Networks for Systemic Risk: Indian Market Experience

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What is Systemic Risk?

Magnitude (Large Impact)

Widespread

Ripple Effect

Attributes of Systemic Risk Measures

Systemic risk is an attribute of the economic system and not that of a single entity. Its measurement should have two important features:

1. Quantifiability (Aggregation): must be measurable on an ongoing basis.
2. Decomposability (Attribution): Aggregate system-wide risk must be broken down into additive risk contributions from all entities in the system.

Financial institutions that make large risk contributions to system-wide risk are deemed "systemically important."

Systemic Analysis

The Dodd-Frank Act (2010) and Basel III regulations characterize a systemically risky FI as one that is

1. Large;
2. Complex;
3. Interconnected;
4. Critical, i.e., provides hard to substitute services to the economy.

The DFA does not provide quantification guidance.

Systemic Analysis

Definition: the measurement and analysis of relationships across entities with a view to understanding the impact of these relationships on the system as a whole.

Challenge: requires most or all of the data in the system; therefore, high-quality information extraction and integration is critical.

An Extensive Literature

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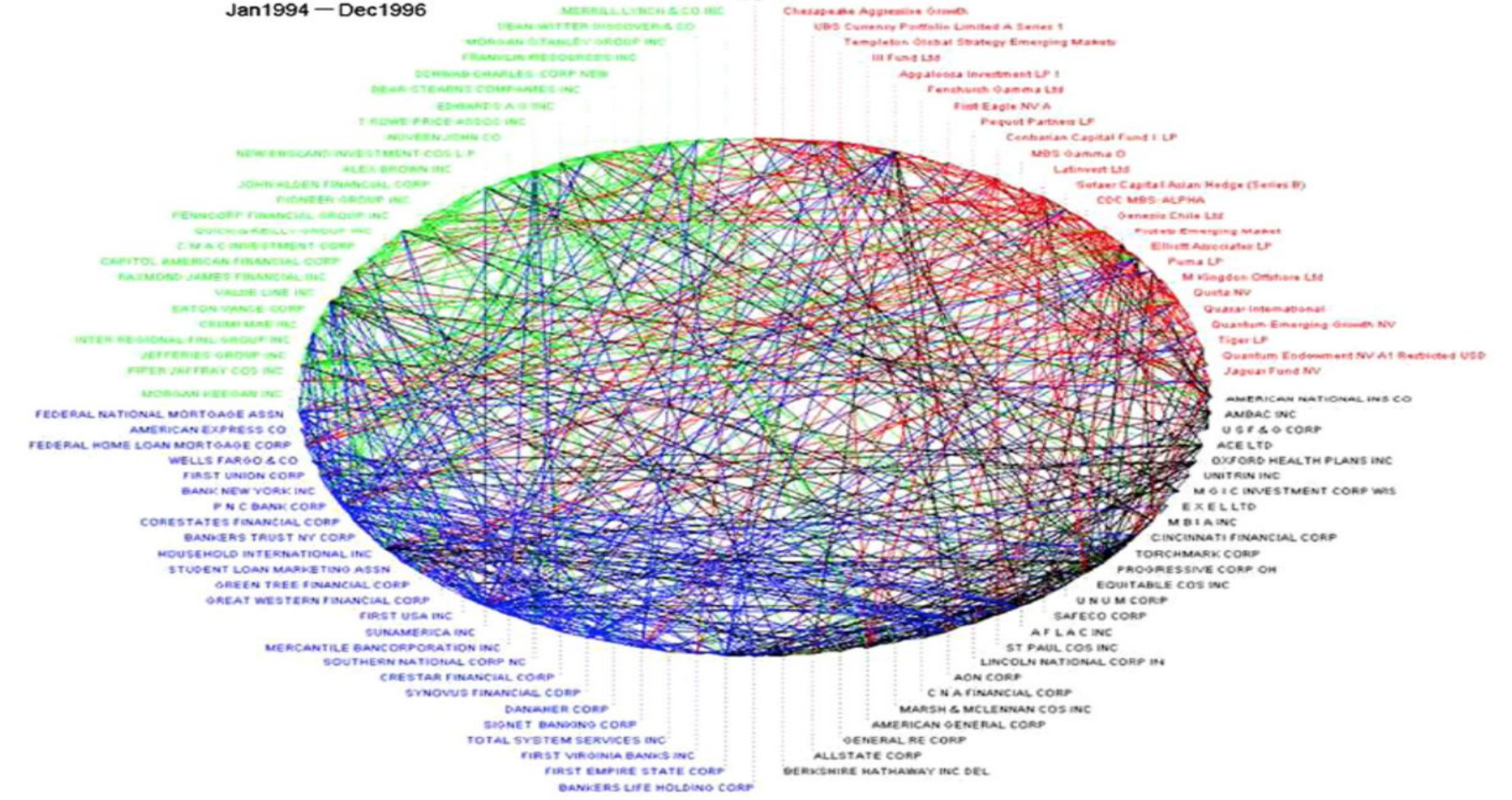
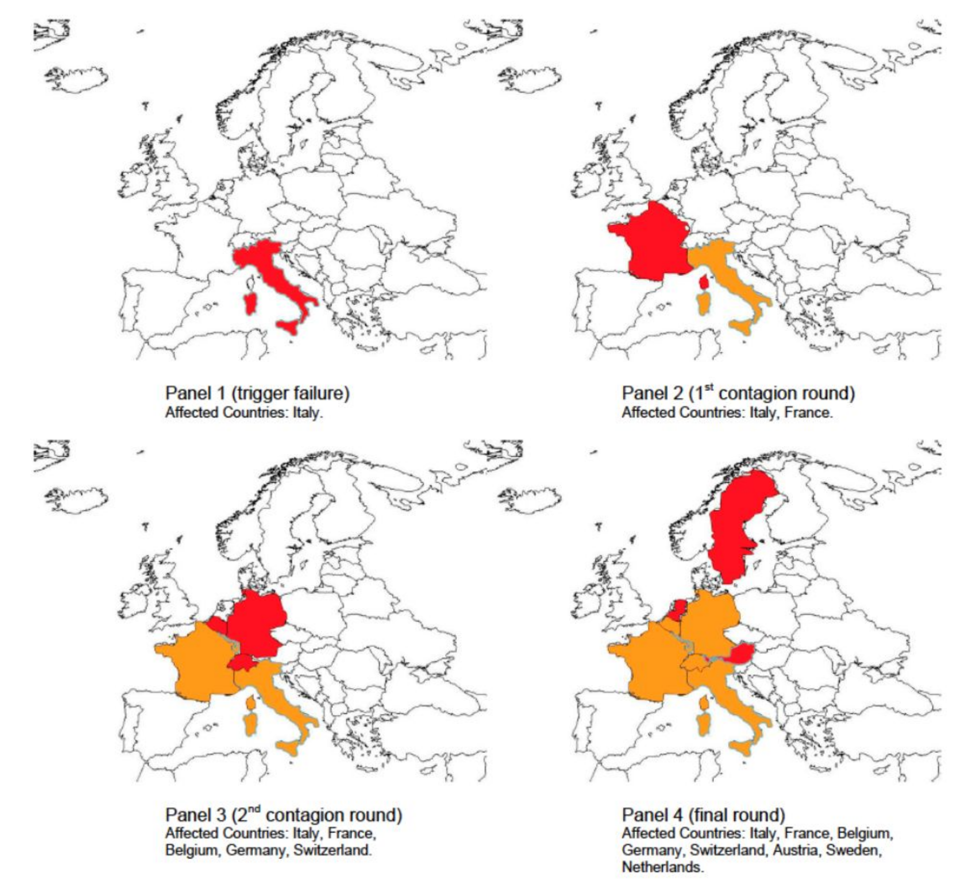


Fig. 2. Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average market cap and AUM) banks, broker/dealers, insurers, and hedge funds over January 1994 to December 1996. The type of institution causing the relationship is indicated by color: green for broker/dealers, red for hedge funds, black for insurers, and blue for banks. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

Contagion Networks (Espinosa-Vega & Sole, IMF 2010)



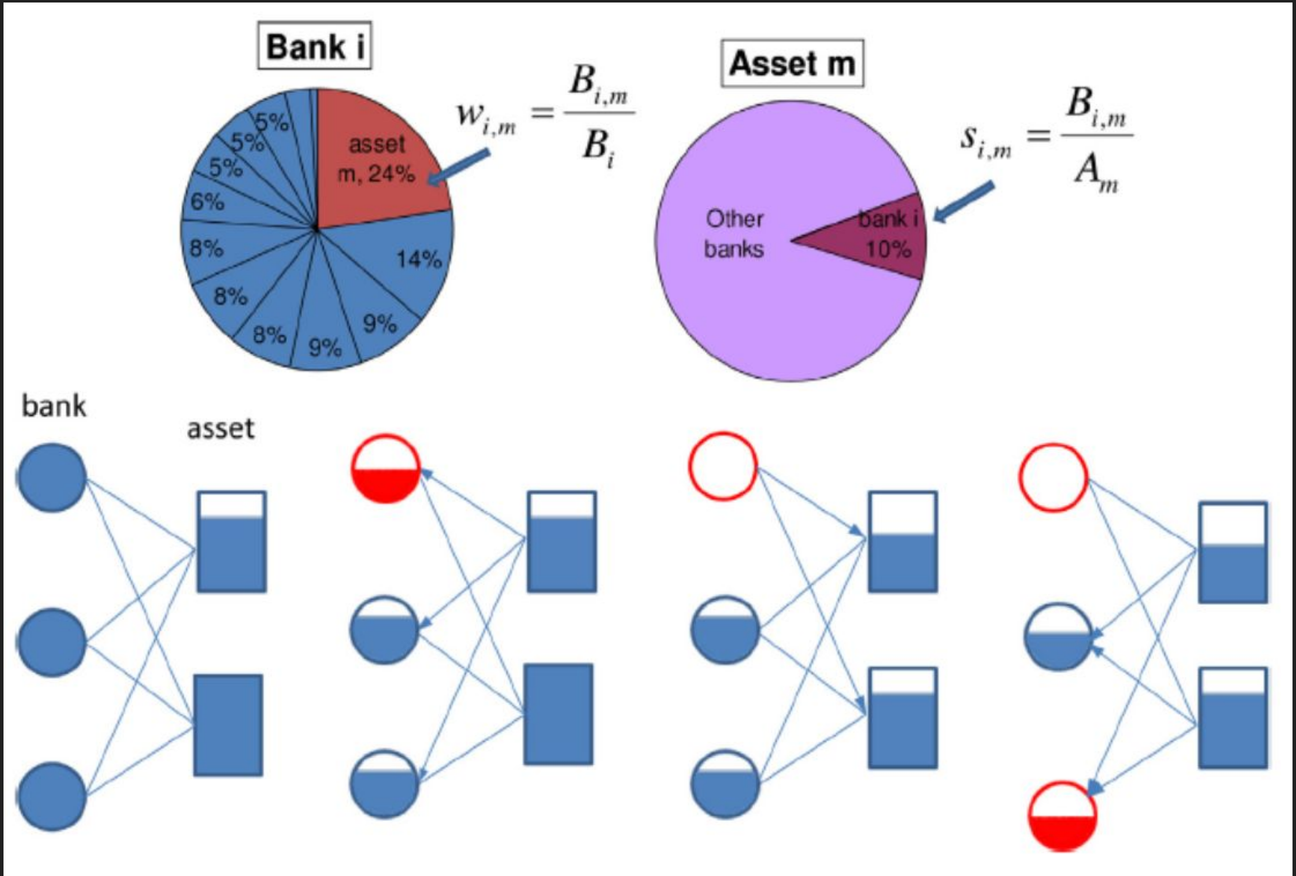
Panel 1 (trigger failure)
Affected Countries: Italy.

Panel 2 (1st contagion round)
Affected Countries: Italy, France.

