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Bali, Indonesia, 23-26 July 2018

Big data and FinRisk[1]

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[1] This presentation was prepared for the meeting. The views expressed are those of the author and do not necessarily reflect the views of the BIS, the IFC or the central banks and other institutions represented at the meeting.

Big Data and FinRisk

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Bank of Indonesia and BIS/IFC
International Conference on Big Data
Bali, Indonesia, July 26, 2018

Outline

1. Overview of challenges in Big Data for Finance
2. Financial networks for Systemic Risk Measurement.
    a. USA
    b. India
3. Zero-revelation prediction of bank malaise.

Research Challenges in Financial Data Modeling and Analysis

Lewis Alexander[1], Sanjiv R. Das[2,*] Zachary Ives[3] H.V. Jagadish[4] and Claire Monteleoni[5]

http://srdas.github.io/Papers/big.2016.0074_FINAL.pdf

Abstract
Significant research challenges must be addressed in the cleaning, transformation, integration, modeling, and analytics of Big Data sources for finance. This article surveys the progress made so far in this direction and obstacles yet to be overcome. These are issues that are of interest to data-driven financial institutions in both corporate finance and consumer finance. These challenges are also of interest to the legal profession as well as to regulators. The discussion is relevant to technology firms that support the growing field of FinTech.

Big Data
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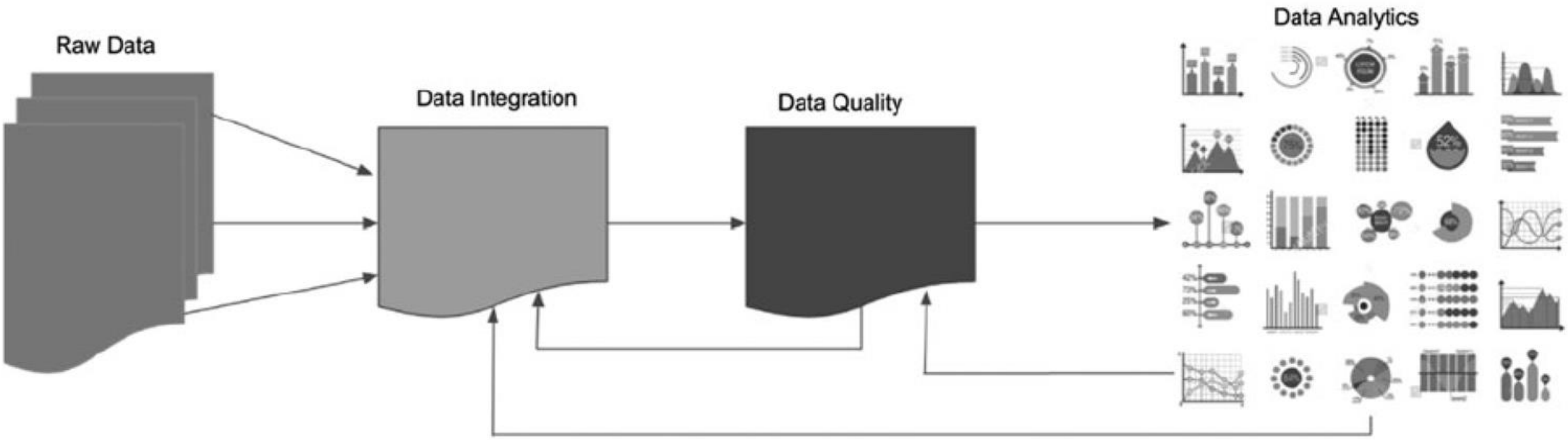

Staging Template

Areas	*Type of issues/problems*			
	Level 1: Curation at the unit level within a firm	*Level 2: Curation and aggregation at the firm level*	*Level 3: Curation and aggregation at the system level*	*Across levels: Quality issues (privacy, veracity, etc.)*
Data integration				
Standards	□	○	○	□
Application-specific tools	□	○	○	○
Text mining tools	□	□	○	○
Data quality management				
BSBS239 (14 principles, 4 areas)	□	○	○	□
Errors in recording, extraction, entity-matching, interpretation	□	□	○	○
Data timeliness: Nowcasting	□	○	○	□
Data manipulation	□	□	○	○
Data analytics				
Feature selection	□	□	□	○
Model selection	□	□	□	○
Online learning	□	○	○	○
AI and deep learning	□	○	○	○
Systemic risk	□	□	□	□
Consumer finance	□	□	□	□
Text analytics	□	□	□	□
High frequency trading	□	—	○	○
Blockchains	□	—	○	○
Cybersecurity	□	□	□	○

Codes: ○ represents nascent solutions; □ represents work underway, not fully developed; and empty cells represent that decent progress has been made.

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.

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.

1. 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.”

An Extensive Literature

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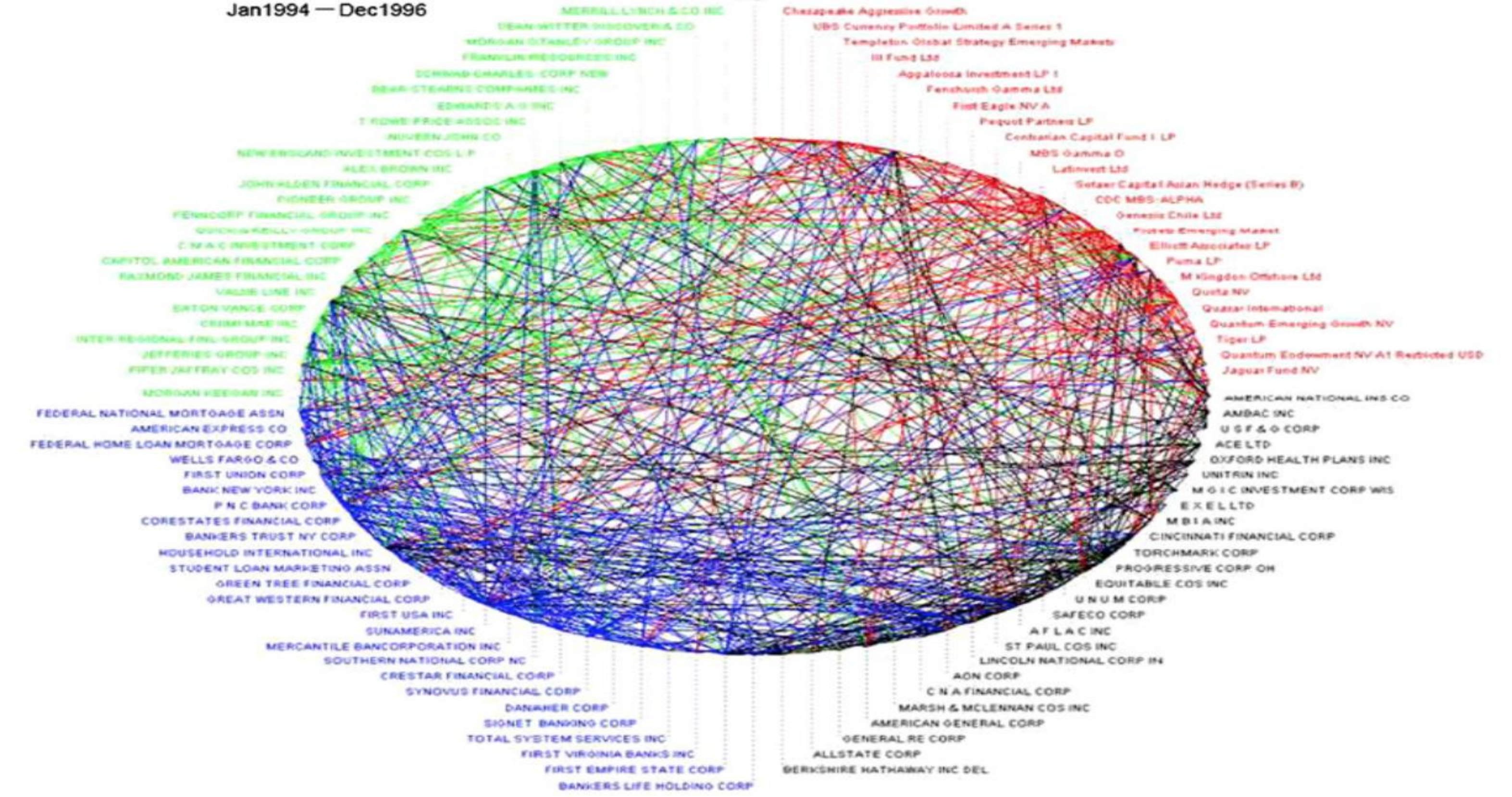
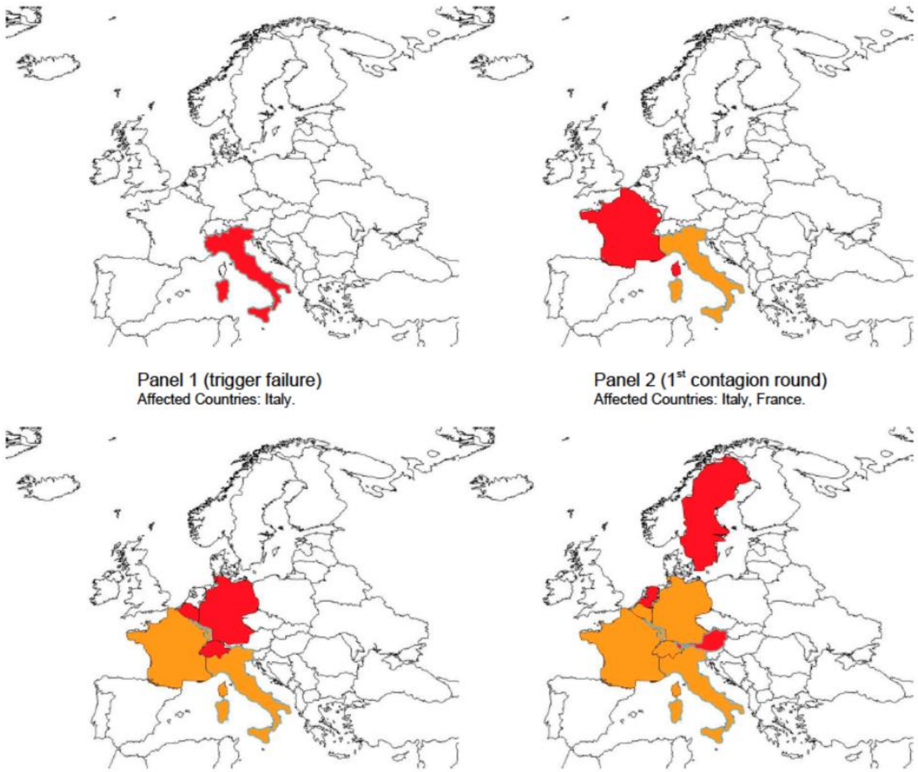


