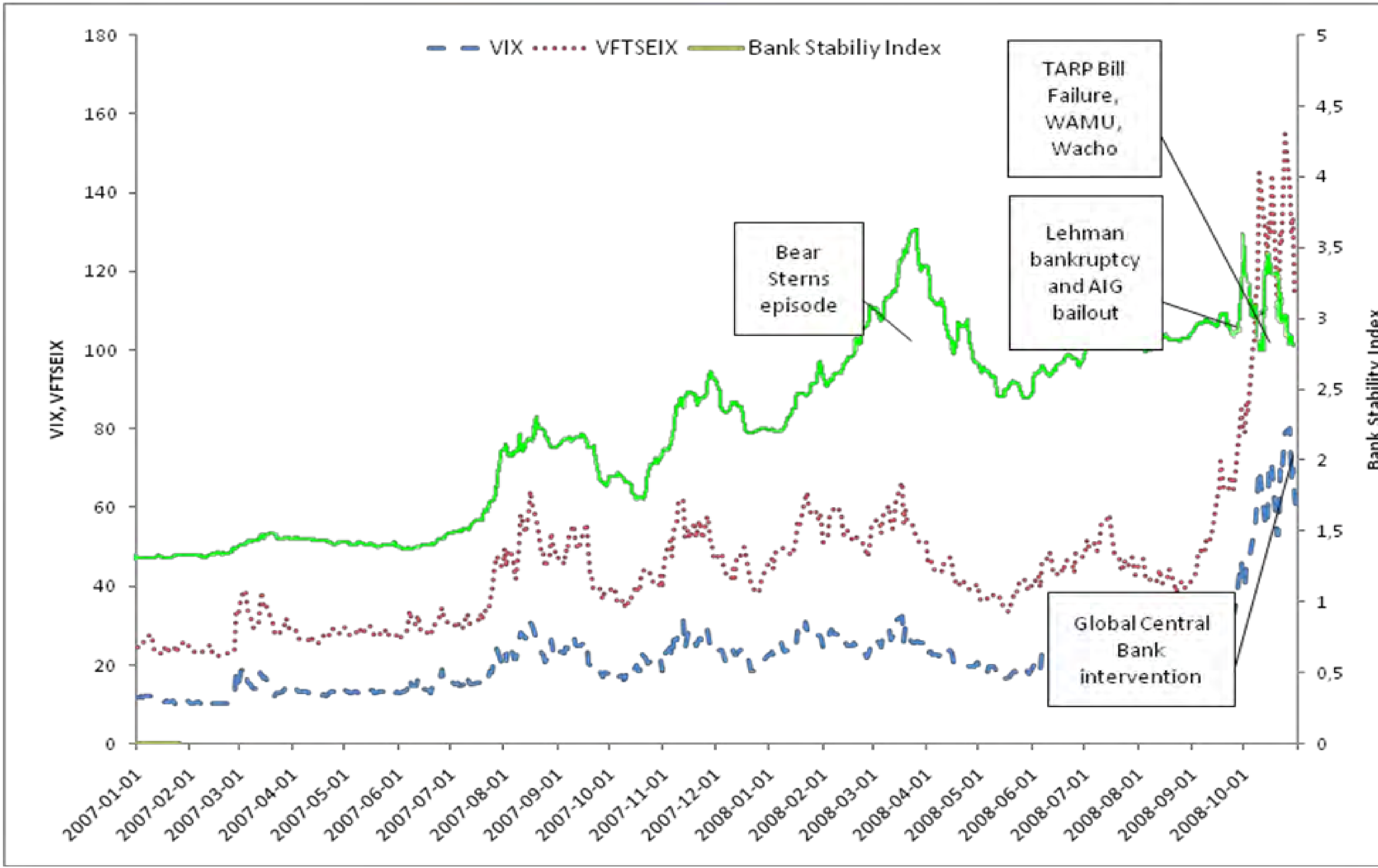
(i)Market Data based Statistical Models of Systemic Risk : A Case of ***Steadfast Refusal to Face Facts*** **(á la Goodhart, 2009) ? Absence of Early Warning Signals**

Major drawback of market price based systemic risk measures: they suffer from *paradox of volatility*(Borio and Drehman ,2009) or *paradox of financial stability* issues first addressed by Hyman Minsky (1982).