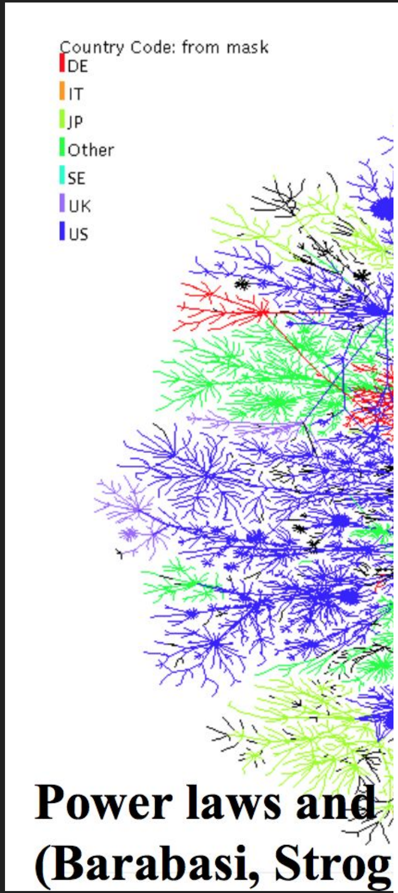
Panel 3 (2nd contagion round)
Affected Countries: Italy, France, Belgium, Germany, Switzerland.

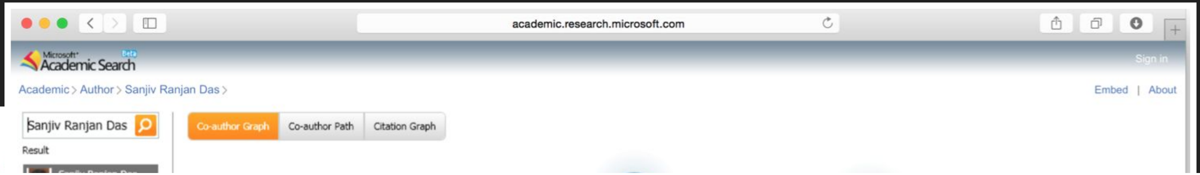
Panel 4 (final round)
Affected Countries: Italy, France, Belgium, Germany, Switzerland, Austria, Sweden, Netherlands.

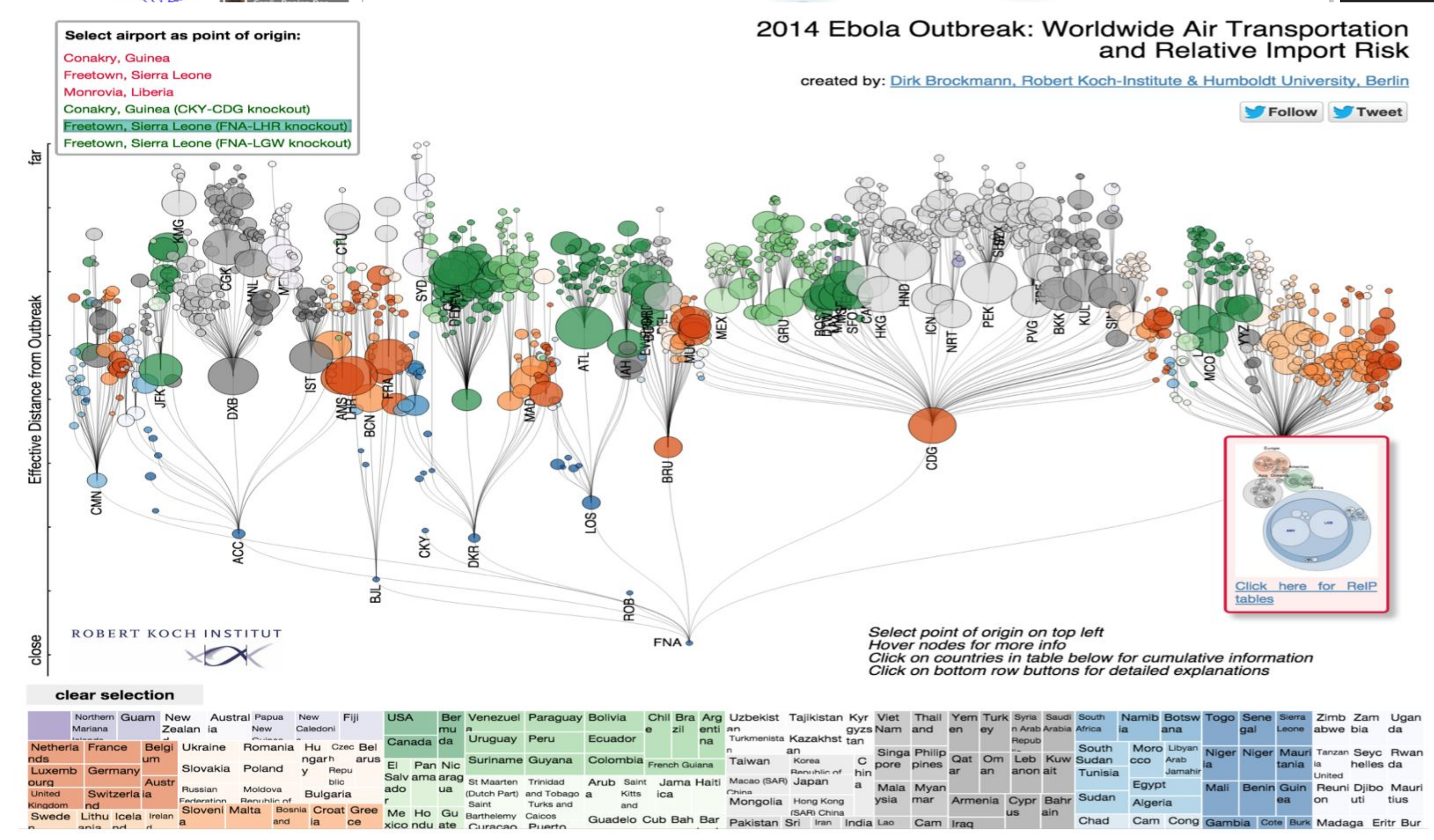
Bivalent Networks
Levy-Carciente, Kennet, Avakian, Stanley, Havlin, JBF 2015



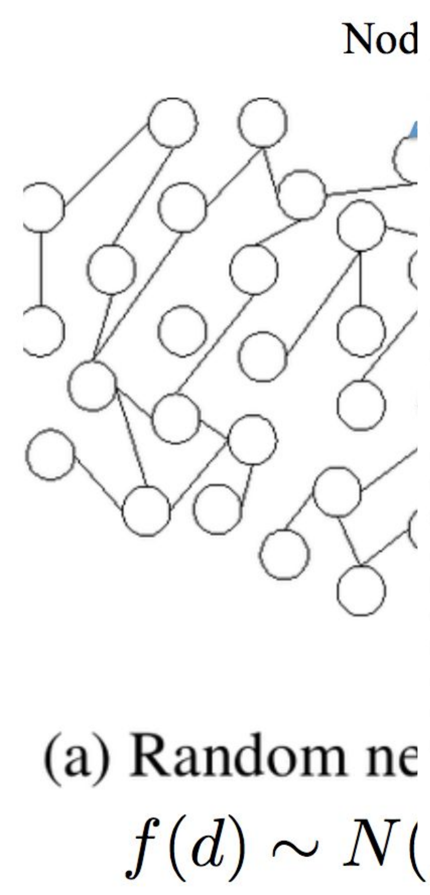
Small Worlds

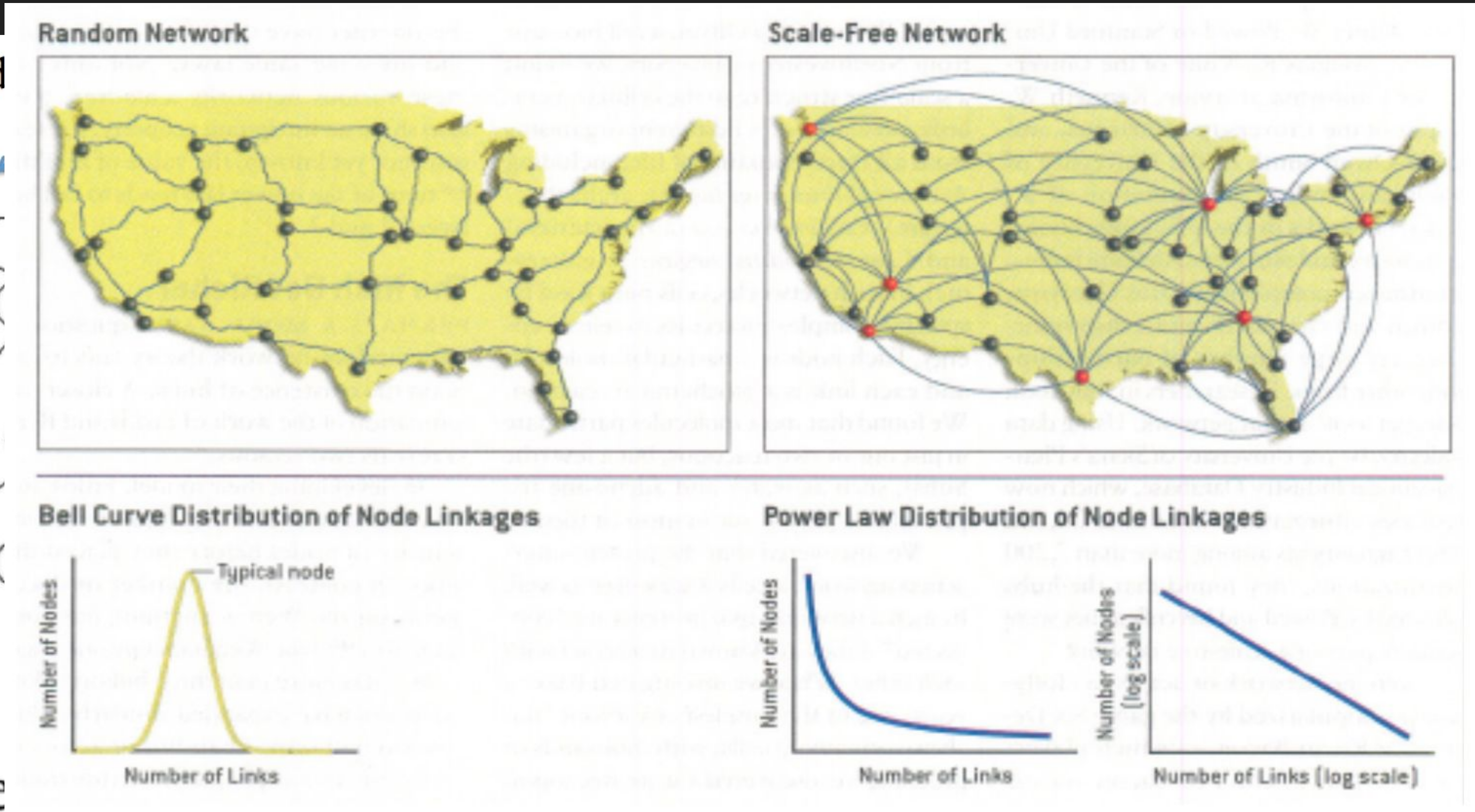






Graph Theory

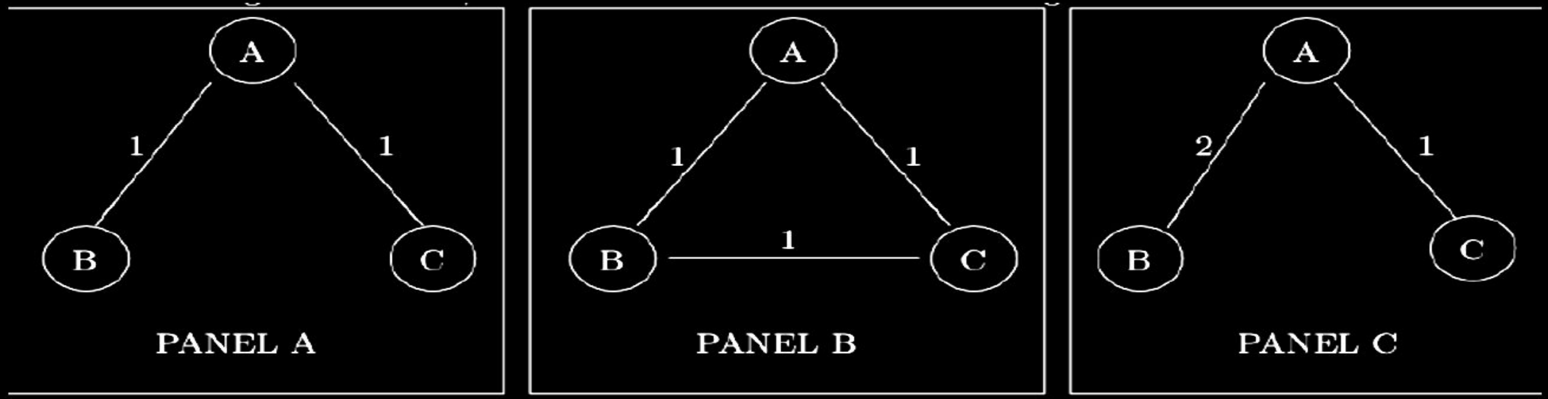




Barabasi, Sciam, May 2003

Centrality (Bonacich 1987)

- Similar to PageRank by Google.
- Adjacency matrix: $A_{ij} \in \mathcal{R}^{N\times N}$
- Influence: $x_i = \sum_{j=1}^{N} A_{ij} x_j$
- $\lambda \mathbf{x} = \mathbf{A} \cdot \mathbf{x}$
- Centrality is the eigenvector $\mathbf{x}$ corresponding to the largest eigenvalue.