Fig. 2. Network diagram of linear Granger-causality relationships that are statistically significant at the 5% level among the monthly returns of the 25 largest (in terms of average market cap and AUM) banks, broker/dealers, insurers, and hedge funds over January 1994 to December 1996. The type of institution 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.

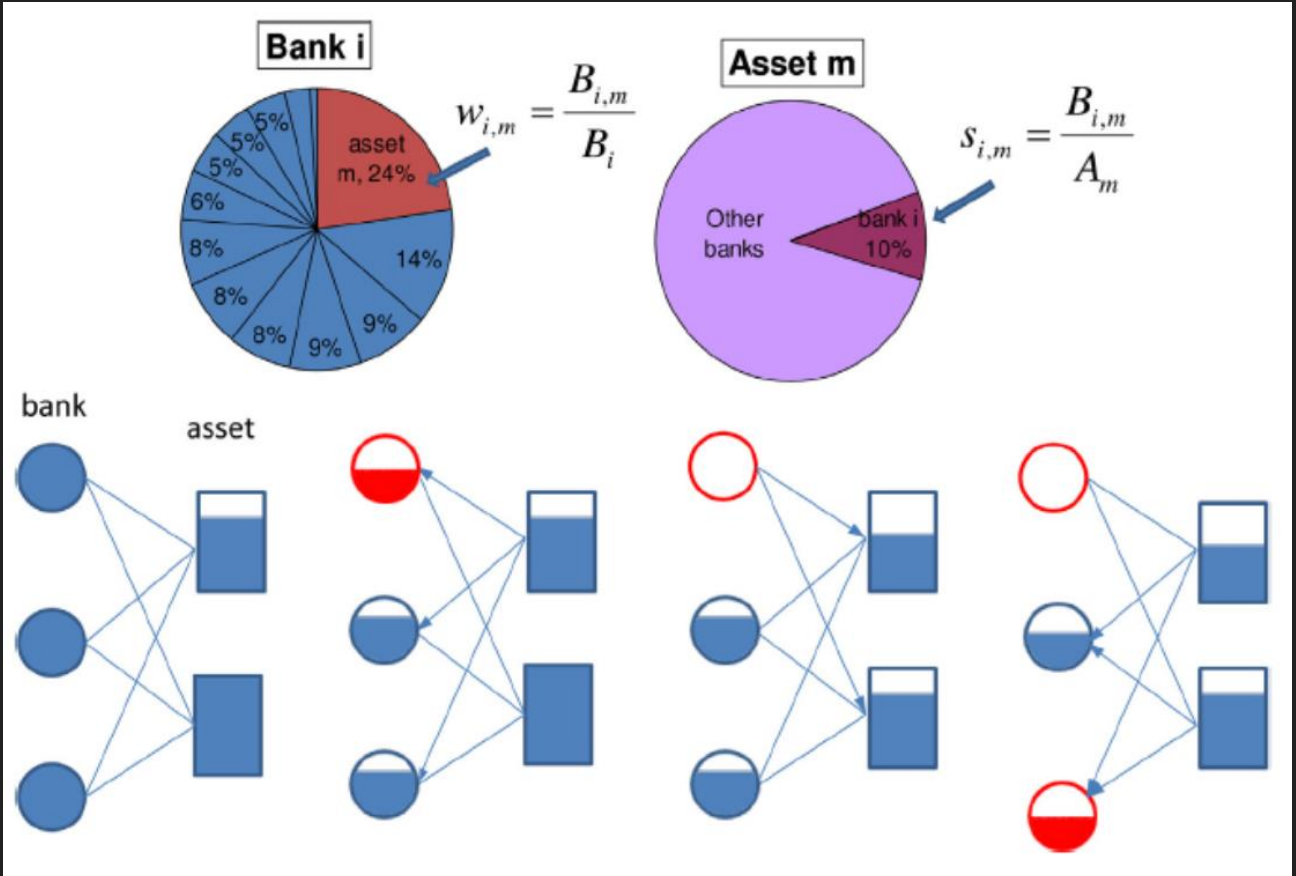
Panel 2 (1st contagion round)
Affected Countries: Italy, France.

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.