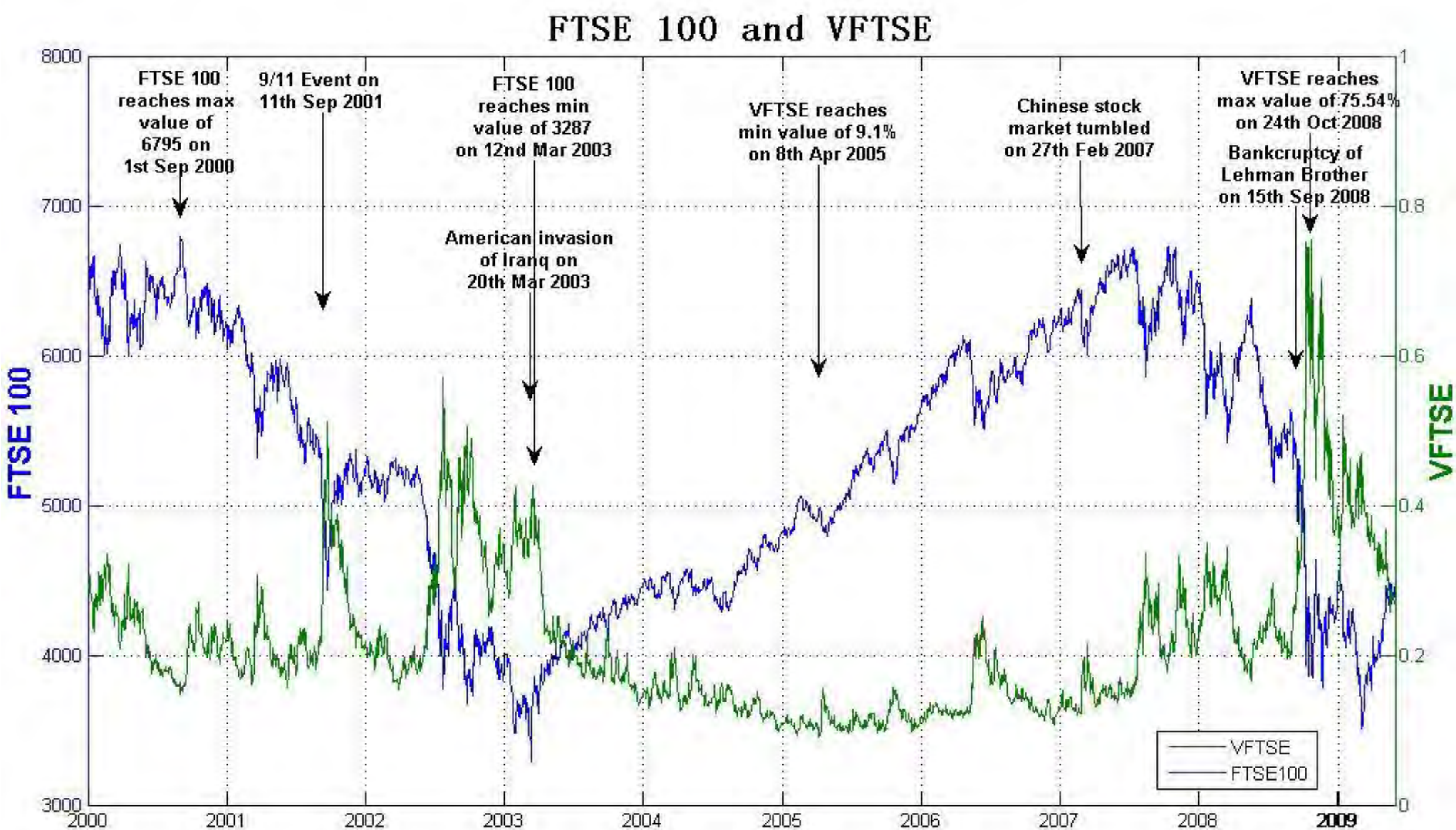
Market based statistical proxies for systemic risk (eg Segoviano and Goodhart (2009) banking stability index, Contingent Claim Analysis Distance to Distress Index of Castern and Kavounis (2011)) ***at best contemporaneous with the crisis in markets, at worst they spike after crisis***. Laura Kodres et al IMF WP /2013/115 now call market based systemic risk indices ***Coincident and Near Coincident*** *Systemic Risk Measures: conceded absence of early warning capabilities.*

As credit growth boosts asset prices, CDS spreads and VIX indices which are inversely related to asset prices are at their lowest precisely before the crash when asset prices peak → Also procyclicality of leverage Adrian and Shin (2010, 2011).

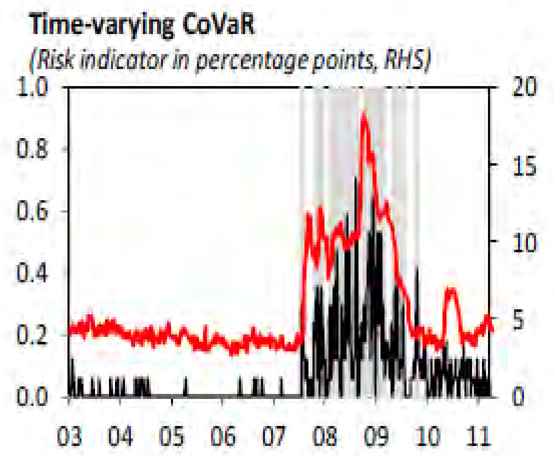
Banking Stability Index (Segoviano, Goodhart 09/04) v Market VIX and V-FTSE Indexes : *Sadly market data based indices spike contemporaneously with crisis ; devoid of requisite info for Early Warning System*

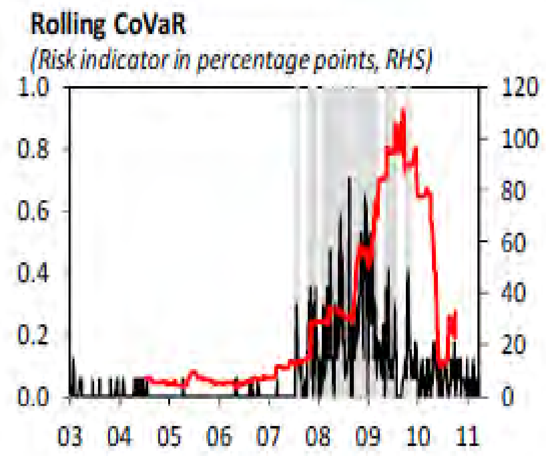


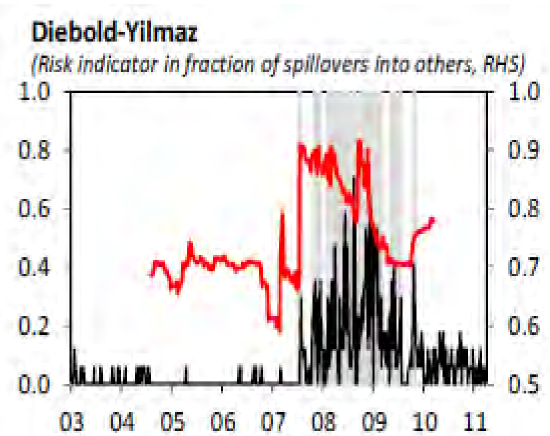
“Paradox of stability” : Stock Index and Volatility Index *Paradox of Volatility (Borio and Drehman(2009); Minsky (1982)) Volatility low during boom and at local minimum before market tanks : hence misled regulators “great moderation”*

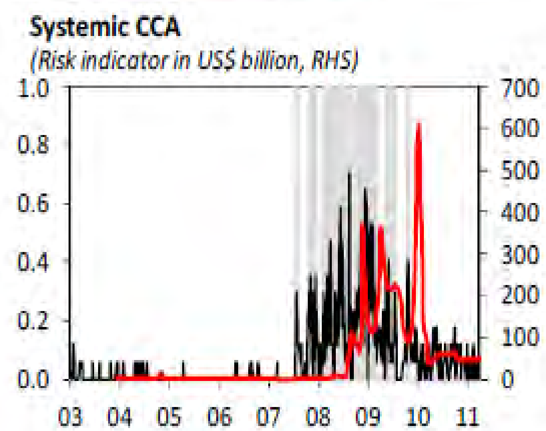


IMF WP /2013/115 Market Data Based Systemic Risk Measures: *Coincident or Near Coincident* Devoid of Early Warning Few Weeks at Best