$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$	$\begin{bmatrix} 0 & 2 & 1 \\ 2 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix}$
Centrality scores = {0.71, 0.50, 0.50}	Centrality scores = {0.58, 0.58, 0.58}	Centrality scores = {0.71, 0.63, 0.32}

Diameter

Longest sh

The diame

Fragility

- Definition: how quickly will the failure of any one node trigger failures across the network? Is network malaise likely to spread or be locally contained?
- Metric:

$$R = \frac{E(d^2)}{E(d)},$$

where d is node degree.

- Similar to a normalized Herfindahl Index.
- Fragility of the sample network = 20

Weak Ties

The Strength of Weak Ties[1]

Mark S. Granovetter
Johns Hopkins University

Analysis of social networks is sugges
and macro levels of sociological theo
by elaboration of the macro implicati
interaction: the strength of dyadic ti
of overlap of two individuals' frien
with the strength of their tie to on
principle on diffusion of influence ar
tunity, and community organization i
cohesive power of weak ties. Most r
with strong ties, thus confining the
defined groups. Emphasis on weak t
relations *between* groups and to analy
ture not easily defined in terms of pri

IN A 2012–2014 STUDY,

17%

OF THOSE WHO FOUND A JOB THROUGH NETWORKING SAID THAT A "WEAK TIE"—USUALLY A FRIEND OF A FRIEND—HAD HELPED THEM. IN A STUDY FROM THE 1970S, THE FIGURE WAS 83%.

DOWN AND OUT IN THE NEW ECONOMY: HOW PEOPLE FIND (OR DON'T FIND) WORK TODAY,
BY ILANA GERSHON

Communities

- Definitio
  commun

Consider a network of five nodes $\{A, B, C, D, E\}$, where the edge weights are as follows: $A : B = 6$, $A : C = 5$, $B : C = 2$, $C : D = 2$, and $D : E = 10$. Assume that a community detecti

$\{D, E\}$ to another, i.e., o

graph is

$\{$

The Kronecker delta matr

$$\begin{bmatrix} 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

Implementation in R

```
> A = matrix(c(0,6,5,0,0,6,0,2,0,0,5,2,0,2,0,0,0,2,0,10,0,0,0,10,0),5,5)
> delta = matrix(c(1,1,1,0,0,1,1,1,0,0,1,1,1,0,0,0,0,0,1,1,0,0,0,1,1),5,5)
> print(Amodularity(A,delta))
[1] 0.4128
```

We now repeat the same analysis using the R package.

```
> g = graph.adjacency(A,mode="undirected",weighted=TRUE,diag=FALSE)
```

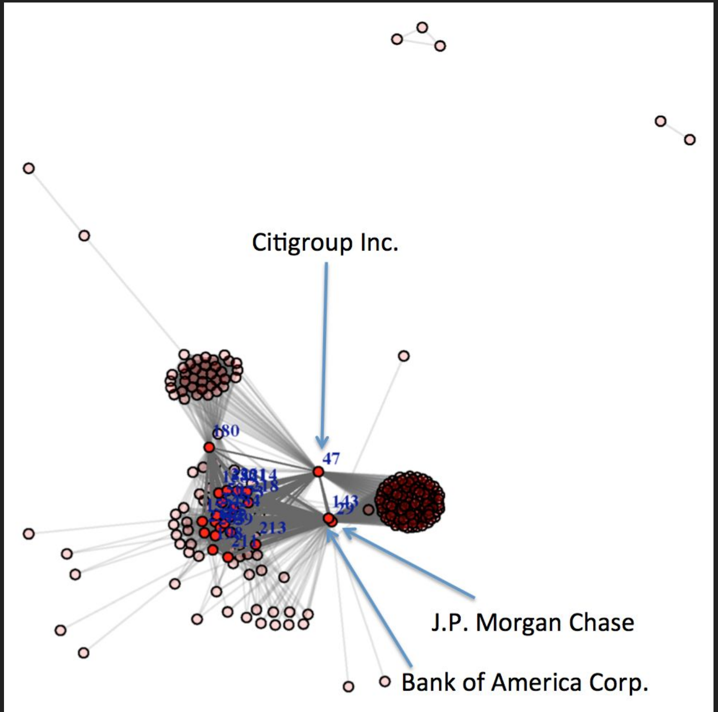
We then pass this graph to the walktrap algorithm:

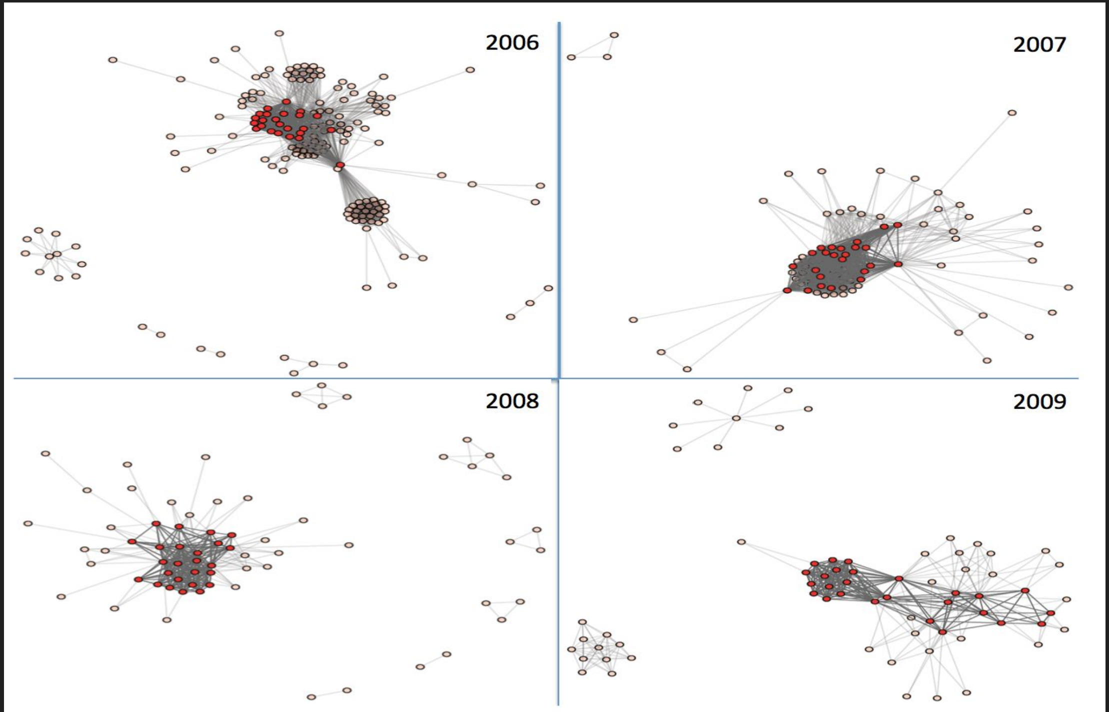
```
> wtc=walktrap.community(g,modularity=TRUE,weights=E(g)$weight)
> res=community.to.membership(g,wtc$merges,steps=3)
> print(res)
$membership
[1] 0 0 0 1 1

$csize
[1] 3 2
```

- Hard co
- Fast-gre
- Walk-tra

Interbank Loan Networks (U.S.)

"Extracting, Linking and Integrating Data from Public Sources: A Financial Case Study," (2011), (Douglas Burdick, Sanjiv Das, Mauricio A. Hernandez, Howard Ho, Georgia Koutrika, Rajasekar Krishnamurthy, Lucian Popa, Ioana Stanoi, Shivakumar Vaithyanathan), *IEEE Data Engineering Bulletin*, 34(3), 60-67.





Systemically Important Financial Institutions (SIFIs)

Year	#Colending banks	#Coloans	Colending pairs	$R = E(d^2)/E(d)$	Diam.
2005	241	75	10997	137.91	5
2006	171	95	4420	172.45	5
2007	85	49	1793	73.62	4
2008	69	84	681	68.14	4
2009	69	42	598	35.35	4

(Year = 2005)

Node #	Financial Institution	Normalized Centrality
143	J P Morgan Chase & Co.	1.000
29	Bank of America Corp.	0.926
47	Citigroup Inc.	0.639
85	Deutsche Bank Ag New York Branch	0.636
225	Wachovia Bank NA	0.617
235	The Bank of New York	0.573
134	Hsbc Bank USA	0.530
39	Barclays Bank Plc	0.530
152	Keycorp	0.524
241	The Royal Bank of Scotland Plc	0.523
6	Abn Amro Bank N.V.	0.448
173	Merrill Lynch Bank USA	0.374
198	PNC Financial Services Group Inc	0.372
180	Morgan Stanley	0.362
42	Bnp Paribas	0.337
205	Royal Bank of Canada	0.289
236	The Bank of Nova Scotia	0.289
218	U.S. Bank NA	0.284
50	Calyon New York Branch	0.273
158	Lehman Brothers Bank Fsb	0.270
213	Sumitomo Mitsui Banking	0.236
214	Suntrust Banks Inc	0.232
221	UBS Loan Finance Llc	0.221
211	State Street Corp	0.210
228	Wells Fargo Bank NA	0.198

One Score for Systemic Risk

$$S = \frac{1}{n}\sqrt{C^\top \cdot A \cdot C} \geq 0$$

banks (normalization across time)

Adjacency matrix

A(i,j) in (0,1)
A(i,i) = 1

Vector of credit risk scores {PD, rating, etc}. Higher = more risk

C(i) > 0

$S(C,A)$ is linear homogenous in C

Apply Euler's Formula

$$S = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + \ldots + \frac{\partial S}{\partial C_n} C_n = \sum_{i=1}^{n} \frac{\partial S}{\partial C_i} C_i$$

Risk Contribution

Risk Increment

$$\frac{\partial S}{\partial C} = \frac{1}{2n^2 S}\left[A \cdot C + A^{\mathsf{T}} \cdot C\right] \in \mathcal{R}^n$$

Closed vector form makes computation facile.

Risk Decomposition in closed form

$$\frac{\partial S}{\partial C_i} \cdot C_i = \frac{1}{2n^2 S} \cdot [A \cdot C + A^{\top} \cdot C] \odot C$$

$$S = \left[\frac{\partial S}{\partial C_i} \cdot C_i \right] \cdot 1$$

Total Systemic Risk Score

Data (India, 2004 -- 2016)

838 Indian firms from the Datastream Database -- explicitly identified as financial firms, are active firms, and have common equity that are major securities trading in a primary exchange in the local (Indian) market.

Reject (a) non-financial firms, (b) inactive (delisted) firms, (c) firms with only preferred stock, (d) foreign firms trading in Indian exchanges, and (e) Indian firms trading exclusively in either a minor exchange in India or a foreign exchange, (f) reject firms with less than 125 active trading days (six months).

Table 1: Bank Identification Data. This table contains a sampling of the bank name, and various other identification information.