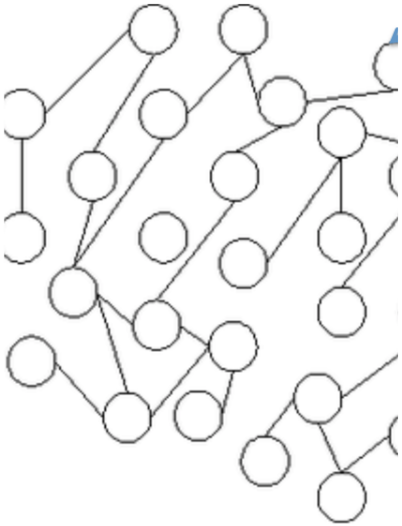
Bivalent Networks

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



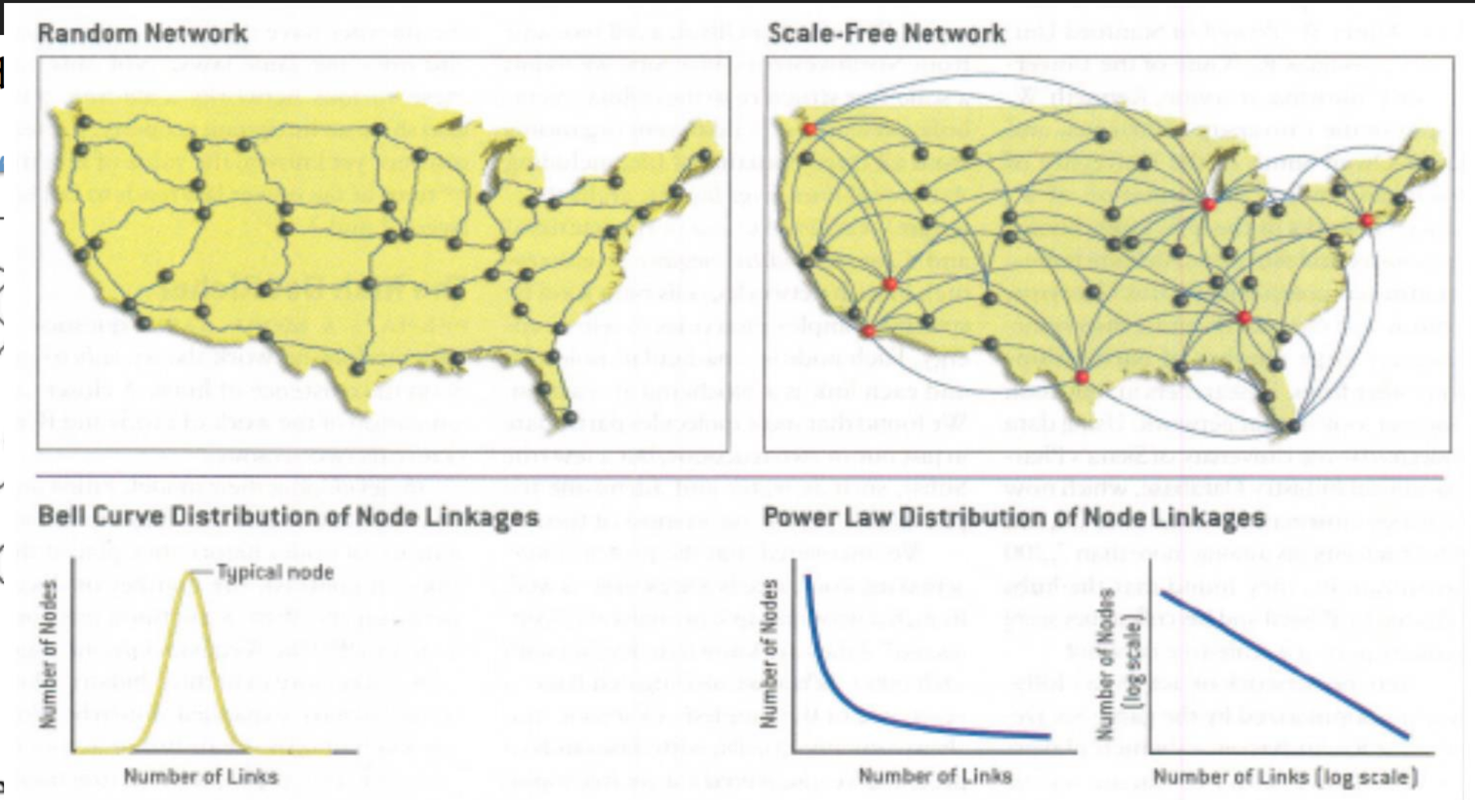
Graph Theory

Nod



(a) Random ne

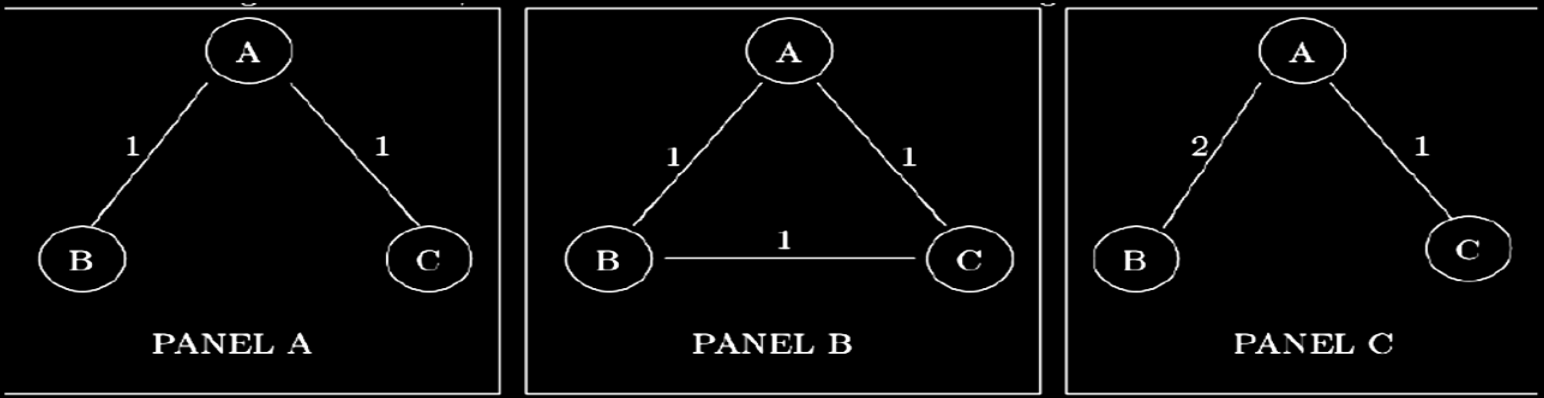
$f(d) \sim N($



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

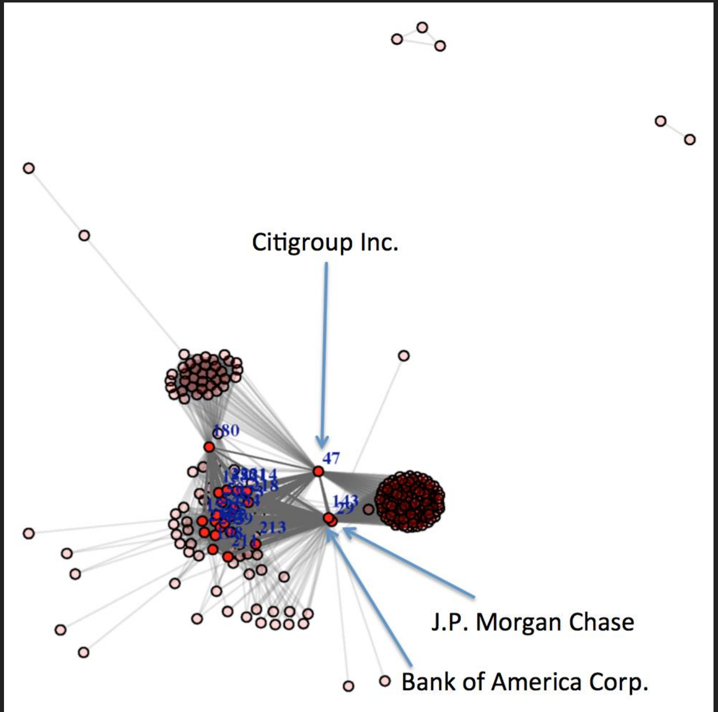
The diame

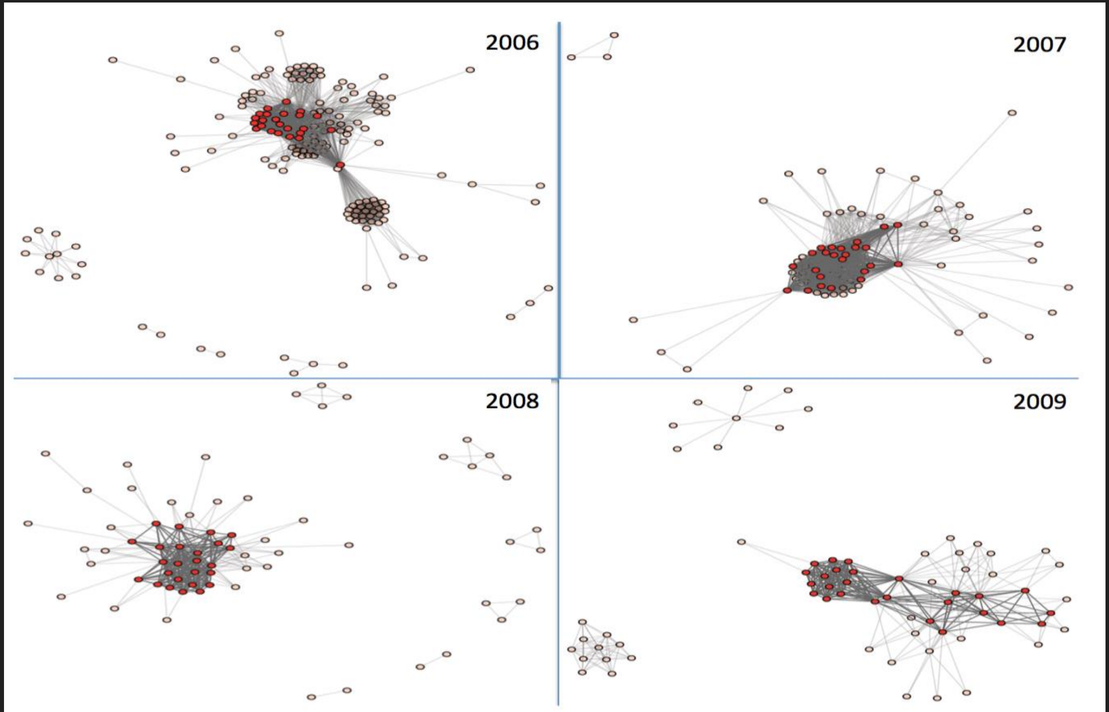
Fragility

- 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 $= 20$