Arsov et. al. (2013) design IMF Systemic Financial Stress (SFS, black above) index which records the extreme negative returns at 5 percentile of the (left) tail for the joint distribution of returns of a selected sample of large US and Eurozone FIs (Ibid Figure 4) Backtesting of popular systemic risk metrics (Red, above)

(ii) Fallacy of Composition In the Generation of Systemic Risk/Negative Externalities: Holistic Visualization Needed

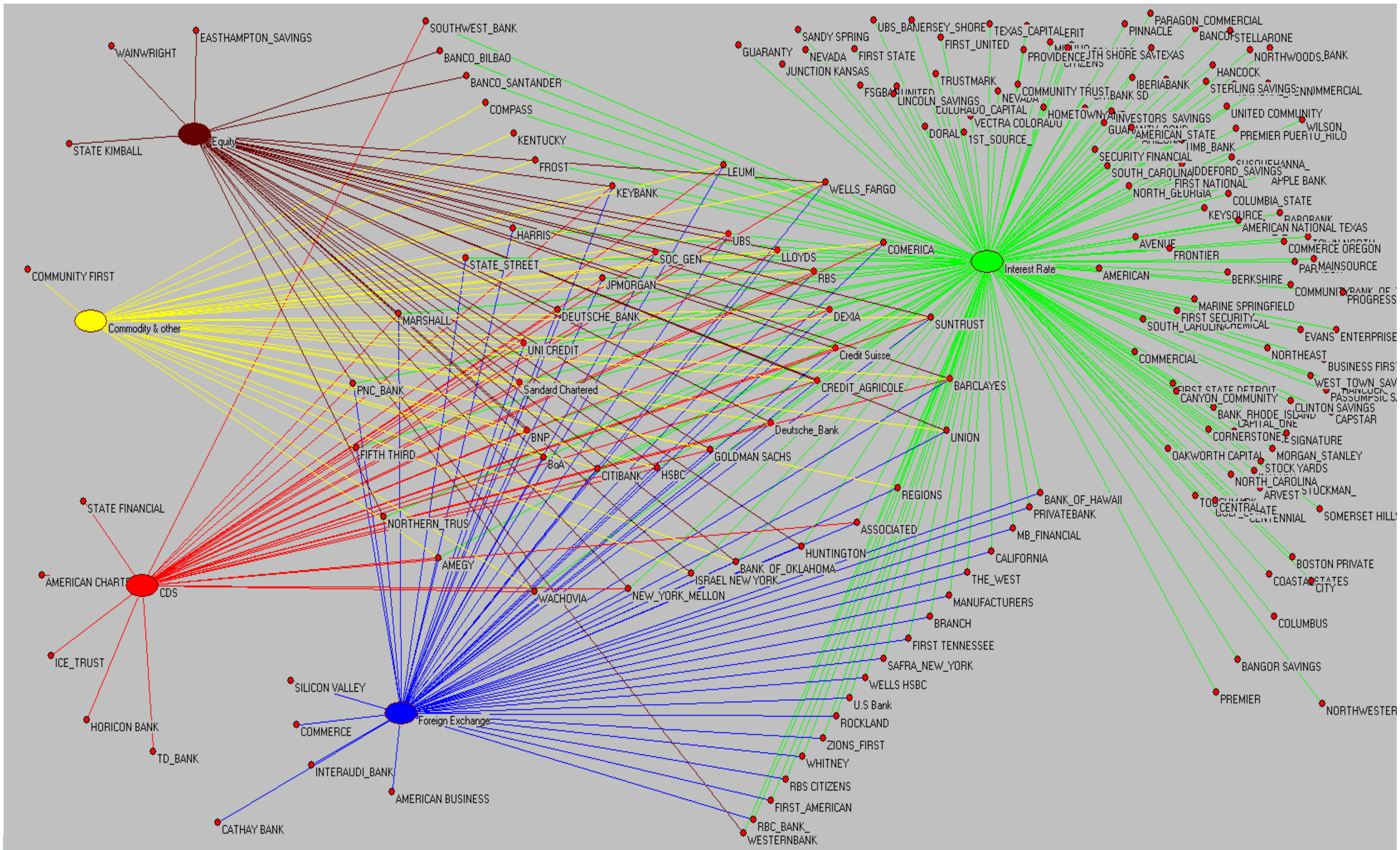
Systemic risk refers to the larger threats to the financial system as a whole that arise from domino effects of the failed entity on others.

At the level of the individual user micro-prudential schemes appear plausible but at the macro-level may lead to systemically unsustainable outcomes.
Example 1 : Risk sharing in advanced economies uses O-T-C derivatives.
Success of risk sharing at a system level depends *on who is providing insurance and structural interconnections involved* in the provision of guarantees.