MNEMONIC	ISIN	SEDOL	NAME	INDUSTRY	GVKEY	SIC
IN:ALN	INE428A01015	6708289	ALLAHABAD BANK	Bank	272772	6020
IN:CKB	INE476A01014	6580012	CANARA BANK	Bank	255701	6020
IN:ICG	INE090A01021	BSZ2BY7	ICICI BANK	Bank	223148	6020
IN:SBK	INE062A01020	BSQCB24	STATE BANK OF INDIA	Bank	203666	6020
IN:UBI	INE692A01016	6579634	UNION BANK OF INDIA	Bank	257156	6020
IN:TYA	INE865C01022	B0HXGC5	ADITYA BIRLA MONEY	Broker-Dealer	289796	6211
IN:ERE	INE143K01019	B56JDC8	ESSAR SECURITIES	Broker-Dealer	293675	6200
IN:KGC	INE929C01018	B03K039	K L G CAPITAL SERVICES	Broker-Dealer	289851	6211
IN:NKK	INE526C01012	B03J1D3	NIKKI GLOBAL FINANCE	Broker-Dealer	296350	6211
IN:UEI	INE519C01017	B5NH8B9	SUMMIT SECURITIES	Broker-Dealer	296724	6211
IN:BFS	INE918I01018	B2QKWK1	BAJAJ FINSERV	Insurer	288902	6300

Filtering the sample

- Based on International Securities Identification Number (ISIN) and/or Stock Exchange Daily Official List (SEDOL) identifiers, we match the Indian financial firms to the Compustat Global Database and obtain the corresponding GVKEYs and Standard Industrial Classification (SIC) codes.
- Based on SIC codes, we categorize firms as (a) Banks (SIC: 6000-6199), (b) Broker-Dealers (SIC: 6200-6299), (c) Insurers (SIC: 6300-6499), and (d) Others (all other SICs).
- Eliminate firms with no SIC code and firms classified as others (which include financial subsidiaries of non-financial corporations and specialized investment vehicles such as funds, REITs and securitized assets).
- Final screened sample consists of 387 Indian financial institutions -- 193 Banks, 191 Broker-Dealers and 3 Insurers.

Table 2: Industry groups, sample count.

	TOTAL	NUMBER WITH VALID			
INDUSTRY	NUMBER	RETURNS	RATINGS	DTD	PD
Bank	193	193	20	176	177
Broker-Dealer	191	191	0	177	177
Insurer	3	3	0	2	2
Total	387	387	20	355	356

Additional Firm Level Data

1. Log(Assets) and Log(Market Cap) as measures of firm size in terms of book value of assets and market value of equity, respectively;
2. Loans/Assets and Loans/Deposits ratios to capture banks' focus on traditional lending activities and core financing activities (these ratios are set to zero for non-bank financial institutions);
3. Debt/Assets and Debt/Equity ratios to capture leverage;
4. Debt/Capital as a measure of the liquidity position of the financial firm;
5. ROA (return on assets) and ROE (return on equity) as measures of operating performance of the financial firm; and
6. Market/Book value of equity ratio of the financial institution as a measure of the stock price based performance.

Network Construction

Billio, Getmansky, Lo, Pelizzon (2012)

$$r_{j,t} = a + b \cdot r_{j,t-1} + c \cdot r_{i,t-1} + e_{j,t}$$

return

Significant,
p-value <0.025

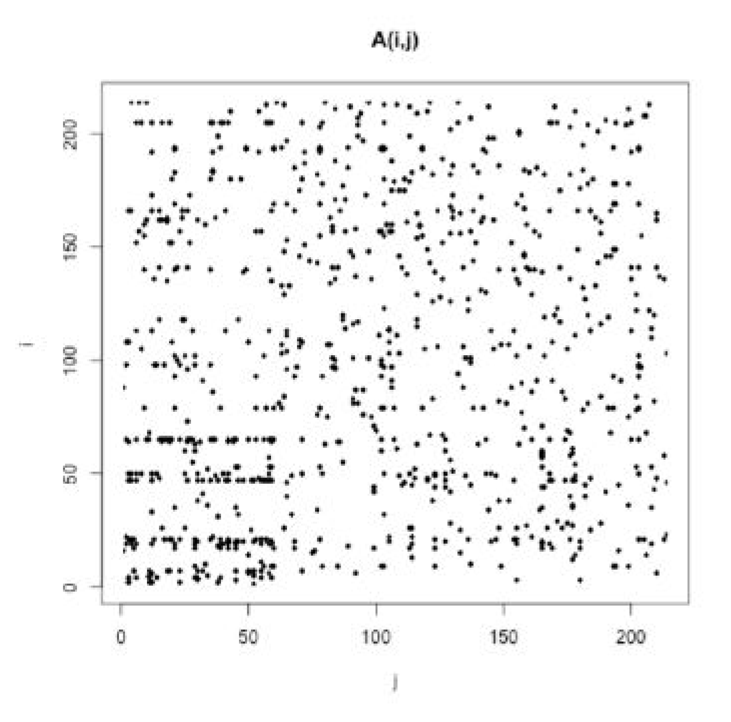
$$r_{j,t} = a + b \cdot r_{j,t-1} + c \cdot r_{i,t-1} + d \cdot r_{EW,t-1} + e_{j,t}$$

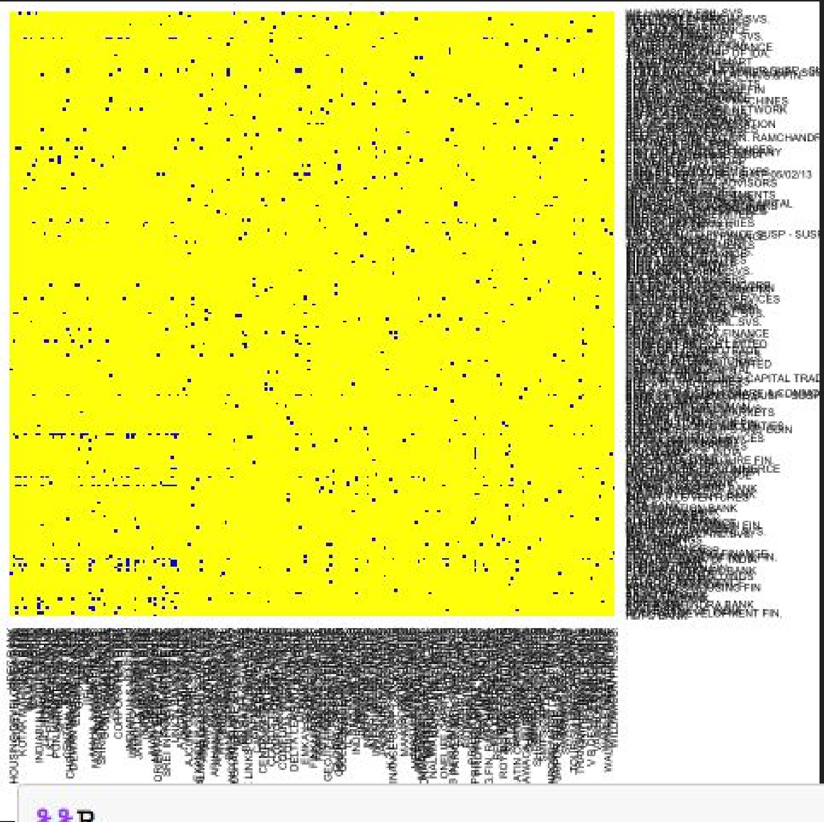
Lookback period = 130 days

Equally weighted return

Exclude banks that have more than ⅓ days with zero returns

Adjacency Matrix





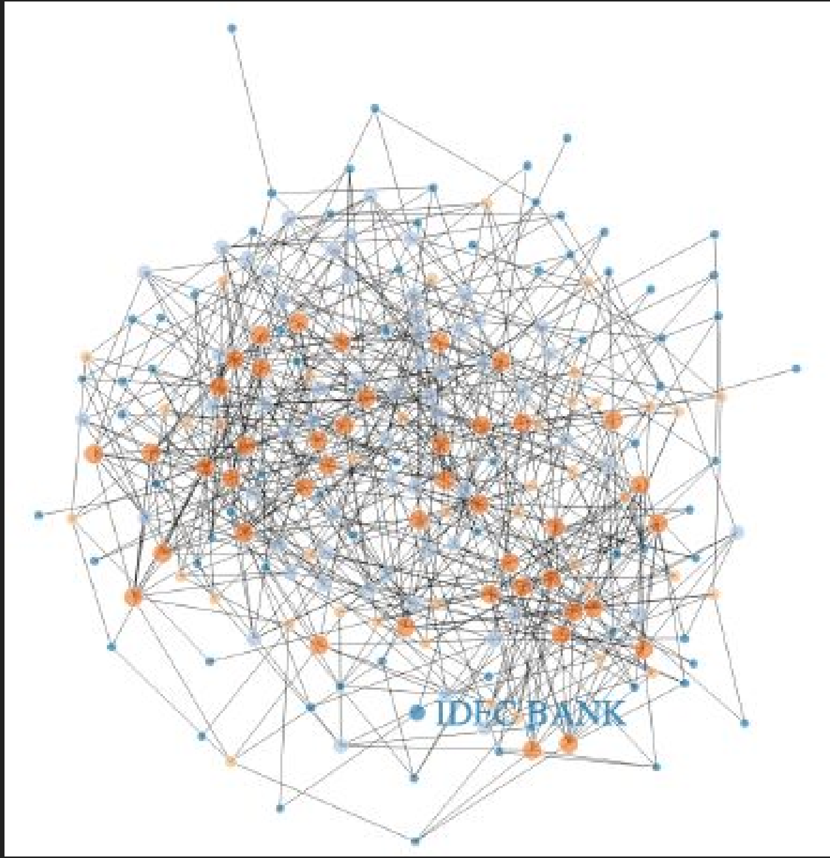
```
Pct of possible directed links:[1] 0.01827476
No of banks: [1] 214
No of regressions: [1] 45582
```

```
%%R
system.time(Amat <- genAdjMat(df_rets))
```

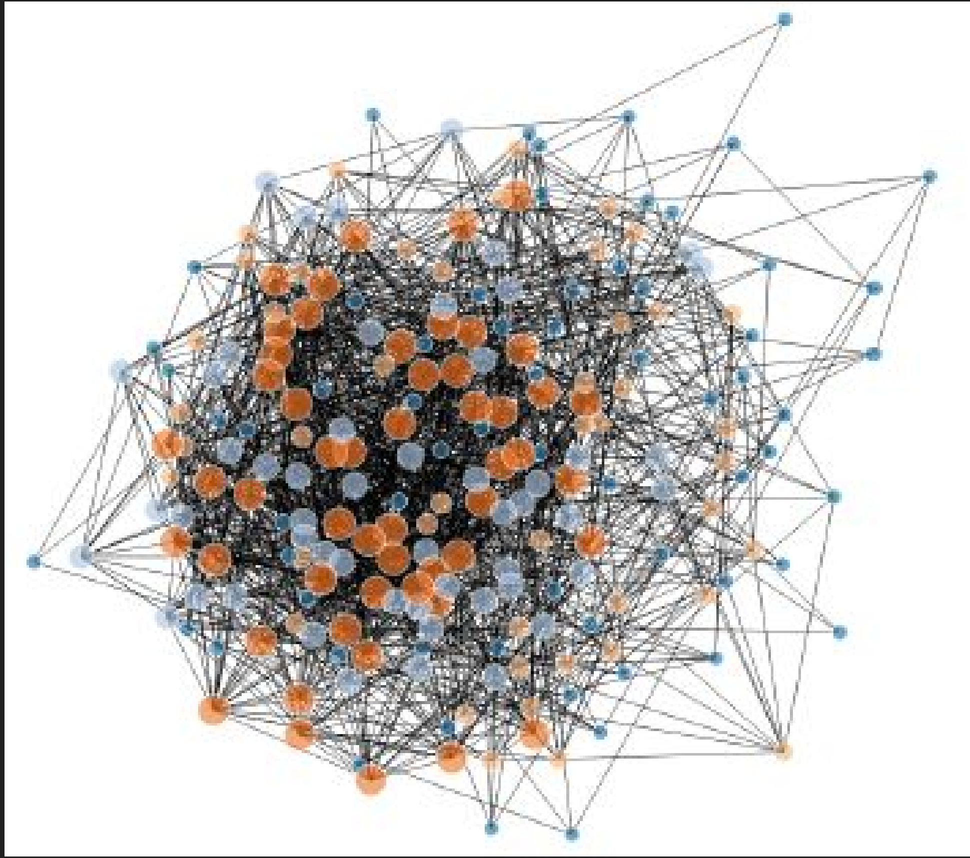
```
   user  system elapsed
 31.741   0.173  31.832
```

Network

P = 0.025



P = 0.050



Centrality

$$c_i = \sum_{j=1}^{n} A_{ij} c_j, \forall i$$

Eigenvalue Centrality

$$b_v = \sum_{\substack{i,j \\ i \neq j \\ i \neq v \\ j \neq v}} \left[\frac{g_{ivj}}{g_{ij}} \right]$$