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

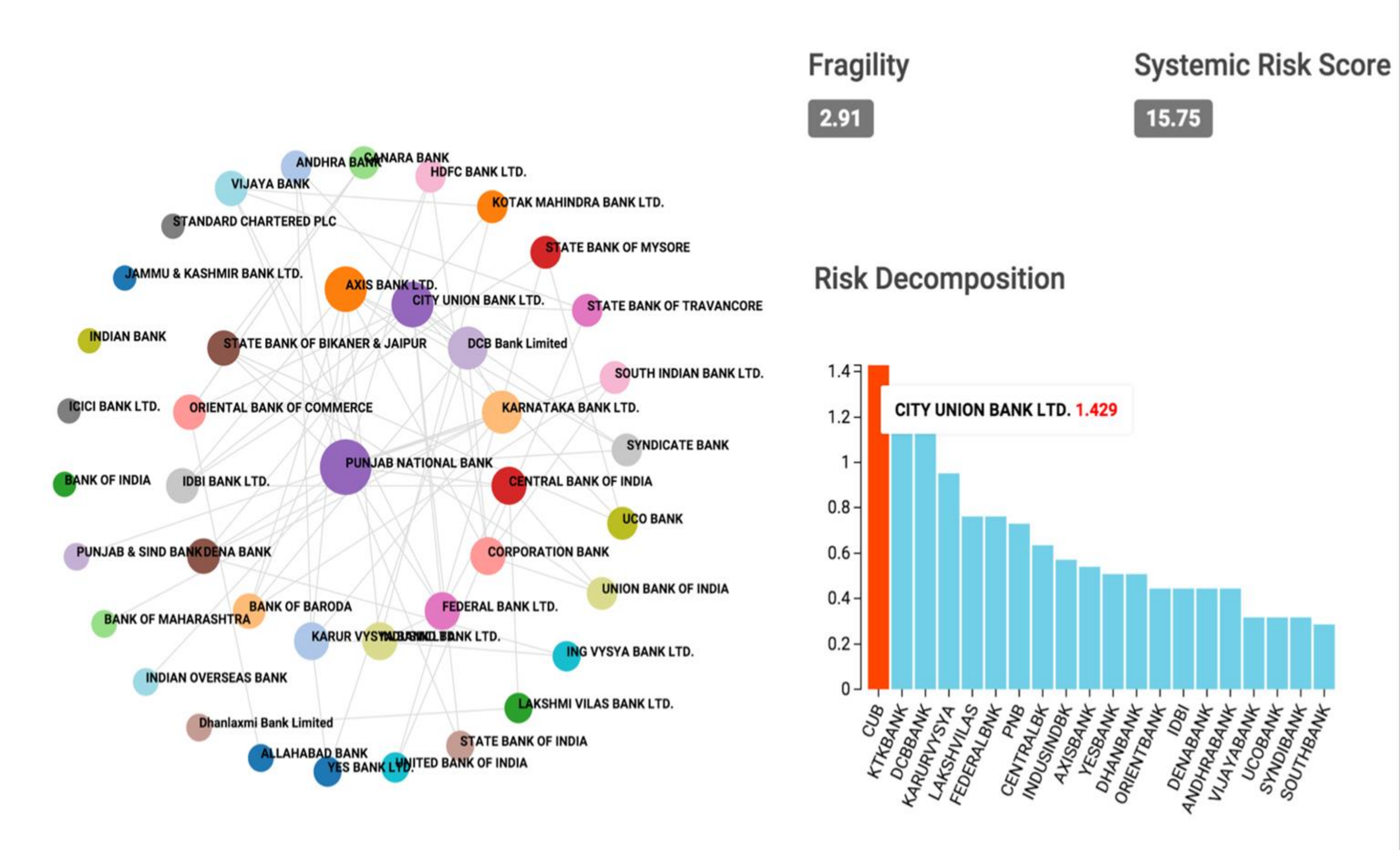
S(C,A) is linear homogenous in *C*

Apply Euler's Formula

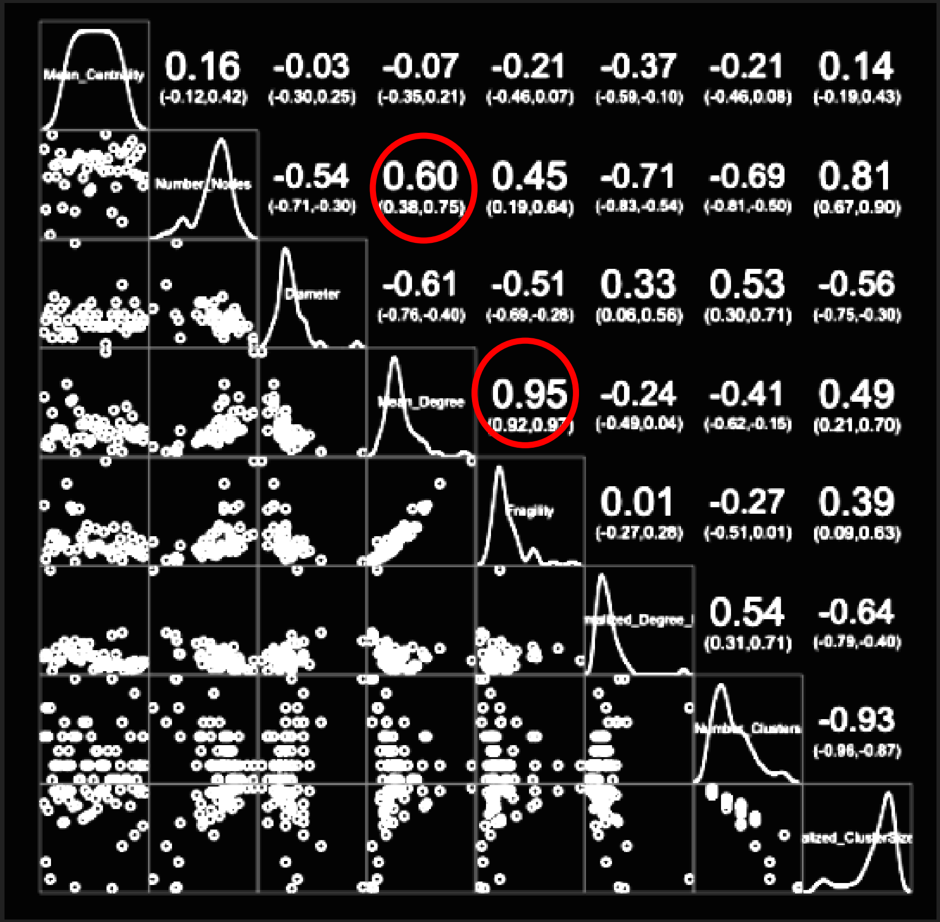
$$S = \frac{\partial S}{\partial C_1} C_1 + \frac{\partial S}{\partial C_2} C_2 + \ldots + \frac{\partial S}{\partial C_n} C_n = \sum_{i=1}^{n} \frac{\partial S}{\partial C_i} C_i$$

Risk Contribution

First iteration : India



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)