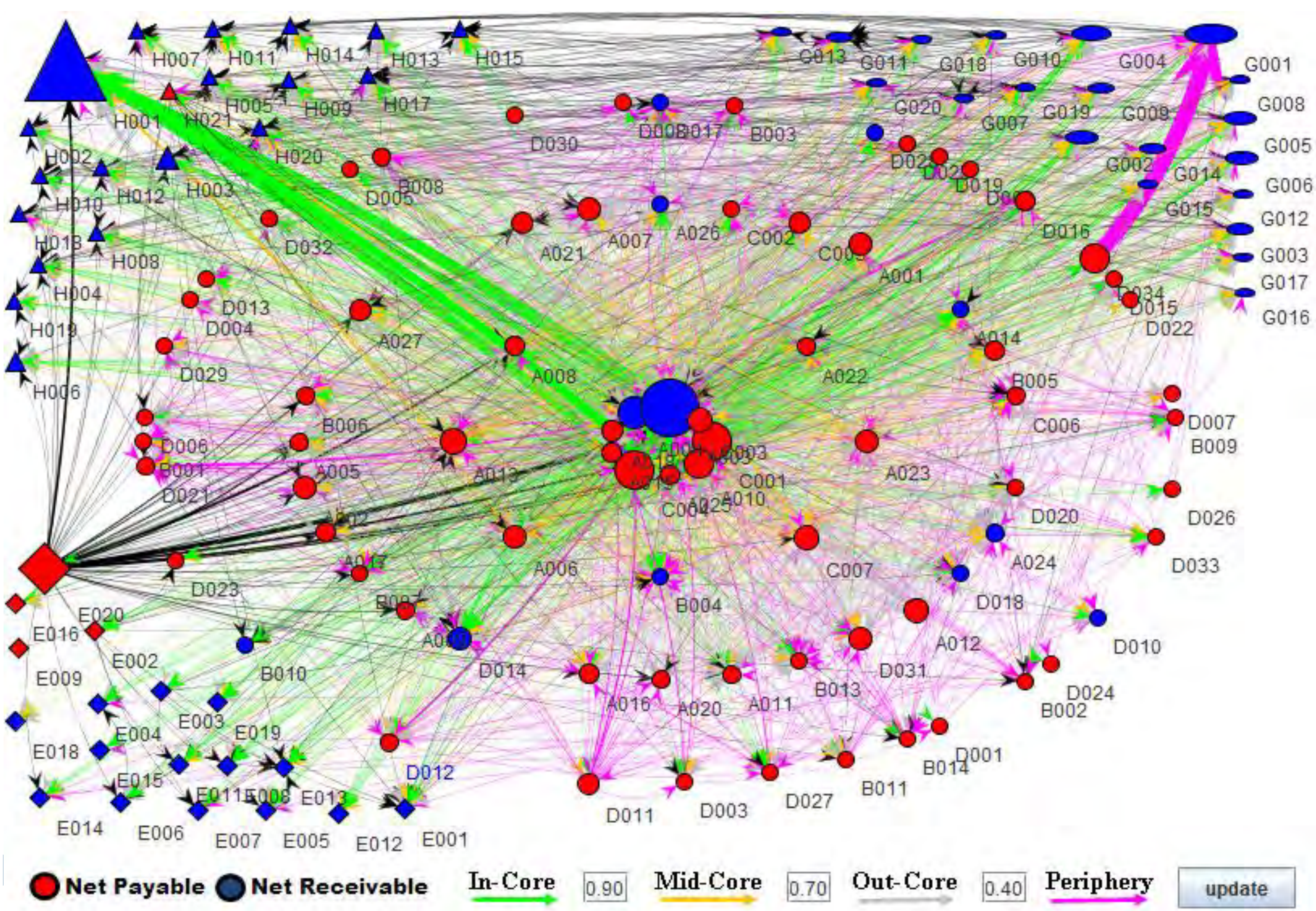
Only 5% of world OTC derivatives is for hedging purposes

Credit Risk Transfer in Basel 2 gave capital reductions from 8% to 1.6% capital charge if banks got CDS guarantees from 'AAA' providers

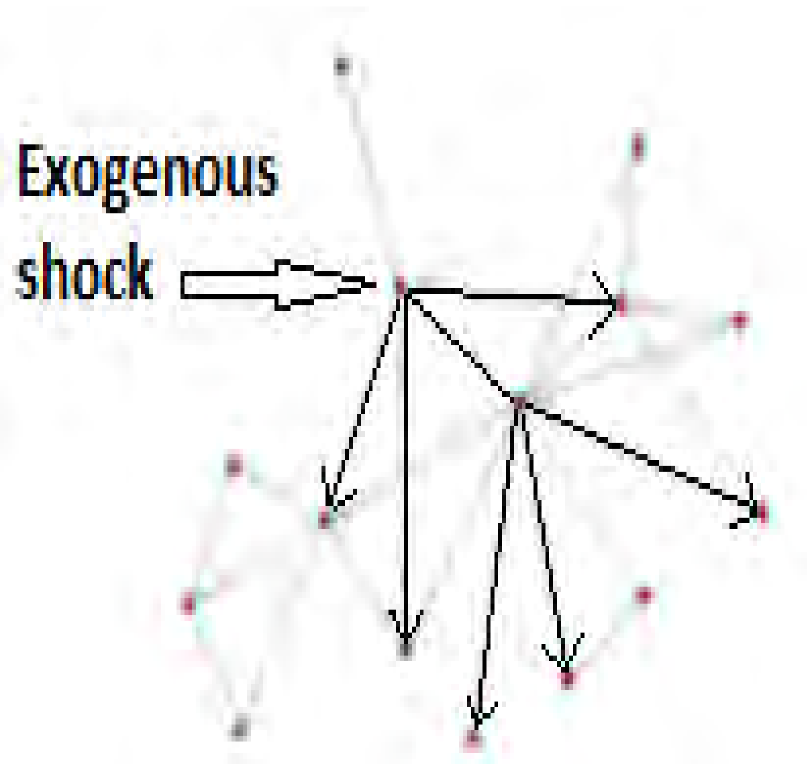
Structure of Global Financial Derivatives Market:Modern Risk Management based on Fragile Topology that Mitigates Social Usefulness (2009,Q4 204 participants): Green(Interest Rate), Blue (Forex), Maroon (Equity); Red (CDS); Yellow (Commodity); Circle 16 Broker Dealers in all markets (Source Markose IMF W, 2012)



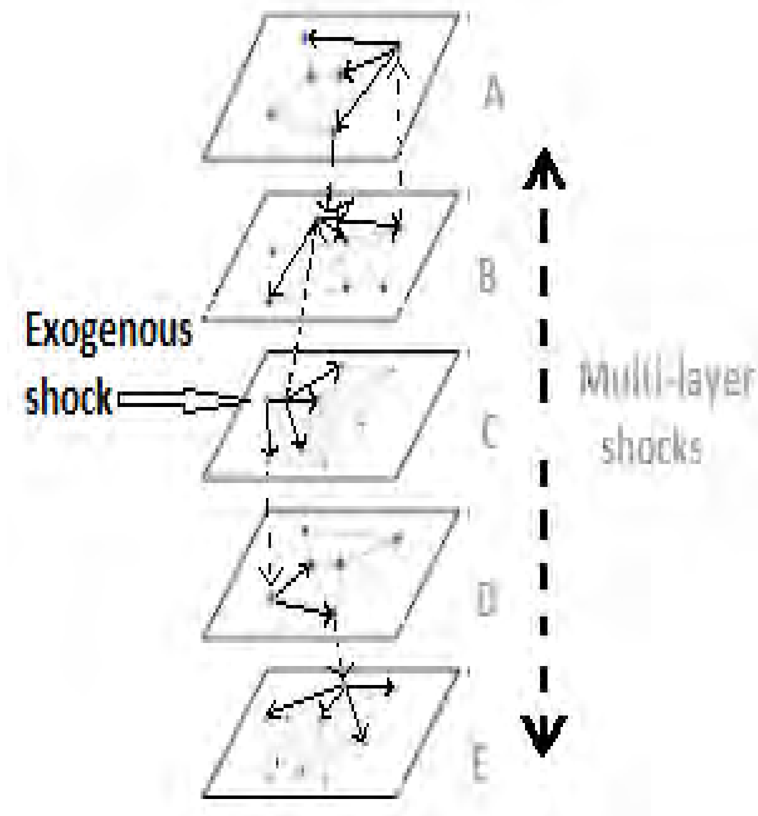
Granular Banks and Non Bank Financial Intermediaries (Dec 2012)- Note that insurance companies (H codes) mutual funds(G codes) and *not* banks (A-D codes) are net liquidity providers: Fact can be missed in banks only models !