Betweenness Centrality

Distribution of Centrality

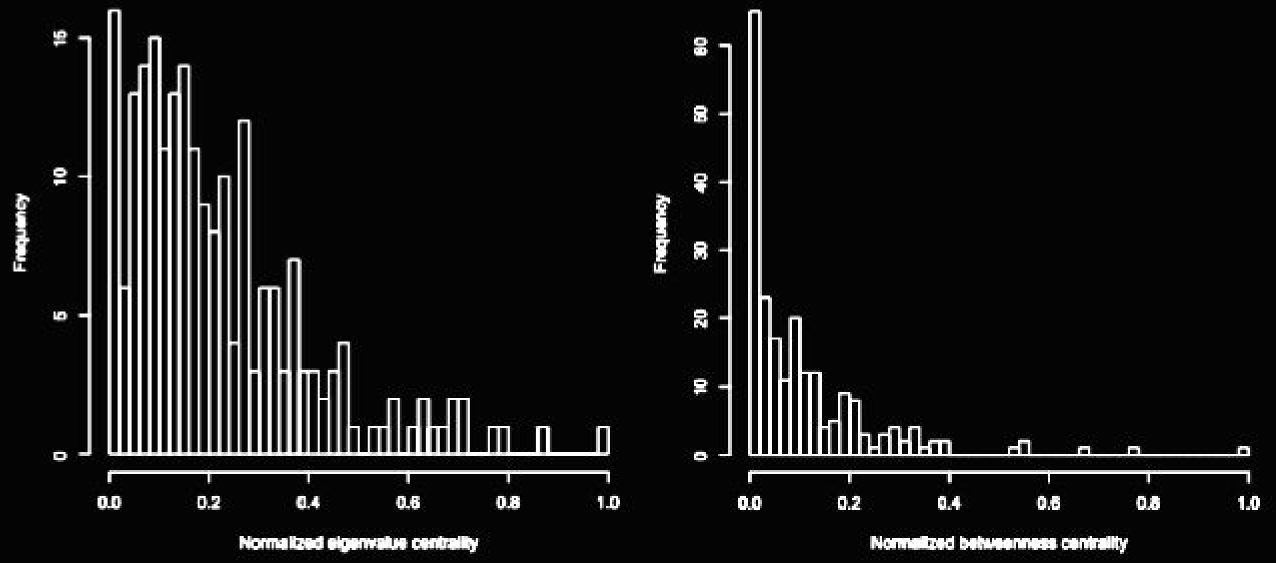


Figure 3: Distribution of Eigenvalue Centrality and Betweenness Centrality for all the nodes in the network, for Q4 2016. The centrality is normalized, so that it ranges from 0 to 1.

Top 20 Banks, Q4 2016

Bank	EVCENT	BCENT
PRITI MERCANTILE COMPANY	1.000000	0.217527
DHANLAXMI BANK	0.879521	0.289056
BANK OF MAHARASHTRA	0.797941	0.033656
INDIAN BANK	0.771766	0.033376
UCO BANK	0.710815	0.082385
UNITED BANK OF INDIA	0.708690	0.033280
RR FINL.CONSULTANTS	0.694695	0.135618
UNION BANK OF INDIA	0.687011	0.047011
CENTRAL BANK OF INDIA	0.675282	0.667370
IFCI	0.656577	0.053150
P N B GILTS	0.633888	0.248902
GLOBAL CAPITAL MARKETS	0.629967	0.375415
J M FINANCIAL	0.601884	0.132343
CORPORATION BANK	0.564888	0.000000
INTER GLOBE FINANCE	0.562848	0.533449
STATE BANK OF INDIA	0.548690	0.175723
BANK OF BARODA	0.539016	0.009665
S P CAPITAL FINANCING	0.497271	0.022460
SOUTH INDIAN BANK	0.476020	0.091634
TRANSWARRANTY FINANCE	0.472221	0.072575

Number of banks in the network

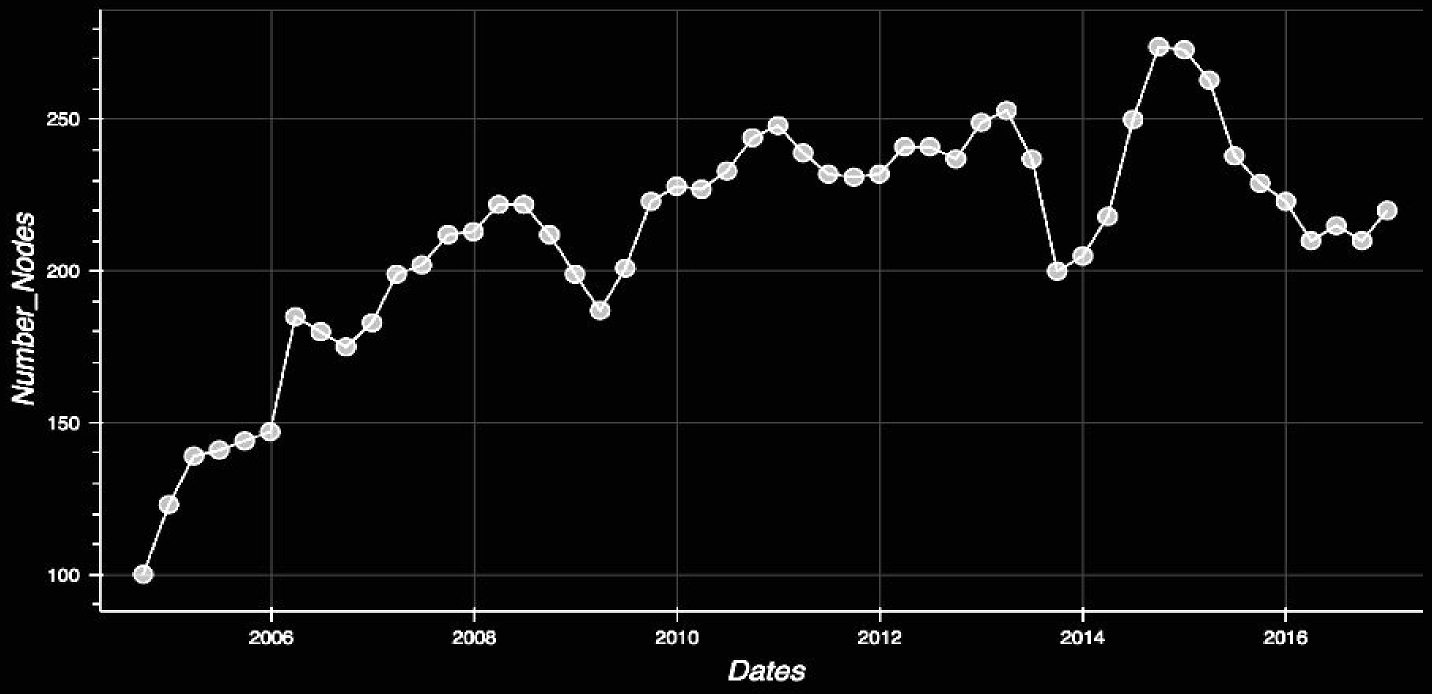
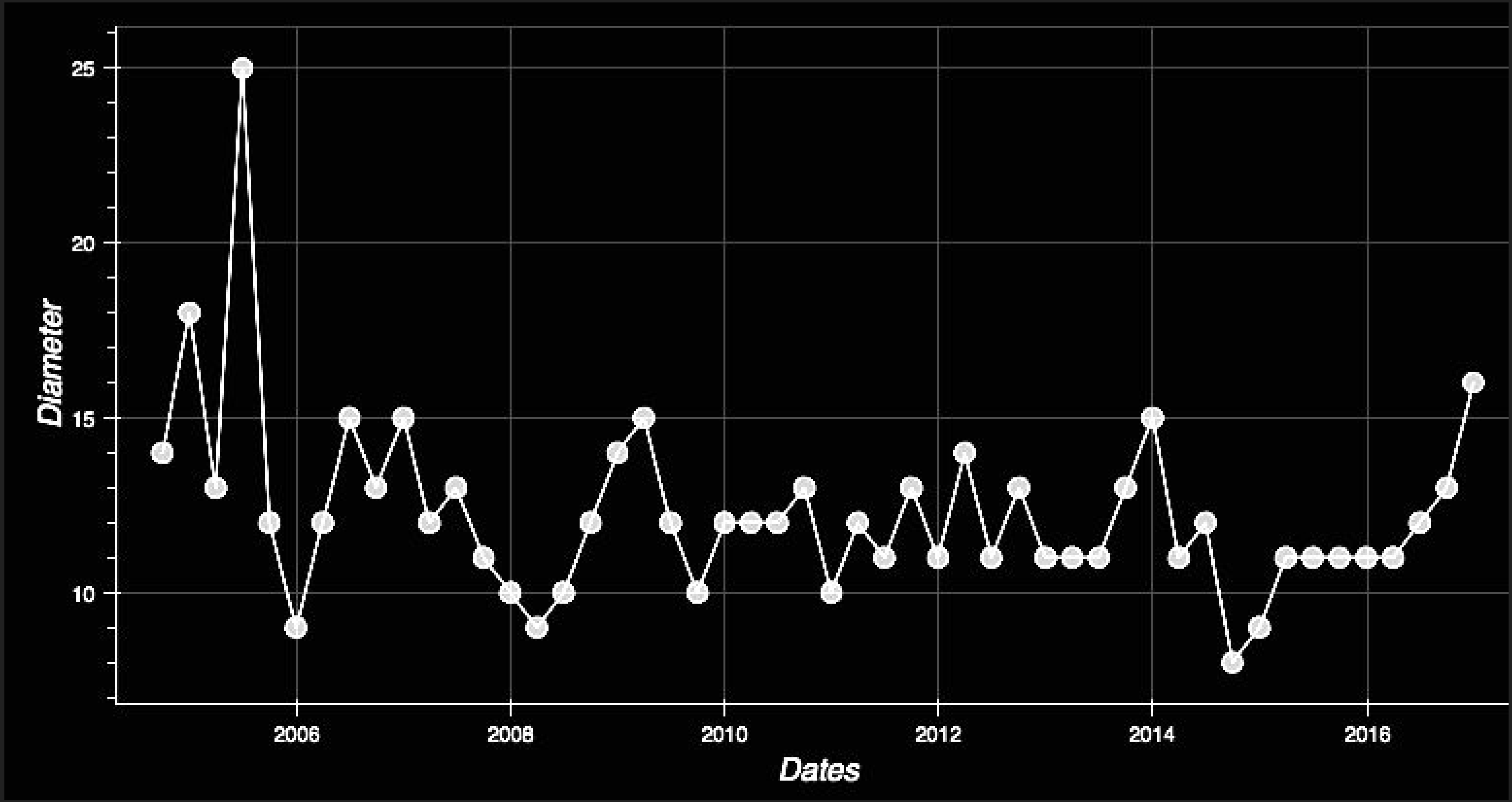
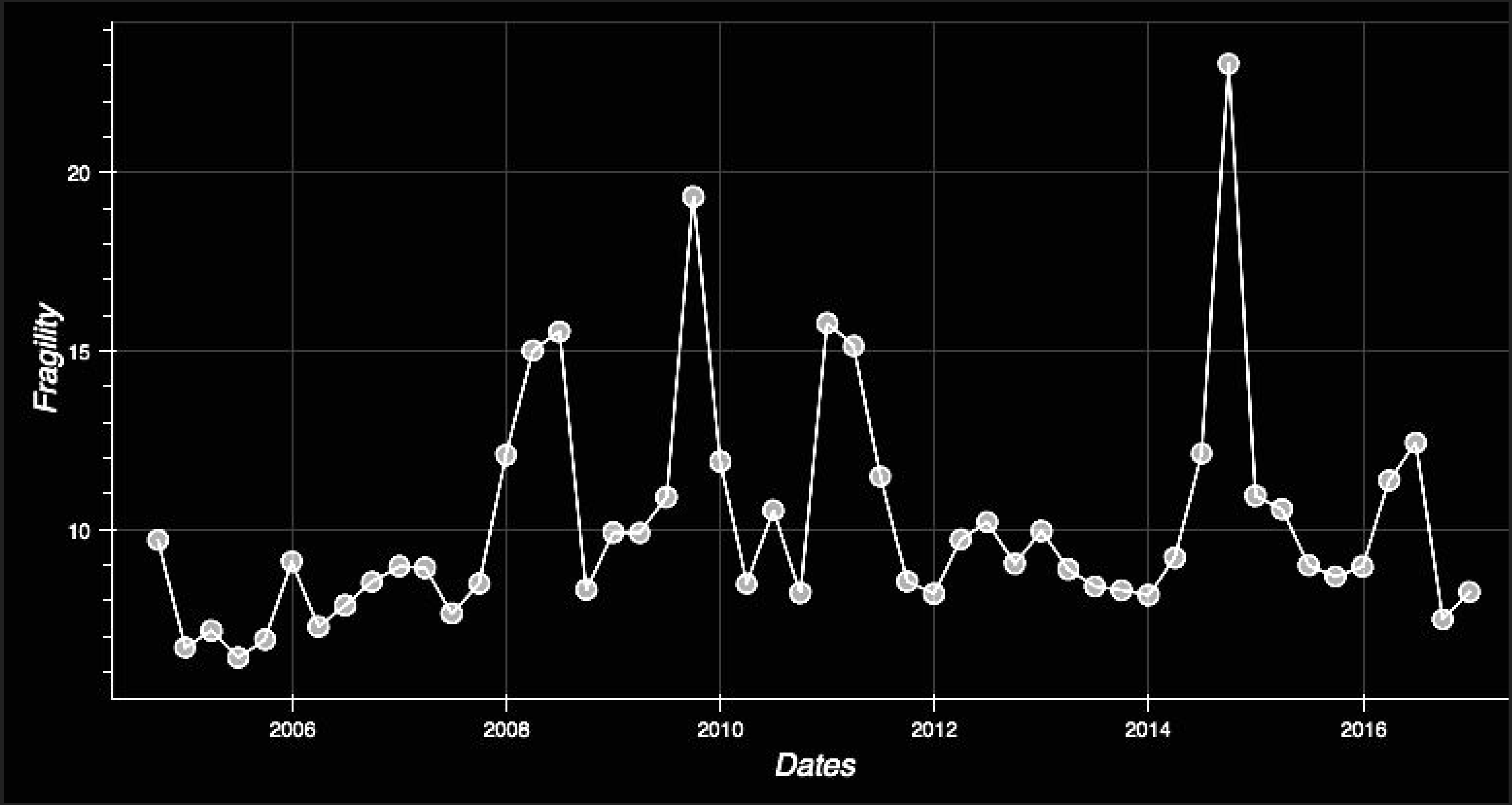


