Irving Fisher Committee on
Central Bank Statistics

BANK FOR INTERNATIONAL SETTLEMENTS

IFC – Bank Indonesia International Workshop and Seminar on *"Big Data for Central Bank Policies / Building Pathways for Policy Making with Big Data"*

Bali, Indonesia, 23-26 July 2018

Introduction to network science & visualisation[1]

Kimmo Soramäki,

Financial Network Analytics

[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.

FNA

Introduction to Network Science & Visualization I

Dr. Kimmo Soramäki
Founder & CEO, FNA

Agenda

Network Science

- Introduction
- Key concepts

Exposure Networks

- OTC Derivatives
- CCP Interconnectedness

Correlation Networks

- Housing Bubble and Crisis
- US Presidential Election

Network Science and Graphs Analytics

Is already powering the best known AI applications

Knowledge Graph	Social Graph	Product Graph	Economic Graph	Knowledge Graph	Payment Graph

Network Science and Graphs Analytics

"Goldman Sachs takes a DIY approach to graph analytics"

For enhanced compliance and fraud detection
(www.TechTarget.com, Mar 2015).

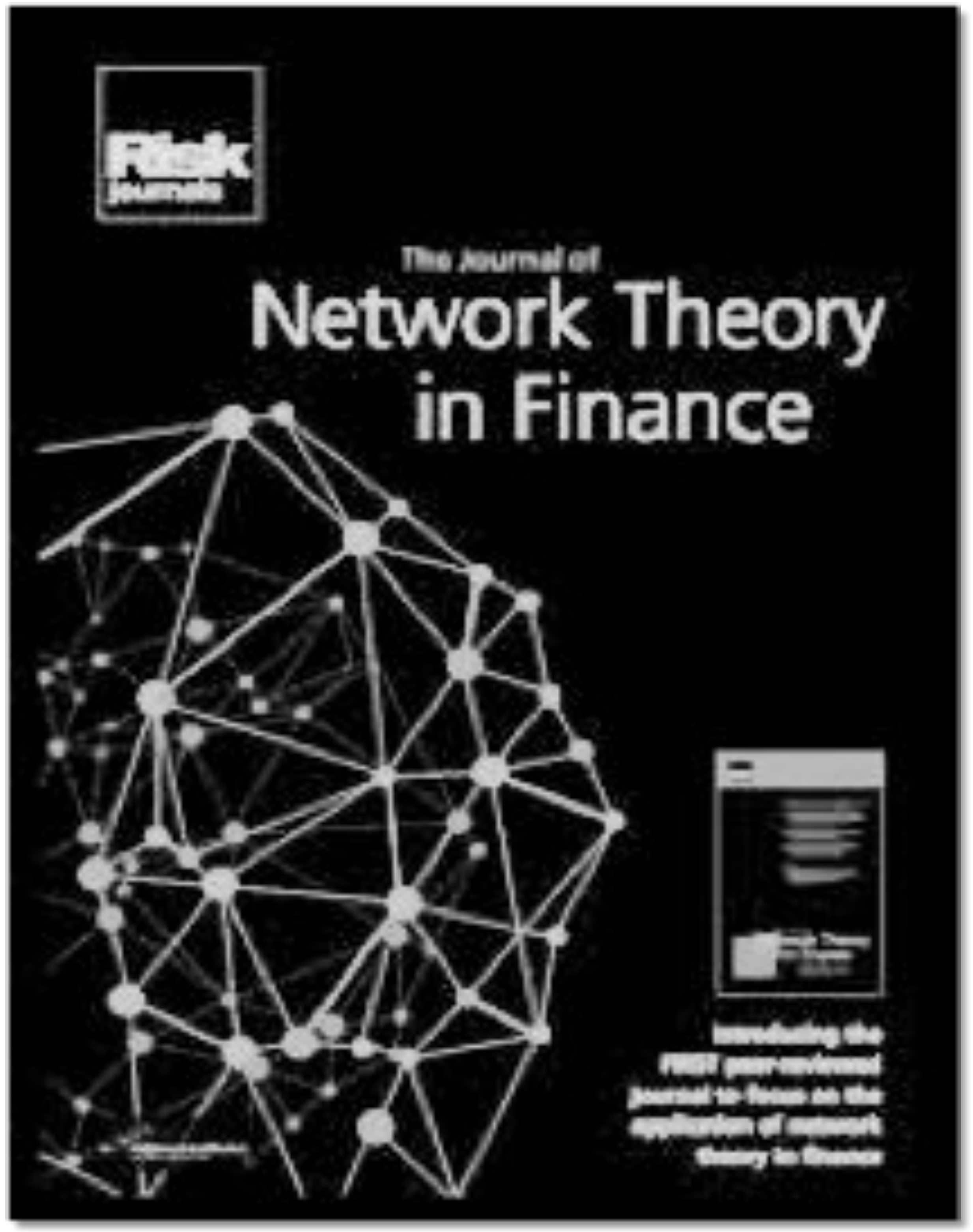
"PayPal relies on graph techniques to perform sophisticated fraud detection"