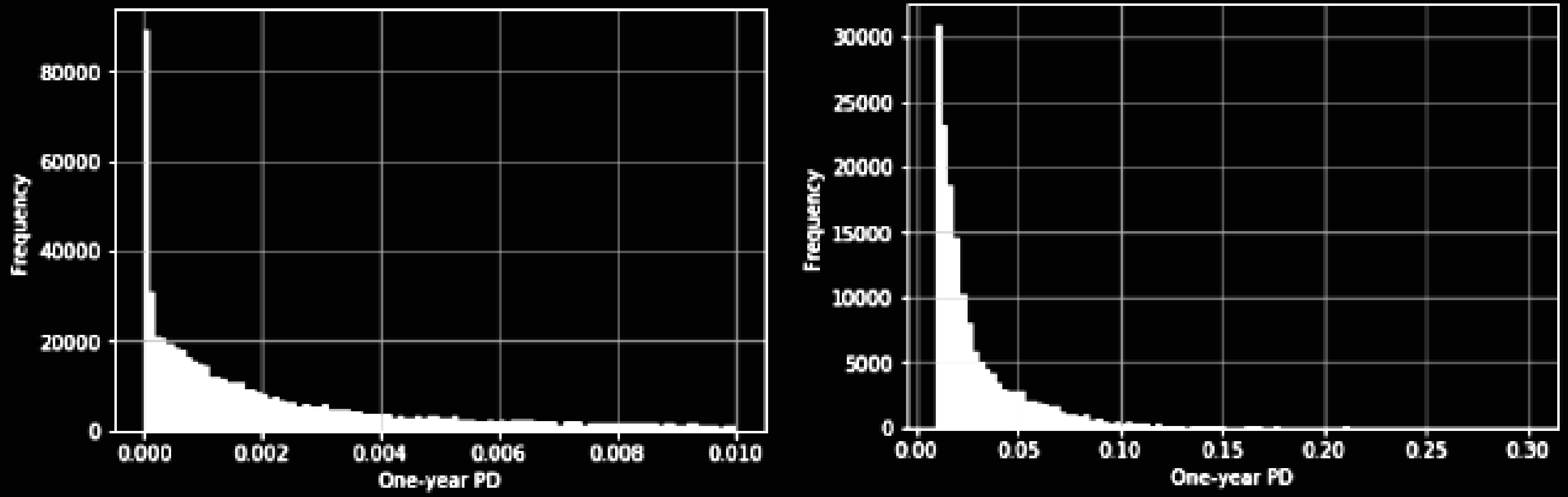


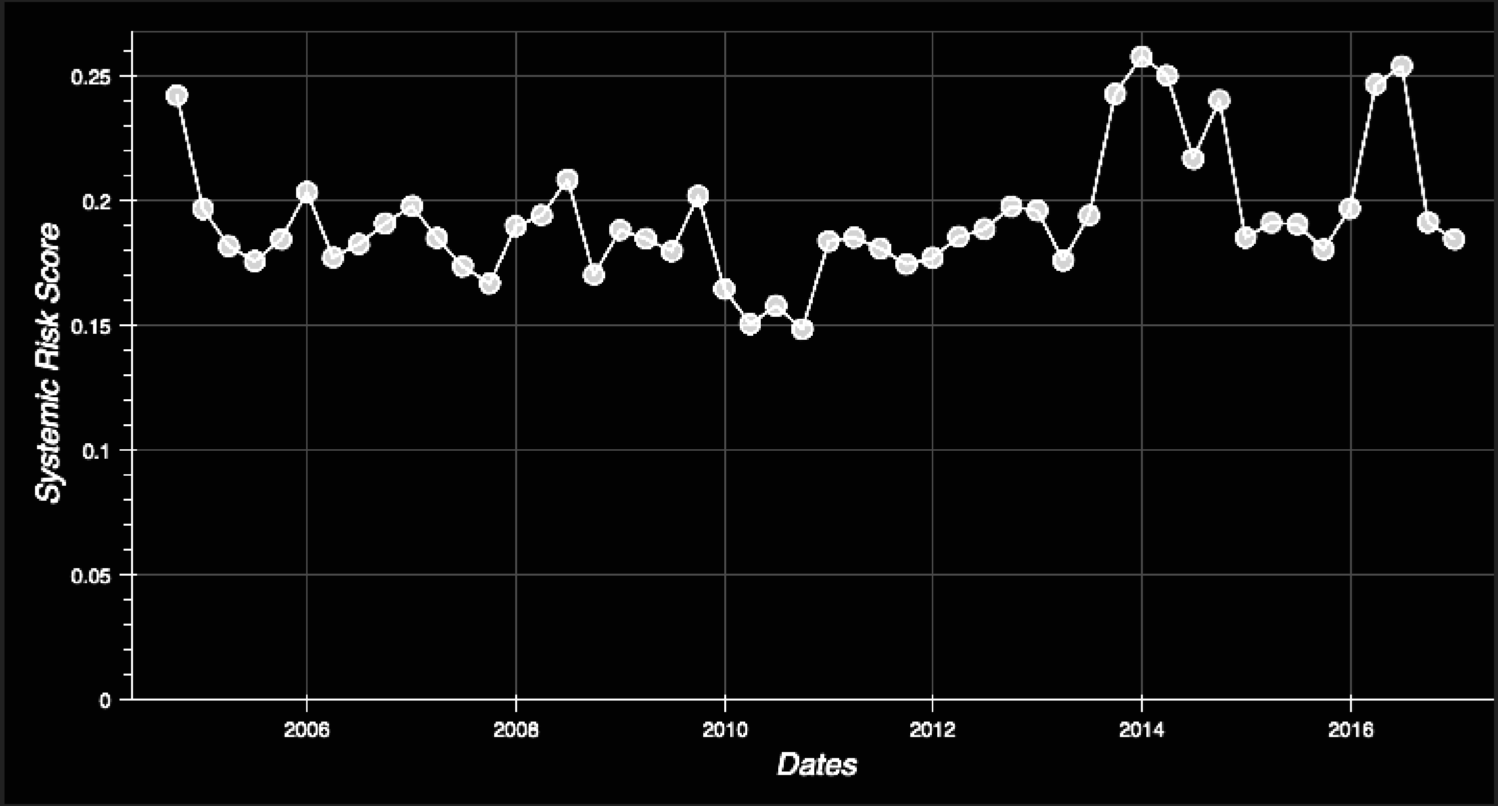
Figure 11: Distribution of PDs of all Indian FIs from 2004 to 2016. The first plot is the histogram of PDs that lie in the interval $(0, 0.01)$, and the second in the interval $(0.01, 0.30)$.

Highest PD = 26.36%

$C = 1 + 30\ PD$

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

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

	(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

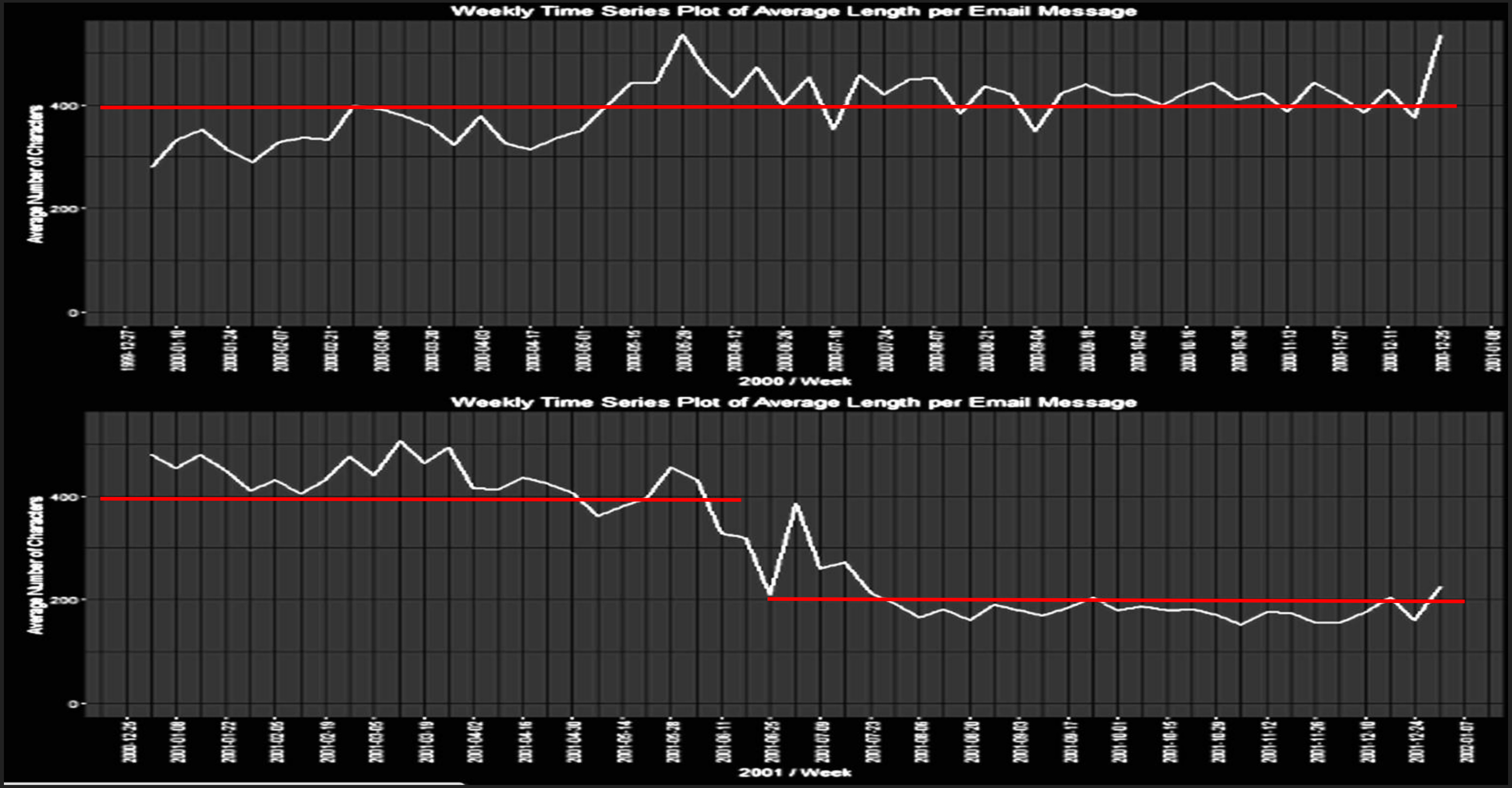
t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Text, Sentiment, and RegTech