Figure 4: The number of banks in the network for all quarters between Q3 2004 and Q4 2016.

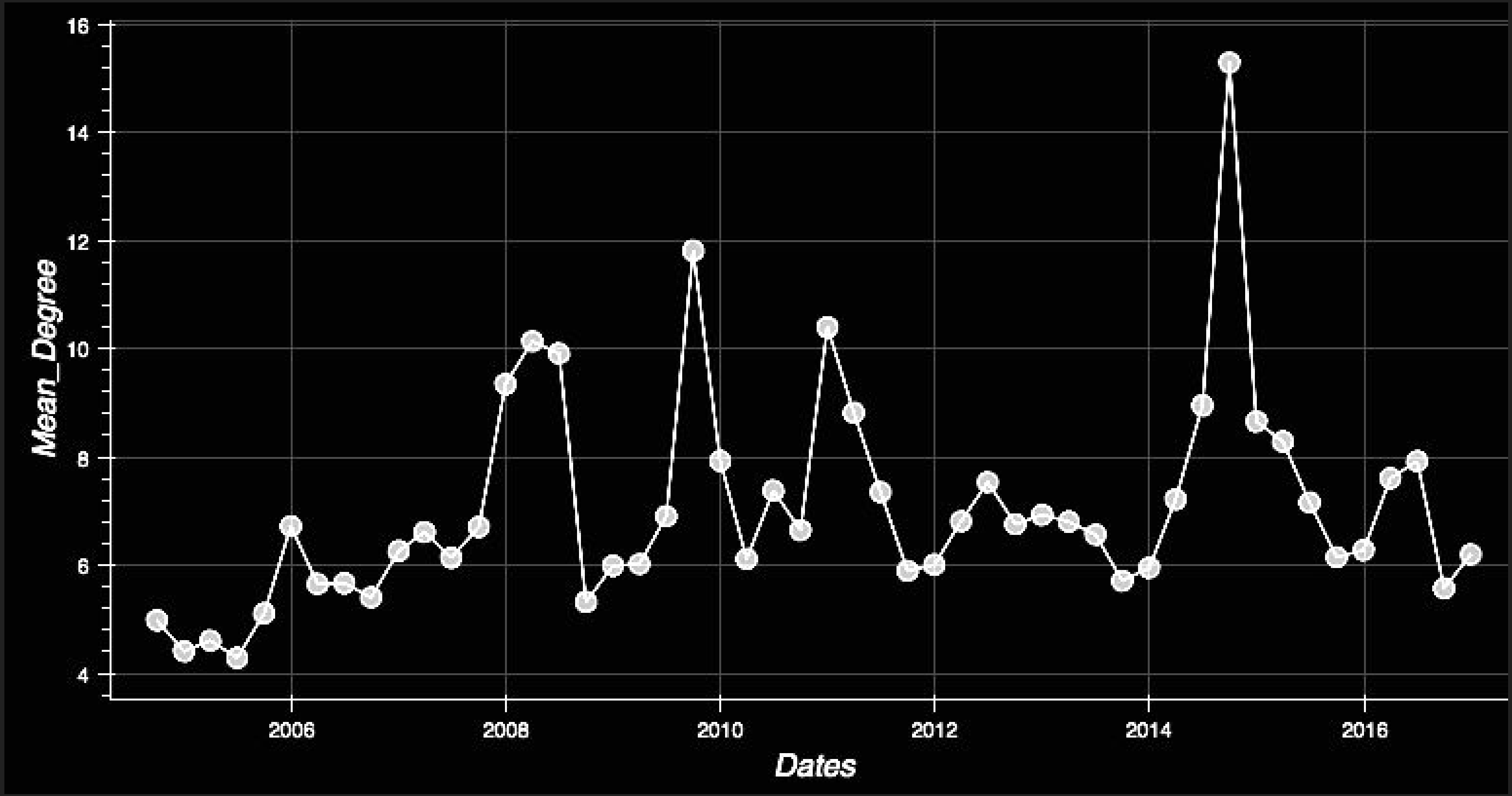
Diameter



Fragility

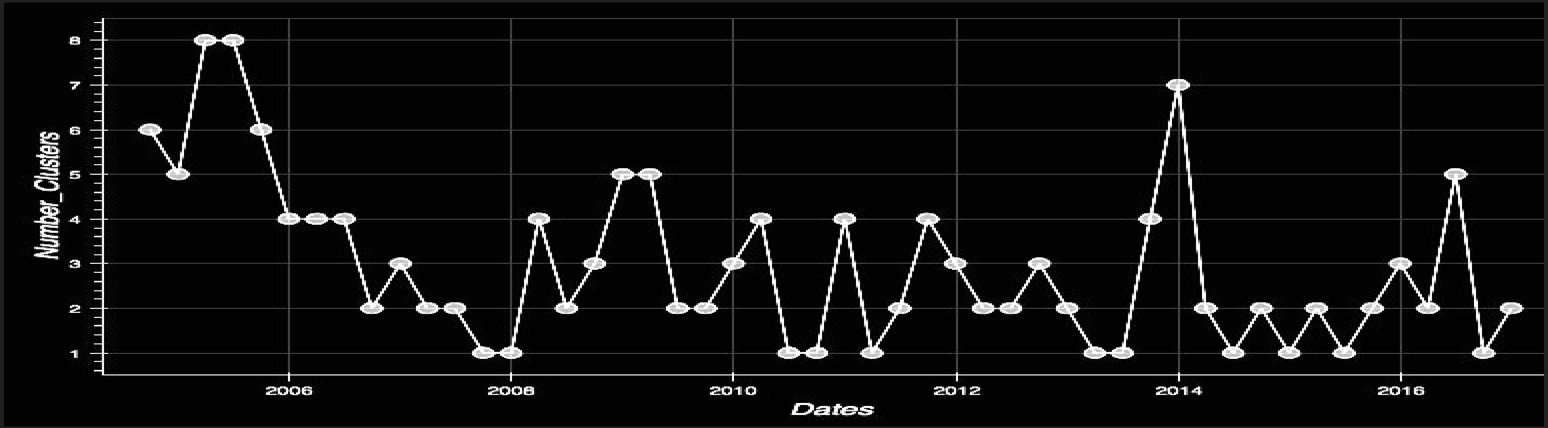


Degree

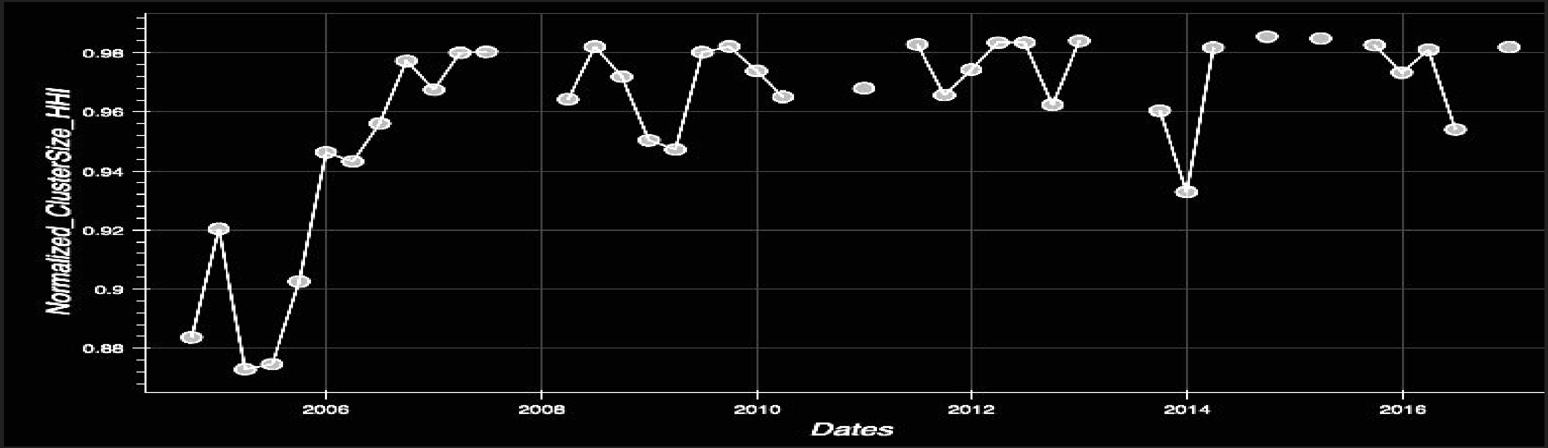


16
14
12
10
8
6
4
Mean_Degree
2006
2008
2010
2012
2014
2016
Dates

Clusters

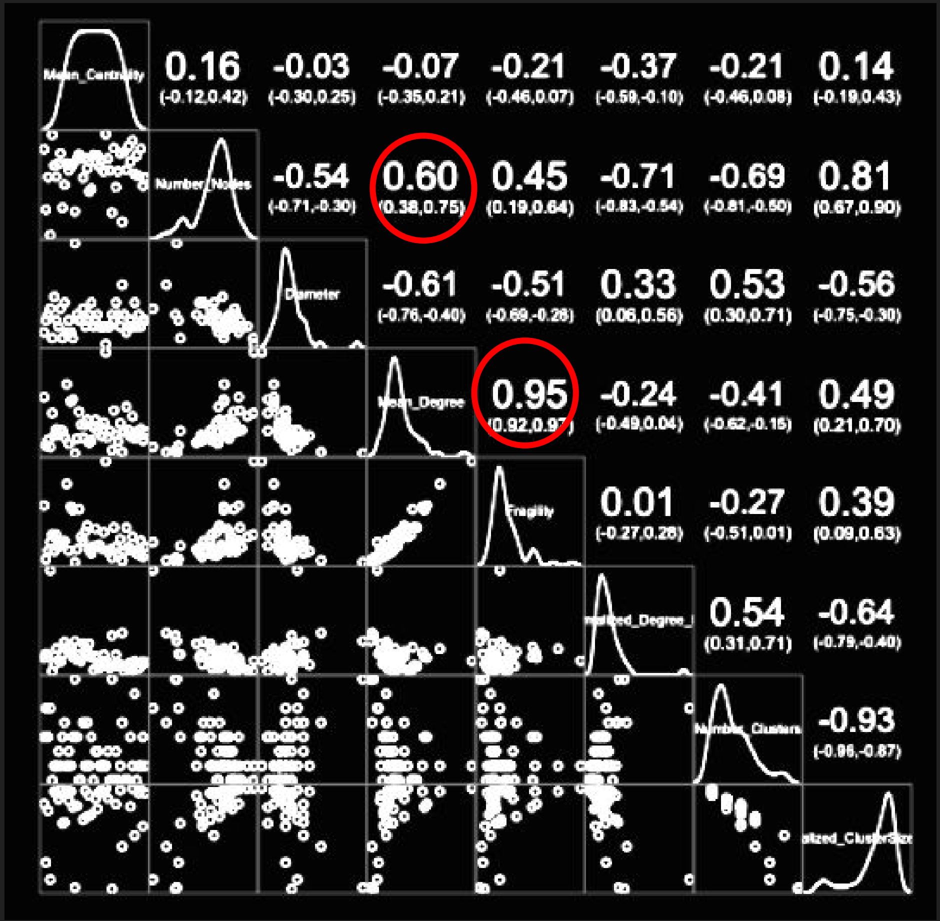


Number_Clusters
8
7
6
5
4
3
2
1
2006
2008
2010
2012
2014
2016
Dates



Normalized_ClusterSize_HHI
0.98
0.96
0.94
0.92
0.9
0.88
2006
2008
2010
2012
2014
2016
Dates