A Financial Intermediary is member of multiple financial markets (multi-layer networks) How to calculate its centrality across the different networks it is present ?Joint Eigen-vector centrality

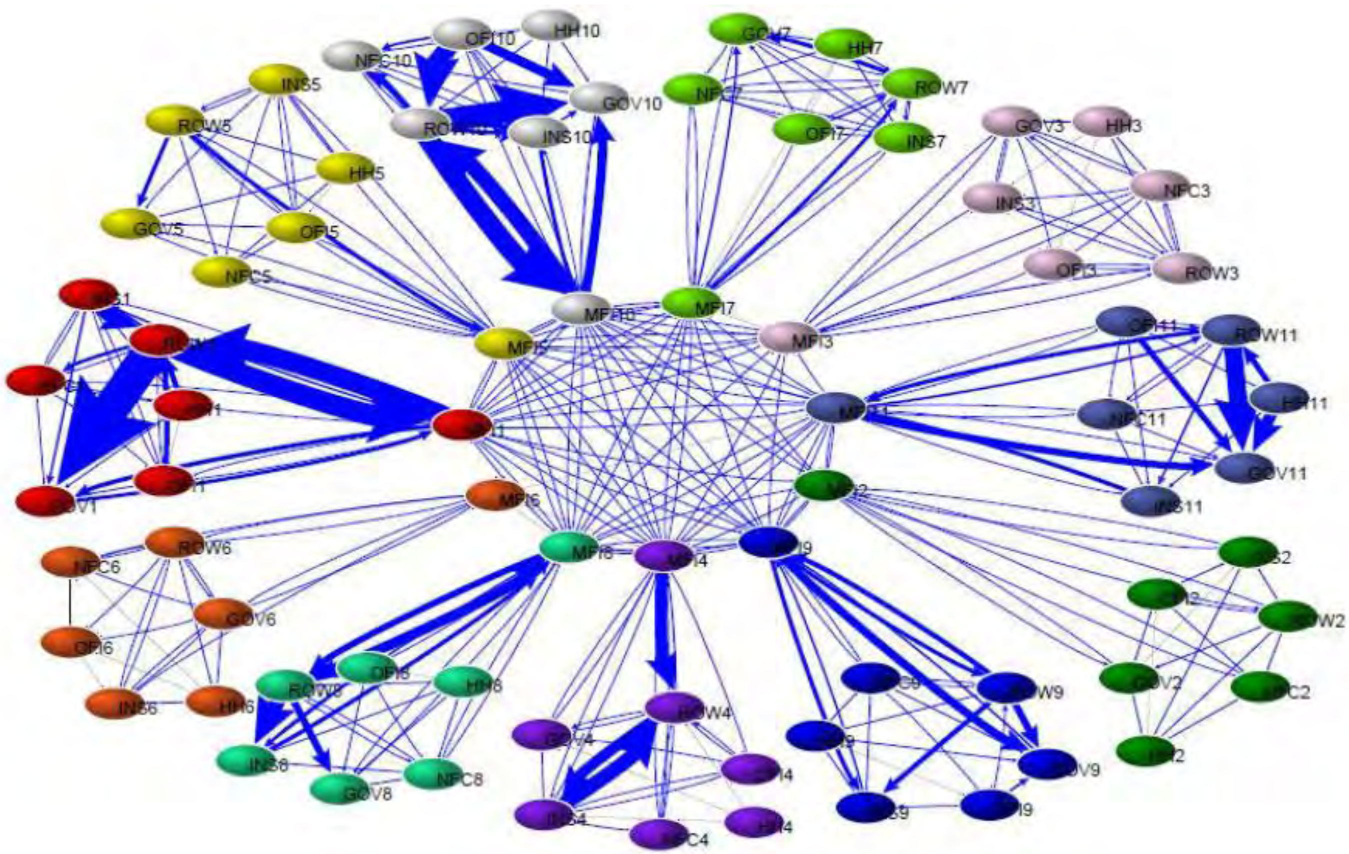


Single network



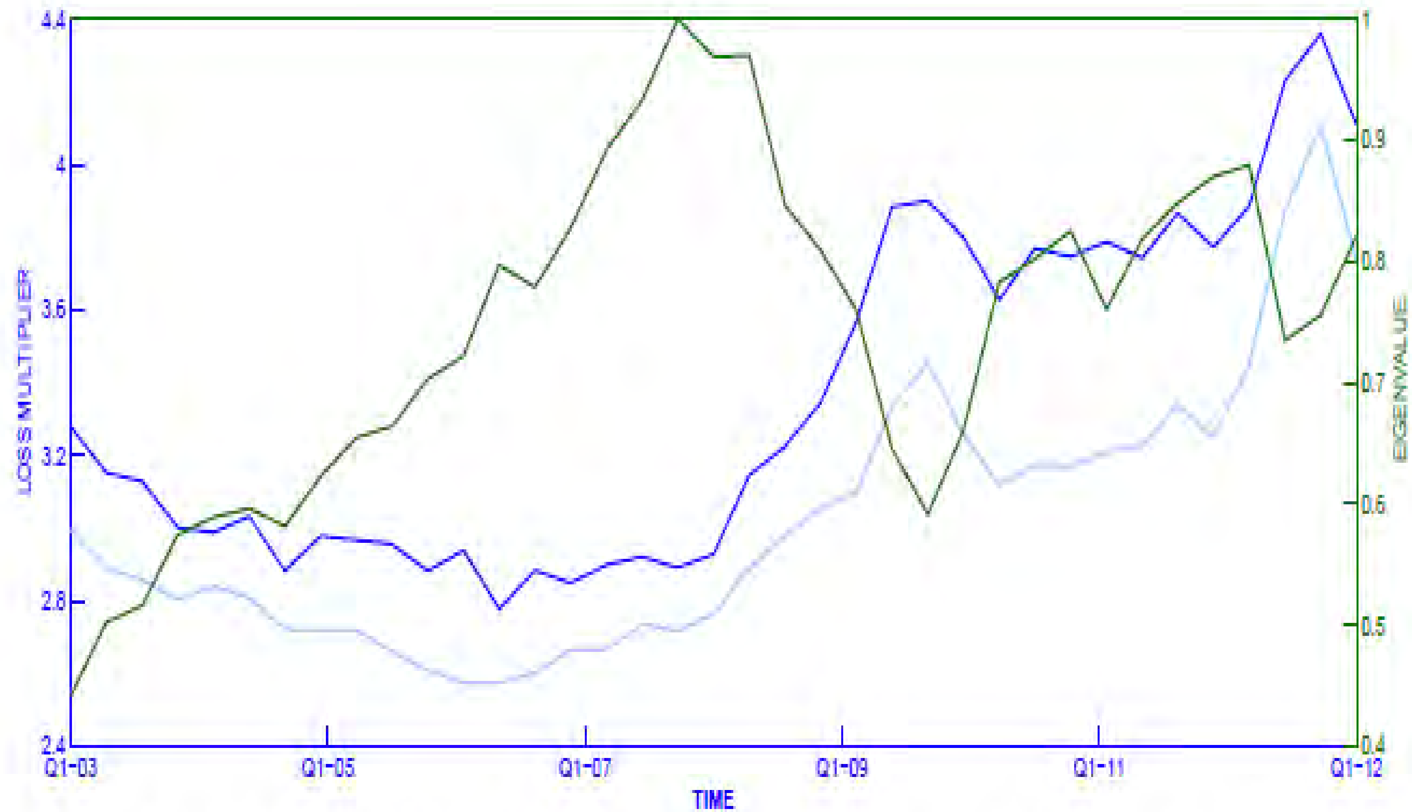
Multi-Layer Network with common nodes in some layers ; m markets

Castren and Racan (ECB 2012 WP) ***Phenomenal*** Global Macro-net Model With National Sectoral Flow of Funds To Track Global Financial Contagion! Only Problem- the Castren-Racan Systemic Risk Analytics Fail to have Early Warning Capabilities



The circle in the center represents banking systems that are exposed to the cross border liabilities of sectors (household, non bank corporate, public etc) within countries. The latter with sectoral flow of funds are given in the outer circle

Castren-Racan (2012) Loss Multiplier Systemic Risk Measure(blue lines) vs. Markose et al (2012, 2013) Maximum Eigenvalue of Matrix of Net Liabilities Relative to Tier 1 Capital (green line)



Castren-Racan loss multiplier (blue lines), unfortunately, peaks well after crisis has started and asset side of FIs is considerably weakened. Markose (2012,2013) direct measure of maximum eigenvalue, (green line)of matrix of liabilities of countries relat Tier1 capital of the exposed national banking systems, will capture growing instabili network relative to distribution of capital buffers well ahead of actual crisis.