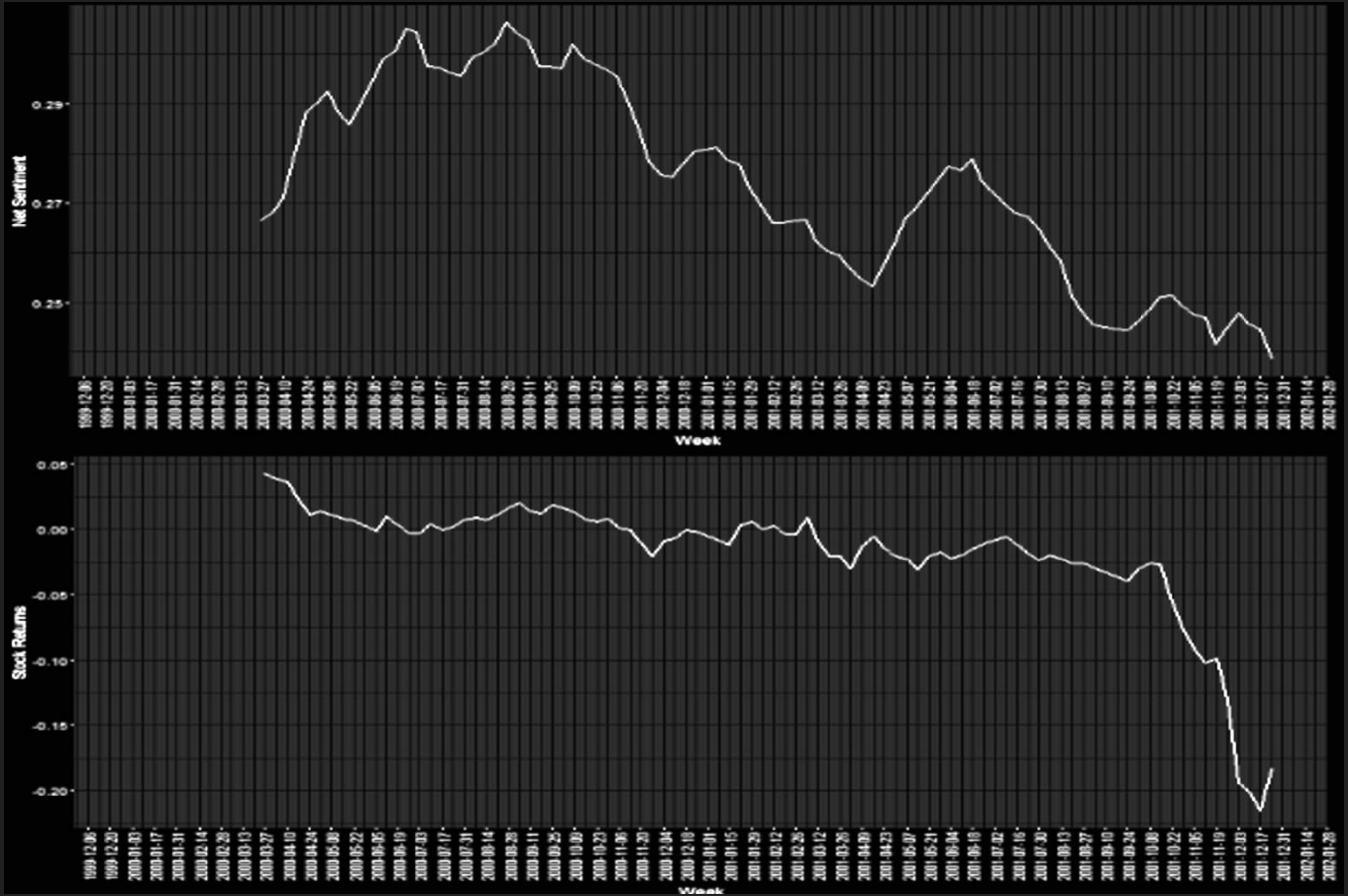
Zero-Revelation Linguistic Regulation: Detecting Risk Through Corporate Emails and News (Das, Kim, Kothari 2016)

- Financials are often delayed indicators of corporate quality.
- Internal discussion may be used as an early warning system for upcoming corporate malaise.
- Emails have the potential to predict such events.
- Software can analyze vast quantities of textual data not amenable to human processing.
- Corporate senior management may also use these analyses to better predict and manage impending crisis for their firms.
- The approach requires zero revelation of emails.

Enron: Email Length



Enron: Sentiment and Returns



Enron: Returns and Characteristics

Variable	Coefficient Estimate (*t*-statistic)			
	(1)	(2)	(3)	(4)
MA Net Sentiment $_t$	XXX*** (XXX)	0.575 (0.63)	2.330*** (3.14)	-1.397 (-1.25)
MA Email Length $_t$		0.584*** (2.97)		1.046*** (4.19)
MA Total Emails $_t$			-0.004 (-0.10)	-0.131*** (-2.83)
Intercept		-0.406* (-1.93)	-0.671*** (-3.08)	0.117 (0.43)
Adjusted *R*-squared	XXX		0.09	0.24
Number of observations	88	88	88	88

Enron: Returns and Characteristics

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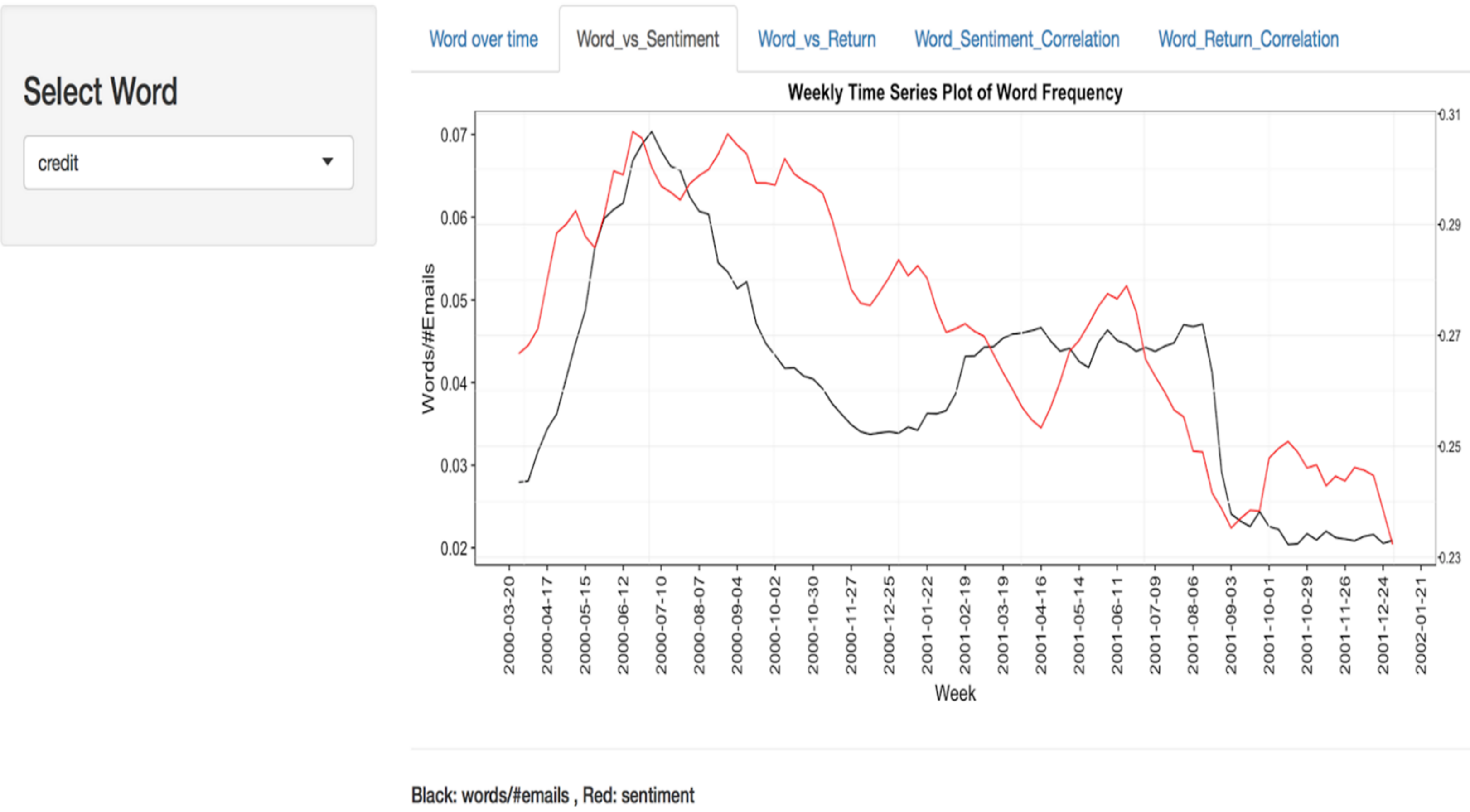
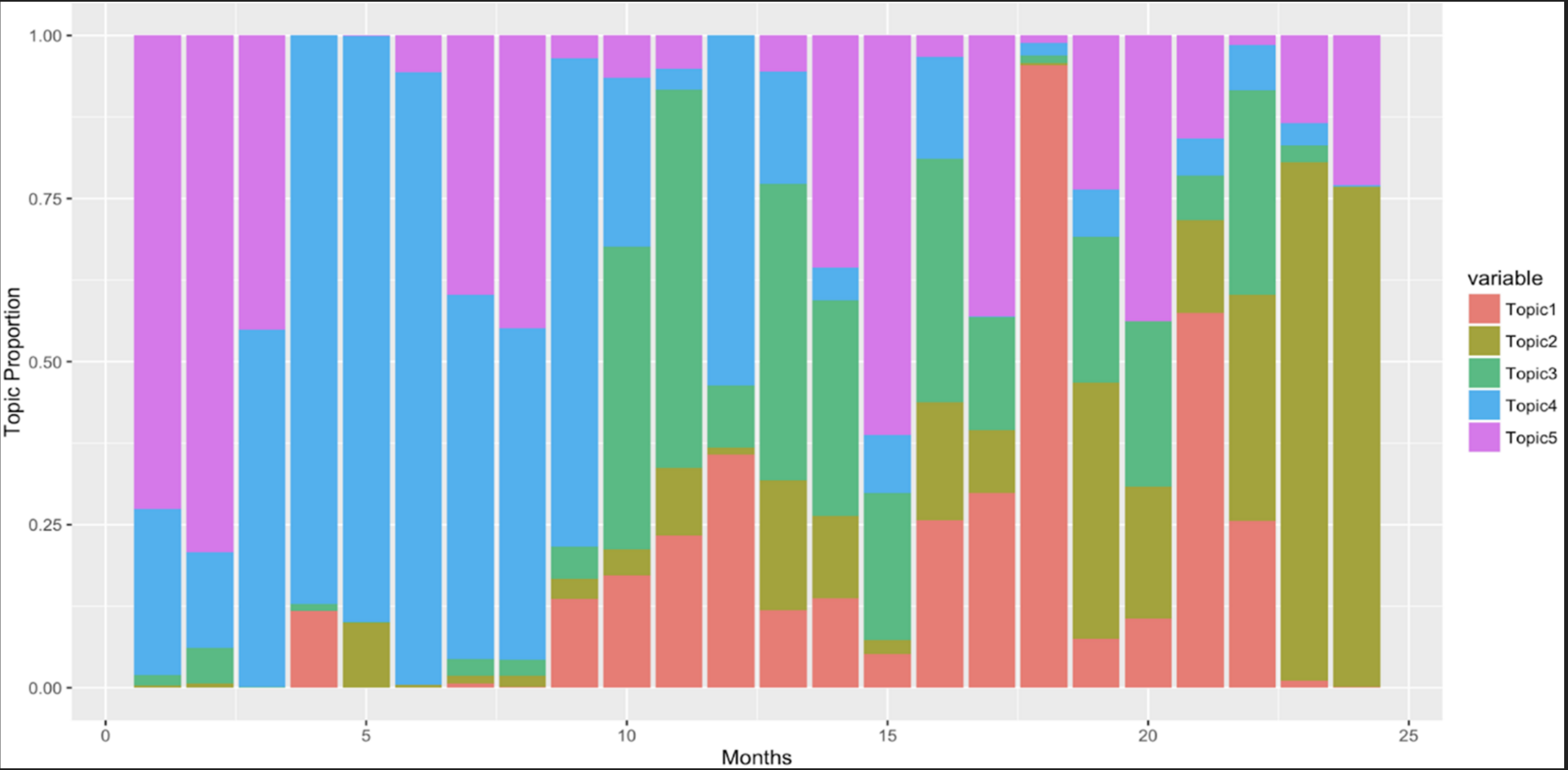
Enron: WordPlay