Correlations



Mean Centrality

Number of Nodes

Diameter

Mean Degree

Fragility

Normalized degree Herfindahl Index

Number of Clusters

Normalized cluster size Herfindahl

Probabilities of Default (PDs)

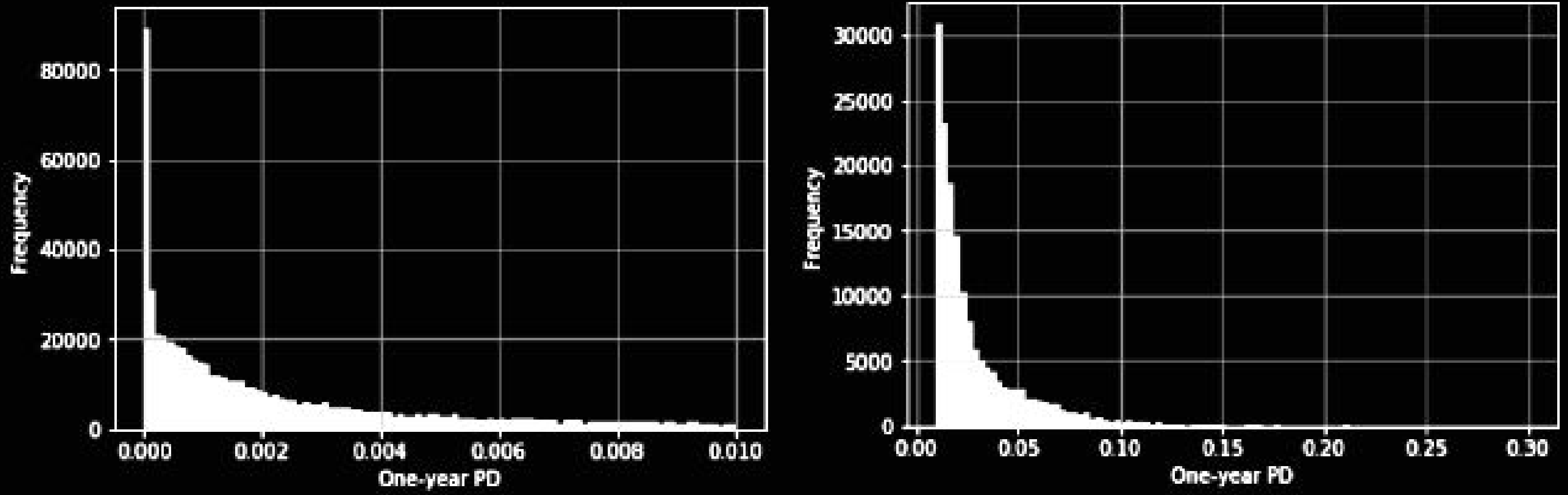


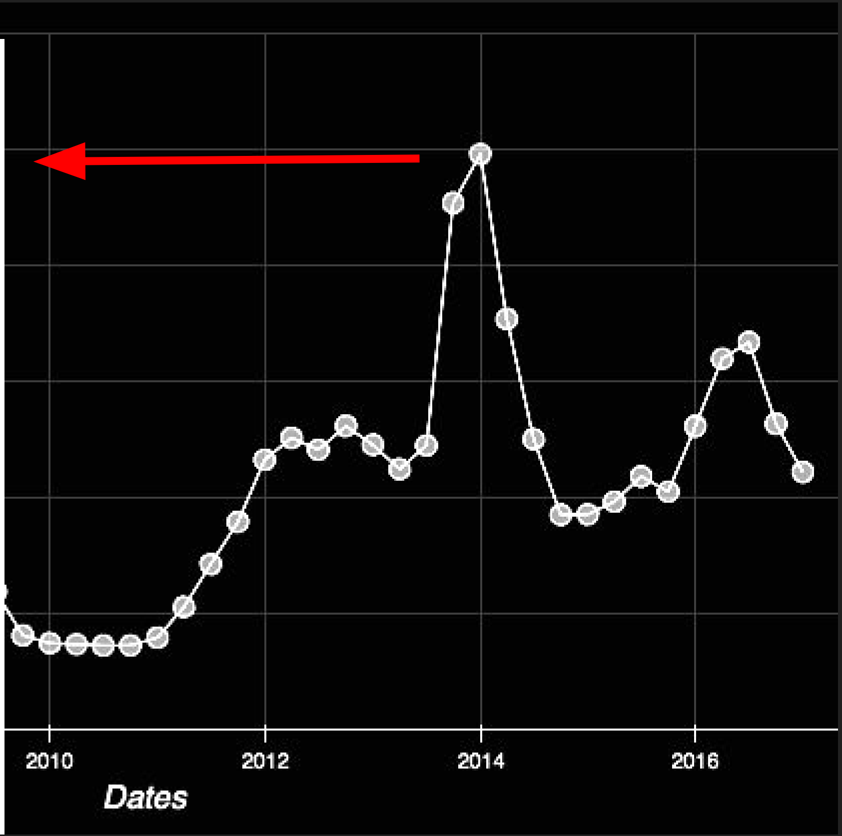
Figure 11: Distribution of PDs of all Indian FIs from 2004 to 2016. The first plot is the histogram of PDs that lie in the interval $(0, 0.01)$, and the second in the interval $(0.01, 0.30)$.

Highest PD = 26.36%

$C = 1 + 30\ PD$

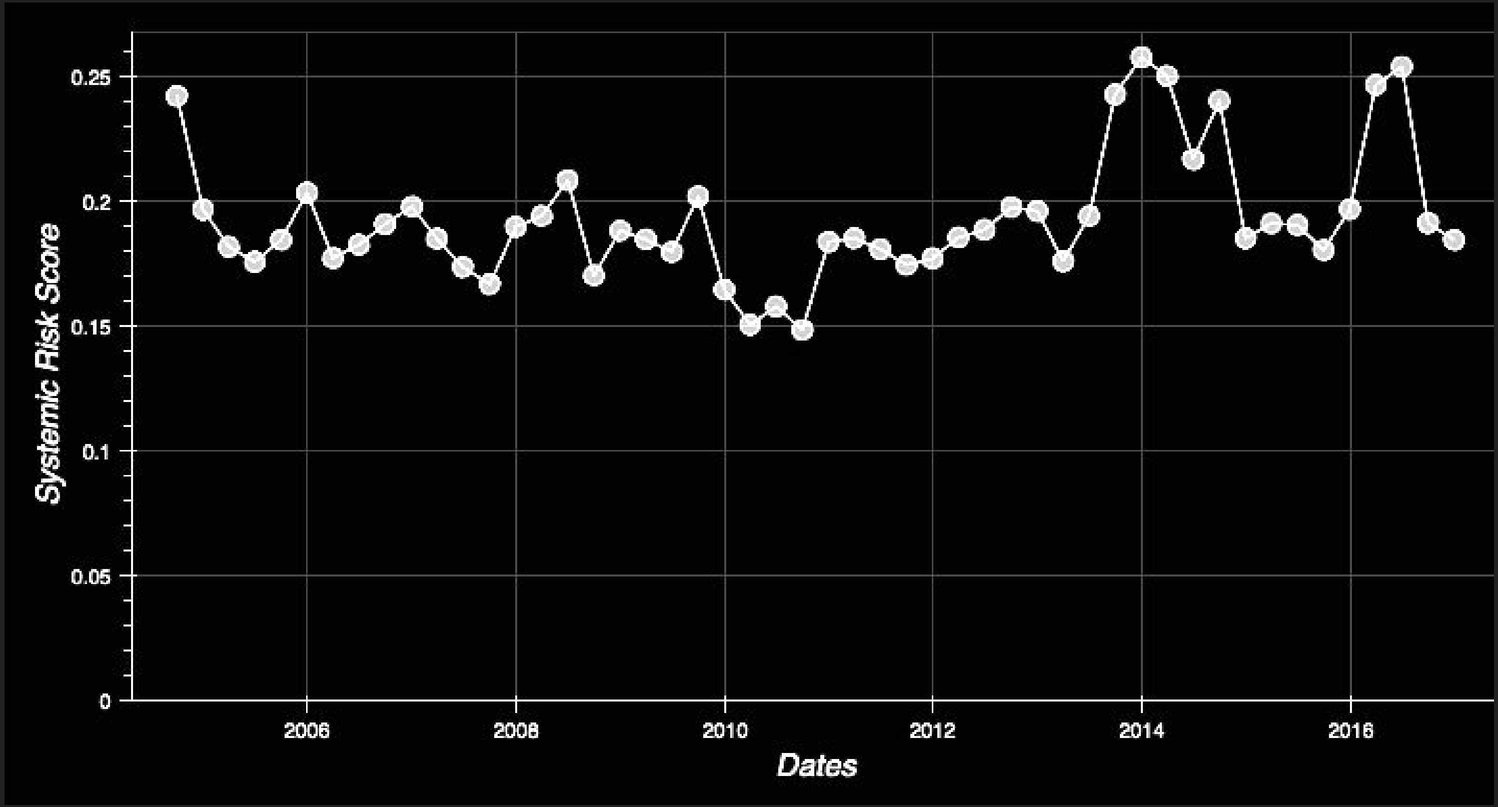
Since PD < 0.30, C lies in (0,10)

Mean PDs



- In the past couple of years, there has been a fall in the rate of growth causing concern that the period of high growth is coming to an end. (growth fell to a low of 4.4% in 2013 – bear in mind, India's rising population mean GDP per capita is less impressive than just real GDP growth)
- India has struggled to keep inflation low. In 2013, inflation was nudging near 10%, hurting the living standards of the poor who are particularly vulnerable to the price of food. High inflation is also harming confidence for investment.
- Current account deficit. India's growth has been at the cost of a persistent current account deficit (which reached over 6% of GDP in 2012). India needs to import crude oil, machinery and many other raw commodities. It's export sector has struggled to match the growth of imports.
- Rupee devaluation. The large current account deficit has caused the Rupee to fall, despite very low interest rates in US and Europe.
- Inequality / poverty. Parts of the Indian economy have made rapid growth, but it has proved difficult for the fruits of economic growth to filter through to all areas of the economy, especially isolated rural areas where there is poor infrastructure.
- Government budget deficit. Despite years of economic growth, the government has found it difficult to balance the budget. The budget deficit is 4.8% of GDP in the year 2012–13. Public sector debt is 68.05% of GDP, one of highest for a developing economy. Tax collection is still limited by tax evasion and corruption (tax collection only accounts for 9% of GDP – one of lowest in the world). The government is committed to reducing the budget deficit, but this may be at cost of social welfare programmes.