Network Stability and Systemic Risk Measure: *Why Does Network Structure Matter to Stability ?*

$\lambda_{max} = \sqrt{NC}\,\sigma < 1$ Formula for network stability

- My work influenced by Robert May (1972, 1974)
- Stability of a network system based on the maximum eigenvalue λ_{max} *of an appropriate dynamical system*
- May gave a closed form solution for λ_{max} in terms of 3 network parameters , C : Connectivity , number of nodes N and σ Std Deviation of Node Strength : $\lambda_{max} = \sqrt{NC}\,\sigma$ All 3 network statistics cannot grow and the network remain stable. Eg a highly asymmetric network with high σ such as core periphery, its connectivity has to be very low for it to be stable

Financial network models to date have yielded mixed results : *None about propagators of 2007 crisis* (C: Core; P Periphery (see Fricke and Lux (2012))

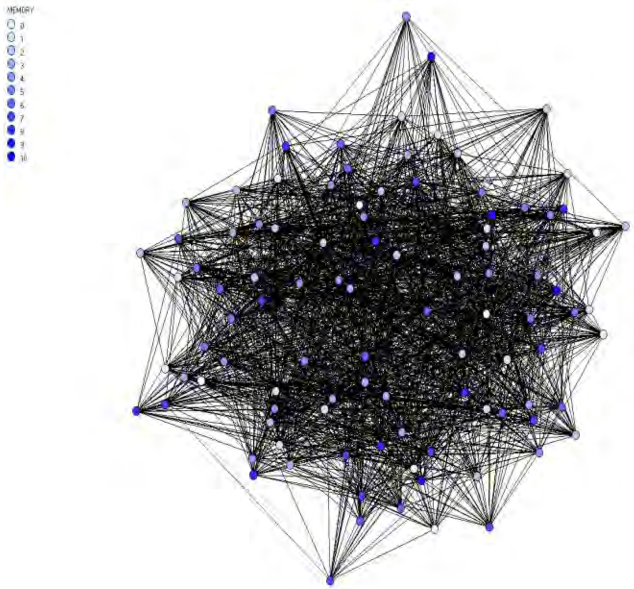
Influential and early paper Allen and Gale (2001): gave rise to mistaken view that is true of network with homogenous flows ie. increasing connectivity monotonically increases system stability