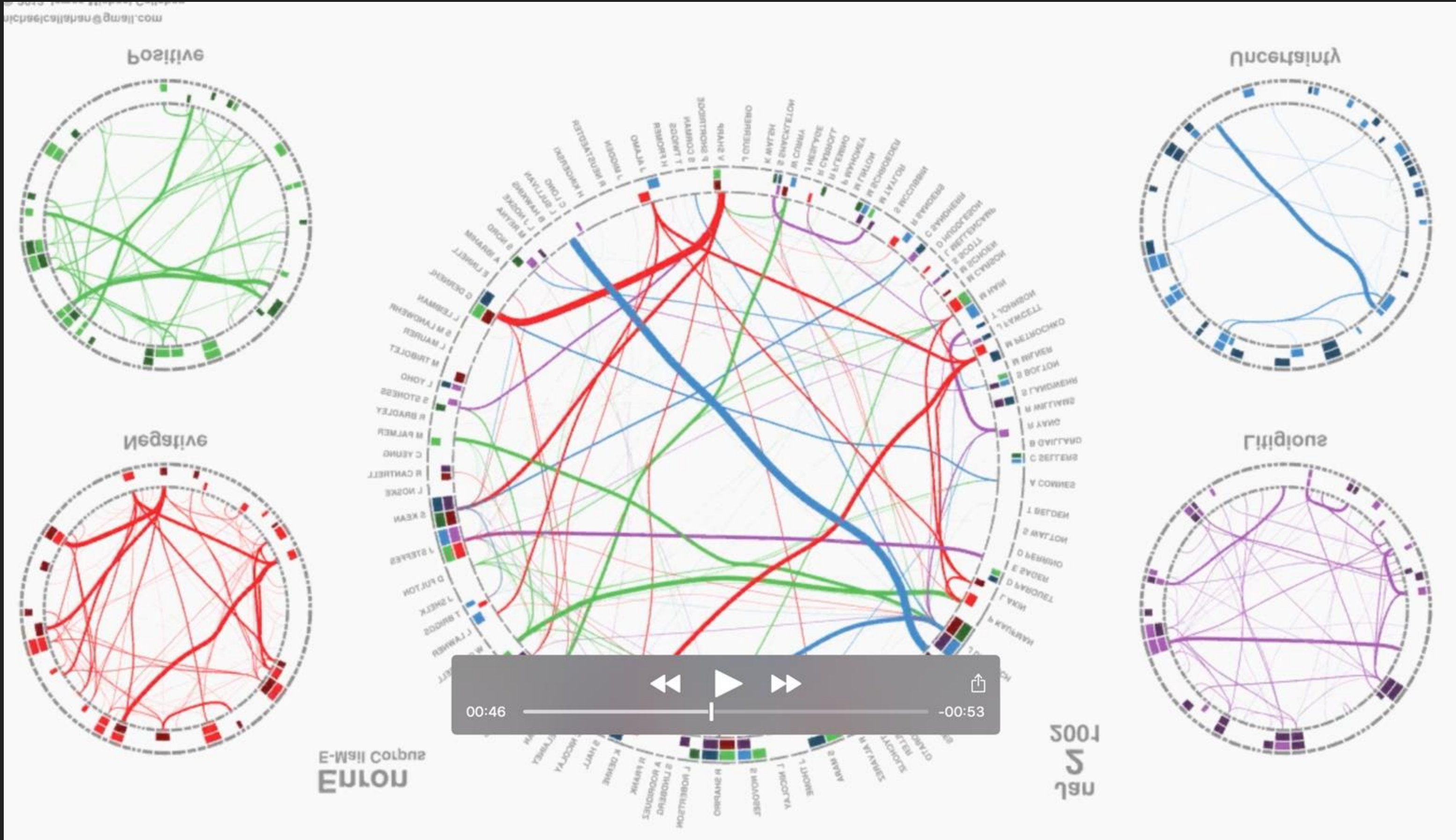


Enron: Topic Analysis



Enron Movie (by Jim Callahan)

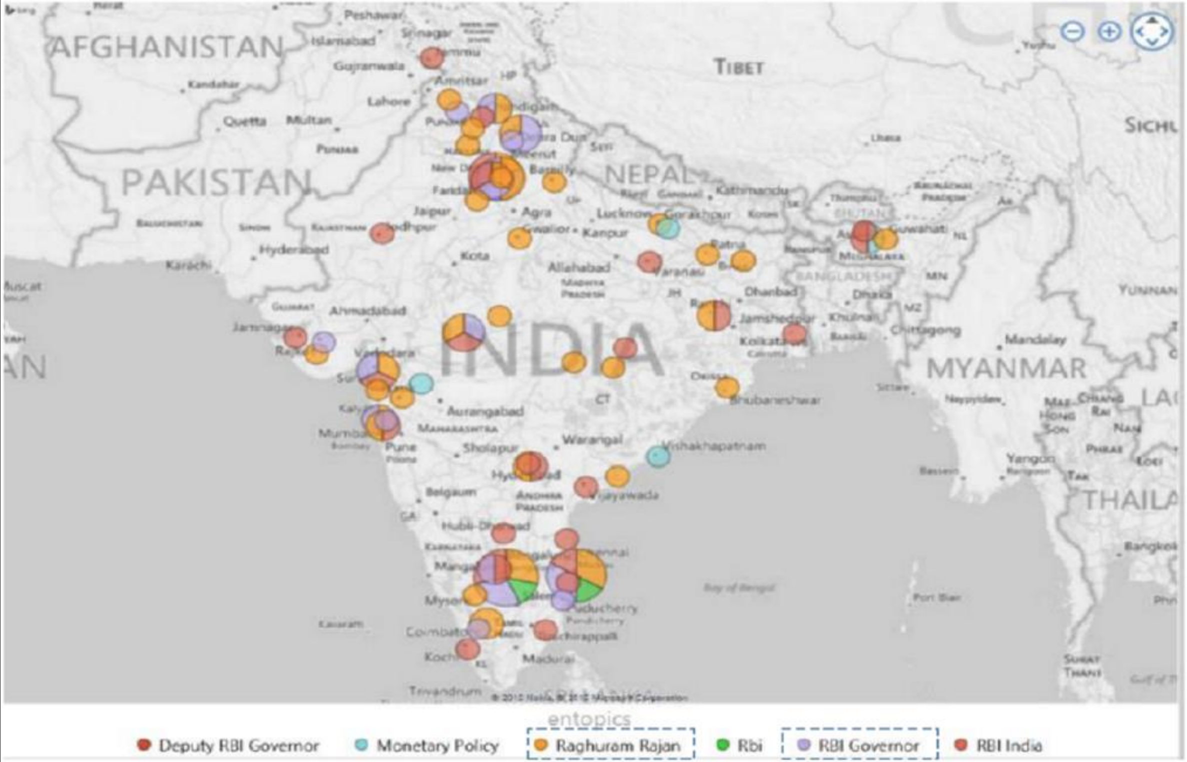
http://srdas.github.io/Presentations/JimCallahan_enron-sm.mov



India: Topic Analysis

Conversations across India and around RBI

topycs



- Conversations across India on RBI, its people and the monetary policy
- Governor features in many conversations across both rural and urban areas
- Some conversations specifically around monetary policy

- Bubbles show split of conversations around Deputy RBI Governor, Monetary Policy, Raghuram Rajan, RBI and RBI Governor.
- Based on count of unique conversations
- Date Range: 1st – 14th April, 2015