Systemic Risk Score (*S*)



Correlation of PDs and S = 69.7%

Risk Contributions of top 20 banks

	2005-Q1		2016-Q1	
	Bank Name	Risk Decomp	Bank Name	Risk Decomp
1	PRIME SECURITIES	2.705139	BANK OF MAHARASHTRA	2.222866
2	STATE BANK OF INDIA	2.476634	UCO BANK	1.698109
3	UCO BANK	2.438924	POWER FINANCE	1.437113
4	CORPORATION BANK	1.882045	UNITED BANK OF INDIA	1.410672
5	GIC HOUSING FINANCE	1.771204	STATE BK.OF BIN.& JAIPUR SUSP - SUSP.15/03/17	1.388539
6	I N G VYSYA BANK SUSP - SUSP.15/04/15	1.696898	DENA BANK	1.343904
7	UNION BANK OF INDIA	1.607279	STATE BANK OF INDIA	1.335314
8	IFCI	1.597618	INDIAN OVERSEAS BANK	1.331388
9	SUNDARAM FINANCE	1.569000	BANK OF TRAVANCORE SUSP - SUSP.15/03/17	1.309907
10	P N B GILTS	1.492469	CIL SECURITIES	1.282169
11	DHANLAXMI BANK	1.328556	COMFORT COMMOTRADE	1.137495
12	JAMMU & KASHMIR BANK	1.322932	BANK OF BARODA	1.093183
13	INDIABULLS FINL.SVS. SUSP - SUSP.18/03/13	1.215547	ANDHRA BANK	1.066791
14	DEWAN HOUSING FINANCE	1.198211	DEWAN HOUSING FINANCE	0.994385
15	ALMOND GLOBAL SECURITIES	1.195593	ORIENTAL BK.OF COMMERCE	0.917884
16	DENA BANK	1.194755	JAGSONPAL FIN.& LSG.	0.917517
17	ANDHRA BANK	1.193921	ELIXIR CAPITAL	0.873306
18	INDUSIND BANK	1.163923	MAHA.& MAHA.FINL.SVS.	0.871946
19	MARGO FINANCE	1.163827	CUBICAL FINANCIAL SVS.	0.855089
20	UNITED CREDIT	1.148539	VAX HOUSING FINANCE	0.852056
	TOTAL	31.36301	TOTAL	24.33963

Explaining quarterly systemic risk

Aggregate Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.1580***	0.1498***	0.2685	-0.0112	-0.0112	0.2730	0.2730
	(26.93)	(9.57)	(1.41)	(-0.04)	(-0.04)	(1.45)	(1.45)
Mean PD	3.8253***		5.2279***	5.0884***	5.0884***	5.2666***	5.2666***
	(6.73)		(18.85)	(9.50)	(9.50)	(10.45)	(10.45)
Mean Degree		0.0041*	0.0134***	0.0065	0.0065	0.0130**	0.0130**
		(2.30)	(3.58)	(1.58)	(1.58)	(2.76)	(2.76)
Degree HHI		6.4870*	5.7260*	4.3454	4.3454	6.2504**	6.2504**
		(2.42)	(2.55)	(2.01)	(2.01)	(3.00)	(3.00)
Mean Bet. Centrality			-0.0001***	-0.0001**	-0.0001**	-0.0001*	-0.0001*
			(-4.65)	(-3.05)	(-3.05)	(-2.67)	(-2.67)
Diameter			0.0003	0.0002	0.0002	-0.0002	-0.0002
			(0.50)	(0.31)	(0.31)	(-0.26)	(-0.26)
Fragility			-0.0039	0.0004	0.0004	-0.0034	-0.0034
			(-1.72)	(0.15)	(0.15)	(-1.26)	(-1.26)
Num. Clusters			-0.0030	-0.0014	-0.0014	-0.0033	-0.0033
			(-1.17)	(-0.52)	(-0.52)	(-1.35)	(-1.35)
Cluster HHI			-0.1429	-0.0110	-0.0110	-0.2230	-0.2230
			(-0.76)	(-0.05)	(-0.05)	(-1.20)	(-1.20)
Median Log(Assets)				0.0046	0.0046		
				(1.04)	(1.04)		
Median Log(Market Cap						0.0040*	0.0040*
						(2.65)	(2.65)
Median Loans/Assets				0.0001	0.0001	0.0122	0.0122
				(0.01)	(0.01)	(0.97)	(0.97)
Median Loans/Deposits				0.0564	0.0564	-0.0035	-0.0035
				(0.59)	(0.59)	(-0.05)	(-0.05)
Median Debt/Assets				0.1058	0.1058		
				(1.29)	(1.29)		
Median Debt/Equity						0.1224*	0.1224*
						(2.16)	(2.16)
Median Debt/Capital				-0.0000	-0.0000	0.0002	0.0002
				(-0.04)	(-0.04)	(0.89)	(0.89)
Median ROA				0.0015	0.0015		
				(1.64)	(1.64)		
Median ROE						0.0001	0.0001
						(0.06)	(0.06)
Median Market/Book				0.0096	0.0096	-0.0020	-0.0020
				(1.23)	(1.23)	(-0.22)	(-0.22)
Observations	50	50	50	50	50	50	50
R^2	0.485	0.160	0.923	0.948	0.948	0.955	0.955
Adjusted R^2	0.475	0.124	0.908	0.925	0.925	0.935	0.935

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Risk by entity

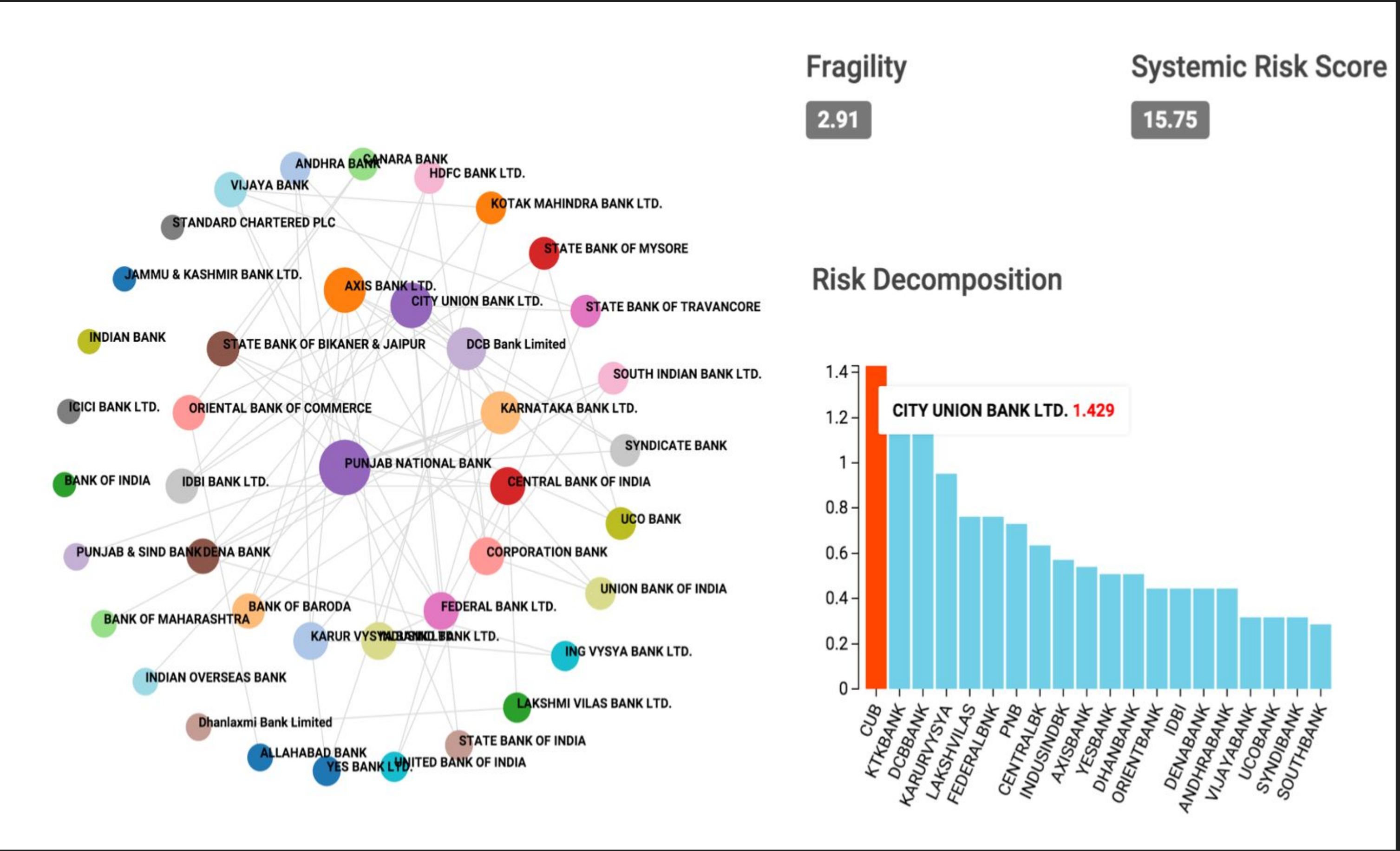
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.3323***	-0.0359**	5.6057***	7.7619***	7.7619***	8.3855***	8.3855***
	(92.03)	(-2.70)	(19.58)	(12.05)	(12.05)	(11.87)	(11.87)
PD	14.8523***		13.4074***	12.5839***	12.5839***	12.6840***	12.6840***
	(40.61)		(47.75)	(28.59)	(28.59)	(29.32)	(29.32)
Degree		0.0454***	0.0531***	0.0580***	0.0580***	0.0605***	0.0605***
		(40.57)	(42.57)	(32.52)	(32.52)	(33.28)	(33.28)
Degree HHI		85.9884***	70.1971***	106.2844***	106.2844***	116.0624***	116.0624***
		(17.51)	(13.07)	(10.60)	(10.60)	(9.19)	(9.19)
Bet. Centrality			-0.0000***	-0.0000*	-0.0000*	-0.0000**	-0.0000**
			(-4.65)	(-2.18)	(-2.18)	(-2.62)	(-2.62)
Diameter			0.0016	-0.0029	-0.0029	-0.0020	-0.0020
			(1.24)	(-1.06)	(-1.06)	(-0.70)	(-0.70)
Fragility			-0.0341***	-0.0465***	-0.0465***	-0.0517***	-0.0517***
			(-30.17)	(-20.76)	(-20.76)	(-19.85)	(-19.85)
Num. Clusters			-0.0673***	-0.0949***	-0.0949***	-0.1061***	-0.1061***
			(-16.95)	(-11.46)	(-11.46)	(-11.44)	(-11.44)
Cluster HHI			-5.3994***	-7.4056***	-7.4056***	-8.0804***	-8.0804***
			(-19.02)	(-11.58)	(-11.58)	(-11.59)	(-11.59)
Log(Assets)				-0.0036	-0.0036		
				(-1.72)	(-1.72)		
Log(Market Cap)						0.0006	0.0006
						(0.28)	(0.28)
Loans/Assets				0.1251***	0.1251***	0.1531***	0.1531***
				(5.29)	(5.29)	(6.43)	(6.43)
Loans/Deposits				-0.0142*	-0.0142*	-0.0203**	-0.0203**
				(-2.06)	(-2.06)	(-2.71)	(-2.71)
Debt/Assets				-0.0626***	-0.0626***		
				(-4.99)	(-4.99)		
Debt/Equity						-0.0001	-0.0001
						(-1.84)	(-1.84)
Debt/Capital				0.0001	0.0001	-0.0005**	-0.0005**
				(0.72)	(0.72)	(-2.76)	(-2.76)
ROA				0.0010***	0.0010***		
				(3.39)	(3.39)		
ROE						0.0004	0.0004
						(1.16)	(1.16)
Market/Book				0.0002	0.0002	0.0003	0.0003
				(0.39)	(0.39)	(0.34)	(0.34)
Observations	10609	10609	10609	4329	4329	3375	3375
R^2	0.358	0.399	0.814	0.843	0.843	0.845	0.845
Adjusted R^2	0.358	0.399	0.814	0.842	0.842	0.845	0.845

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Demo

Python notebook

Previous approach to systemic risk



Further Work

1.Greece.xlsx
2.Brazil.xlsx
3.Bulgaria.xlsx
4.Chile.xlsx
5.China.xlsx
6.Columbia.xlsx
7.Czech.xlsx
8.Egypt.xlsx
9.Greece.xlsx
10.Hungary.xlsx
11.India_Names.csv
11.India.csv
11.India.xlsx
12.Indonesia.xlsx
13.South Korea.xlsx
14.Malaysia.xlsx
15.Malaysia.xlsx
15.Mexico.xlsx
16.Phillipines.xlsx
17.Poland.xlsx
18.Russia.xlsx
19.South Africa.xlsx
20.Taiwan.xlsx
21.Thailand.xlsx
22.Turkey.xlsx
23.Ukraine.xlsx

Within-country Analysis

- Determinants, macroeconomic variables
- Prediction of systemic risk

Cross-country Analysis

- Principal Components Analysis
- Lead-Lag Analysis

The End!!

http://srdas.github.io/Papers/India.pdf