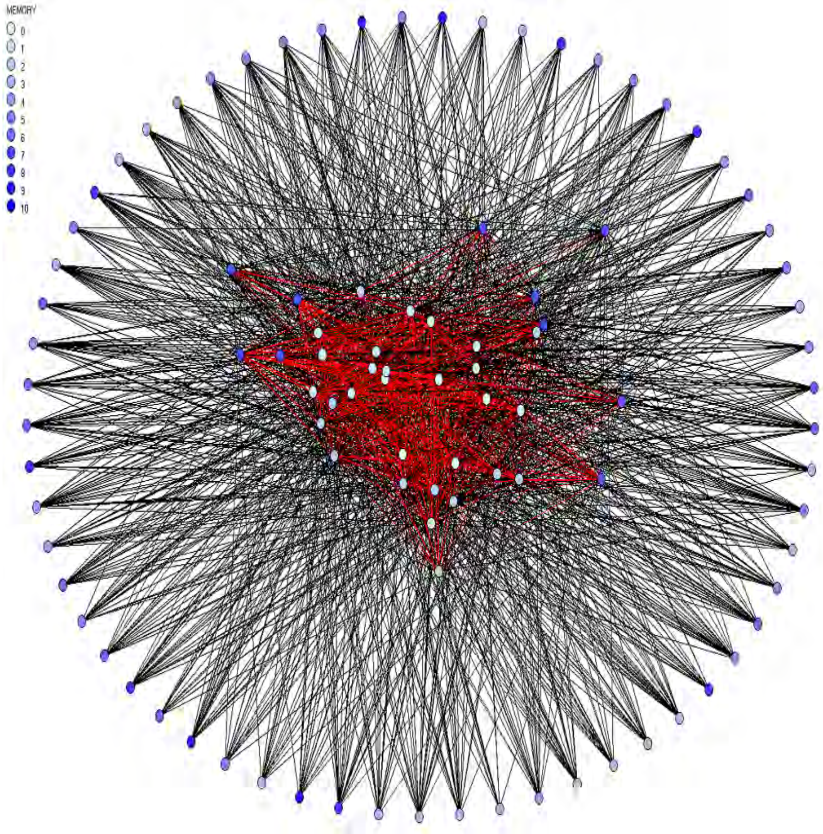
Battiston et al. (2010) show connectivity and stability not a simple monotonic relationship but that beyond a point, connectivity in a network could increase instability
Entropy models (Upper and Worms (2004) and Boss et al. (2004)) for construction of matrix of bilateral obligations. Results in a complete network structure, greatly vitiates potential for network instability or contagion

Majority of studies confined to random graphs (Nier et al. (2007) and Gai and Kapadia (2010)). Stylized agent based models relating to trade-credit relationships and business cycles by Delli Gatti et. al (2009) - Such models have insufficient empirical detail for systemic risk monitoring Craig and von Peter (JEDC, 2011) empirical mapping of German interbank and identifies the highly tiered core-periphery model which I find as well

$$M = \begin{bmatrix} CC & CP \\ PC & PP \end{bmatrix}$$

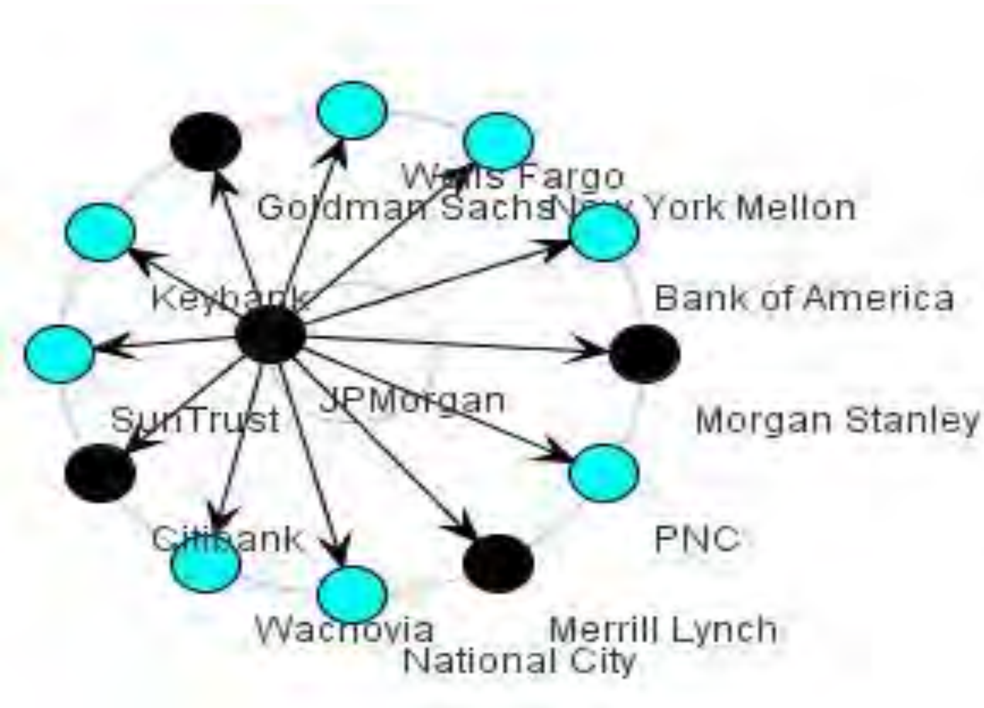
Some Networks: A graphical representation of random graph (left) and small world graph with hubs, Markose et. al. 2004