India: Topic Analysis

Top Topics along with RBI

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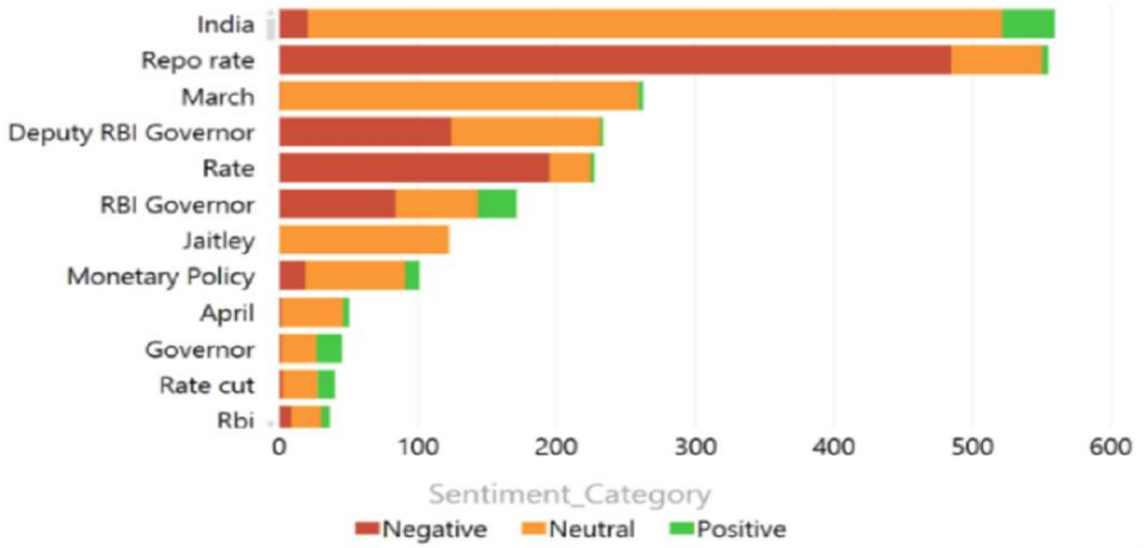


text

"@NDTVProfit: RBI unlikely to change repo rate at policy review smlion

"Digging India's RBI Out of Morass of Debt" by on

"Financial stability is like Pornography. You can't define it but when you see it you know it" - D Subbarao (RBI Governor)

"I was disappointed by the fiscal relaxation." Ex-RBI Governor on India's budget and growth:

"Rajan is perfect, he explains complex economic," PM Modi on RBI governor.

"RBI Conference" shows up as trending topic in India at rank 10

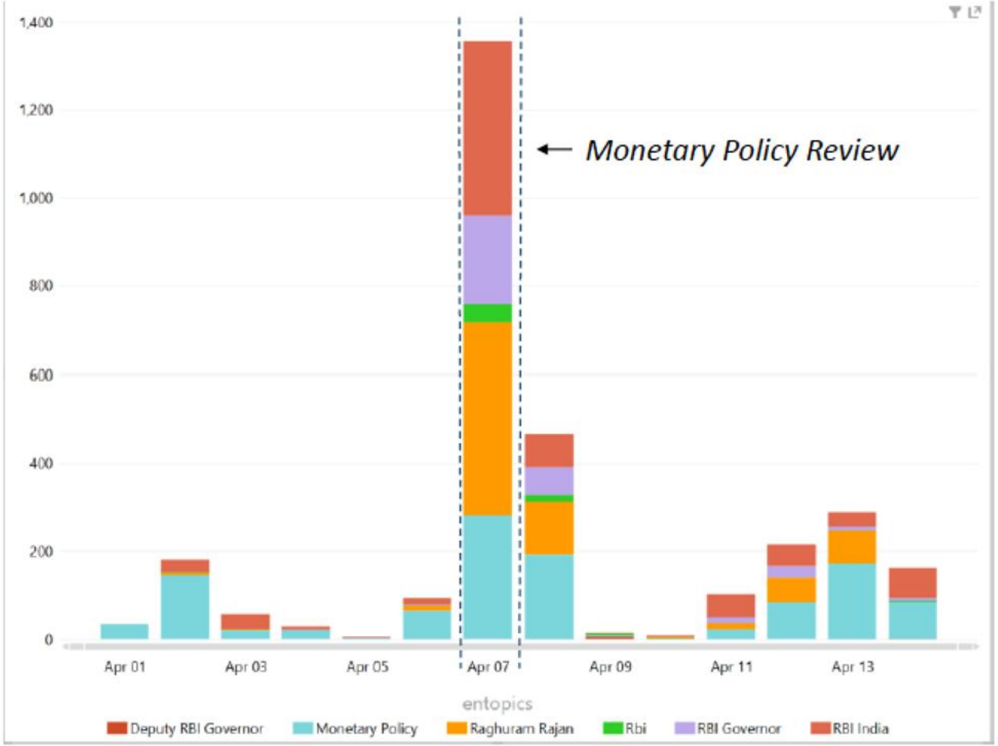
- Repo rate evokes negative sentiment as people don't expect it to be changed
- Repo rate, rate cut and monetary policy are discussed frequently with RBI

- Vertical Axis – Topics of Discussion
- Horizontal Axis – Count of Unique Conversations
- Date – 25th March - 14th of April
- Colors represent sentiment for conversation, Negative – Red, Neutral – Orange, Positive - Green

Monetary Policy (India)

Largest number of conversations around the date of the policy review

topycs



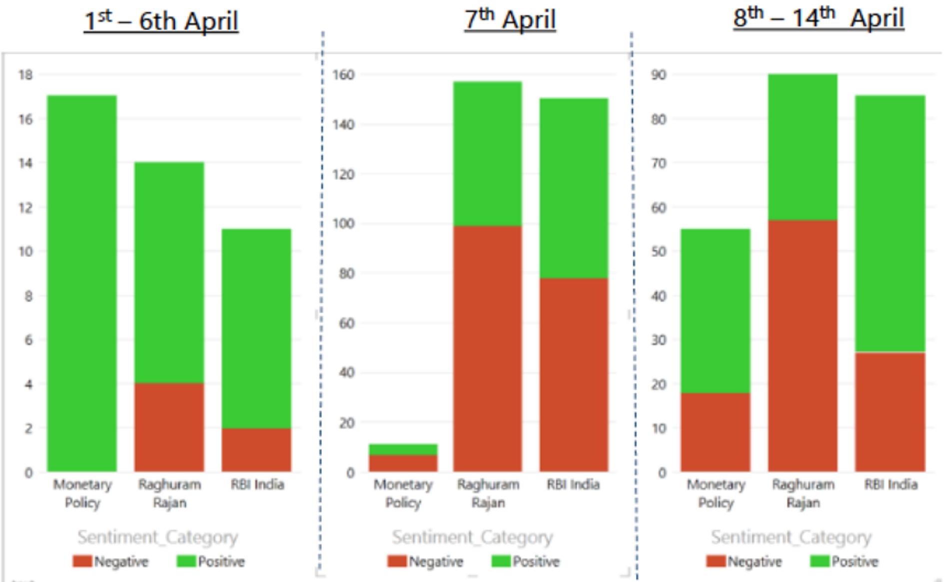
- Largest number of conversations on 7th April and the day after
- People are talking about the monetary policy prior and after the review
- RBI and Governor show up only around the review

- Vertical Axis – Count of Unique Conversations
- Horizontal Axis – Dates between 1st – 14th April
- Colors represent topics of conversation

India

Sentiment around key topics before, during and after the review

topycs



text

"@IndiaToday: SBI, ICICI, HDFC Bank pay heed to Raghuram Rajan's call, cut base rate trending

"@timesofindia: Top 3 banks cut rates after RBIs tough talk" what about you?

"Effectively, monetary policy transmission may move from market forces to fiat which w... - NewsInTweetsIndia

"Effectively, monetary policy transmission may move from market forces to fiat which would be regressive."

"India Inc disappointed with RBI's move on policy rates - SME Times"

"Making monetary policy more potent"

"RBI Conference" shows up as trending topic in India at rank 10

- Conversations positive around monetary policy prior to review, but show more negativity after the review
- More conversations around Raghuram Rajan and RBI India on day of and after the review than prior to the review

- Vertical Axis – Count of Unique Conversations
- Horizontal Axis – Topics of Conversation
- Date – 1st – 14th April
- Colors represent sentiment for conversation, Negative – Red, Positive - Green

Key Principles in Using Big Data for Finance

- Using Theory to develop models to apply to Big Data.
- Questions/problems are primary, data is secondary, in the success of FinTech ventures.
- Simplicity, transparency of models fosters implementability.
- Analytics per se is multidisciplinary.
- Disparate data is the norm.
- Significant investment in hardware and talent.

Thank You!!

http://srdas.github.io/Papers/India.pdf
http://srdas.github.io/Papers/JAI_Das_issue.pdf
http://srdas.github.io/Papers/EnronZeroRev.pdf
http://srdas.github.io/Papers/dyn_syst.pdf