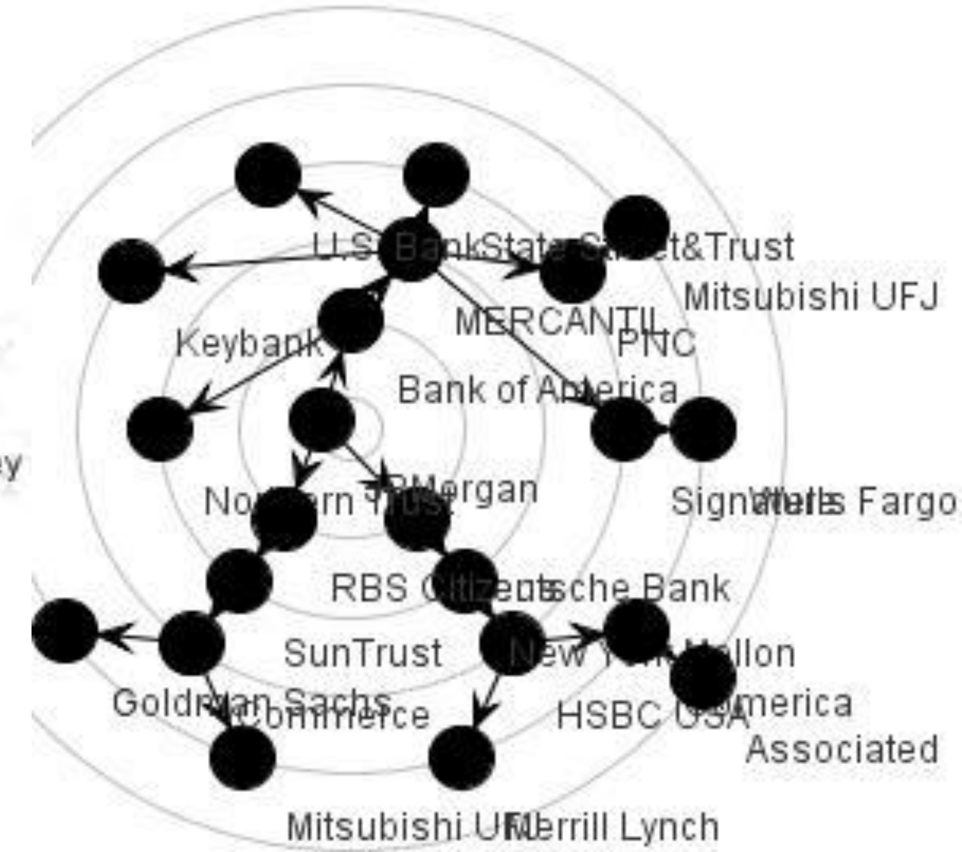




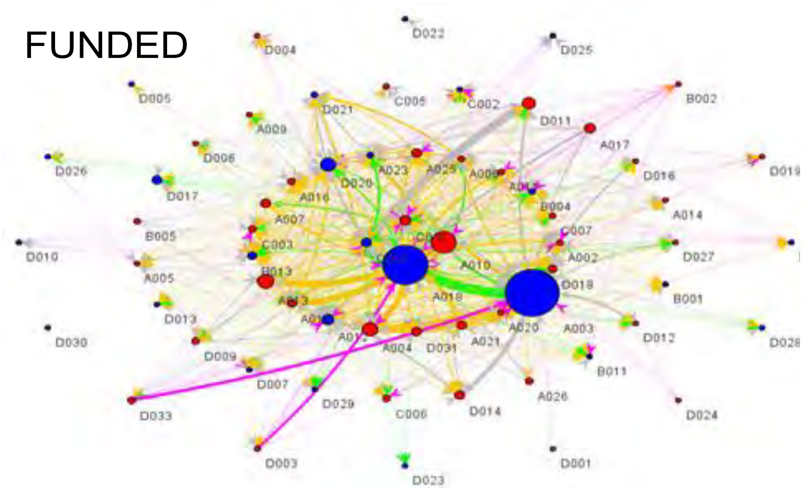
Contagion when JP Morgan Demises in Clustered CDS Network 2008 Q4 (Left 4 banks fail in first step and crisis contained) v In Random Graph (Right 22 banks fail !! Over many steps)

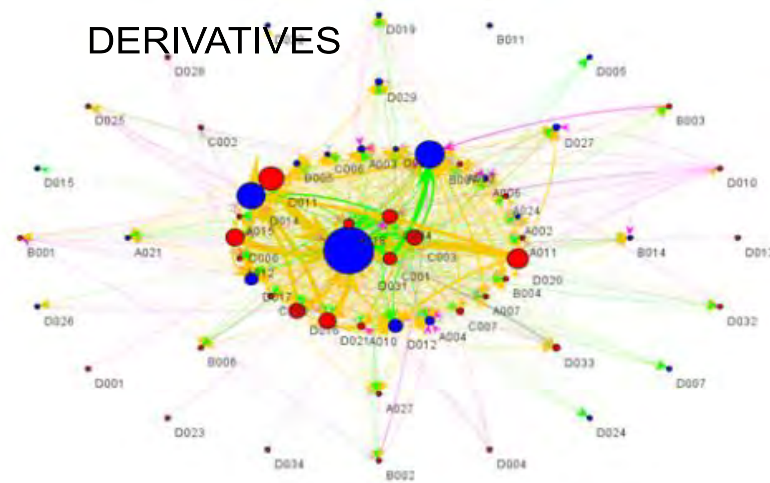
Innoculate some key players v Innoculate all (Data Q4 08)

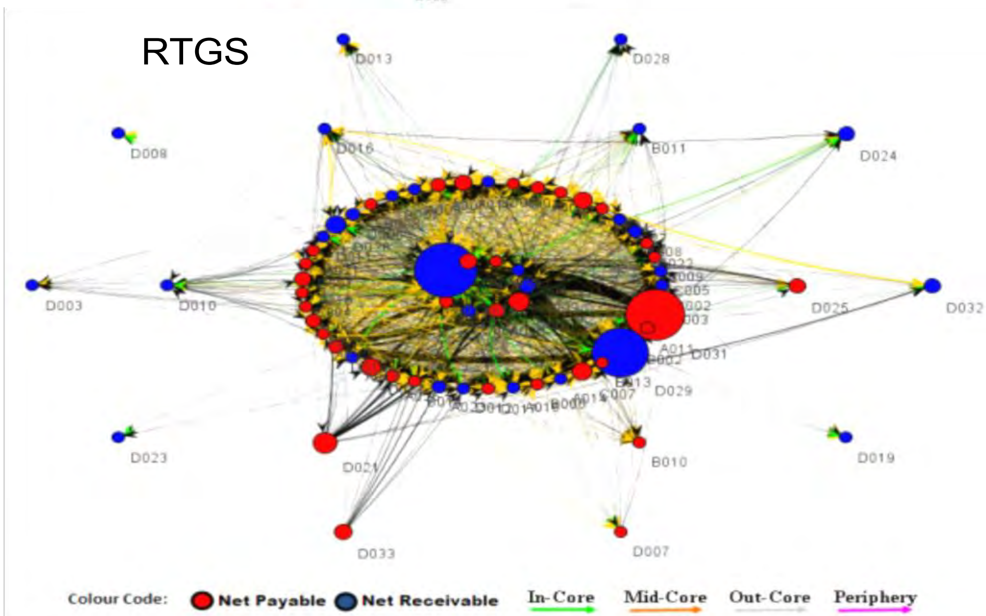




Sheri Markose and Simone Giansante RBI Project in mapping the Indian financial system shows the following networks structures: Why is it important to map topology ? Contagion propagates differently for different network structures







- Top RHS Derivatives Exposures : Shows highly tiered core-periphery structure with large numbers of participants in the periphery and a few in the core
- Top LHS Interbank Exposures: Shows a more diffused core with more numbers of banks in the core
- Bottom: network for Indian RTGS shows no marked tiering with few financial institutions in the periphery

Global Derivatives Market (Θ matrix) : JP and BoA central Tier; 22 other banks in Tier 2 *all banks in the top tiers will fail if any other fails of this group*