Saving them more than $700 million and enabling them to perform predictive fraud analysis, according to the IDC
(www.globalbankingandfinance.com, Jan 2016)

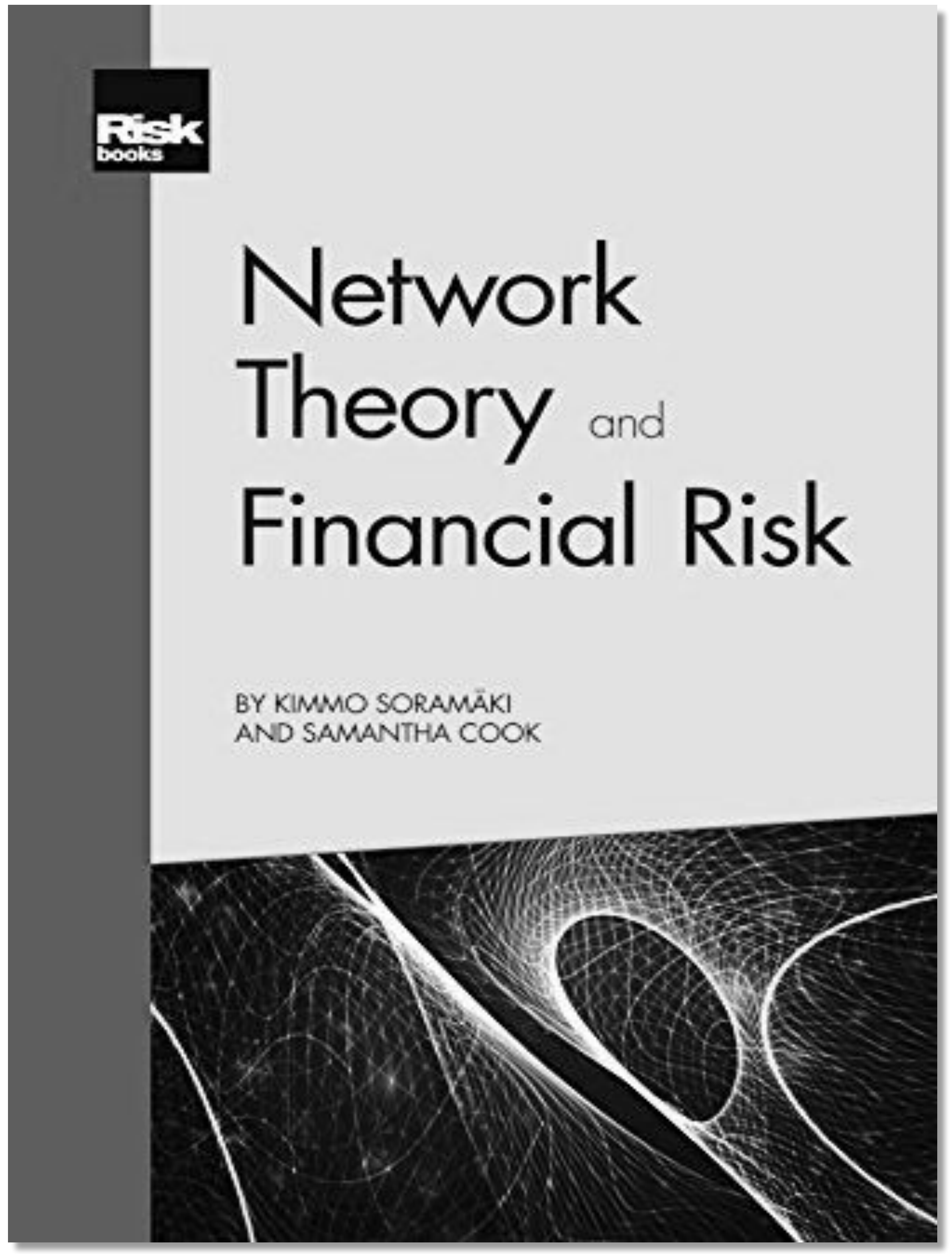
"Network diagnostics .. may displace atomised metrics such as VaR"

Regulators are increasing using network science for financial stability analysis.
(Andy Haldane, Bank of England Executive Director)

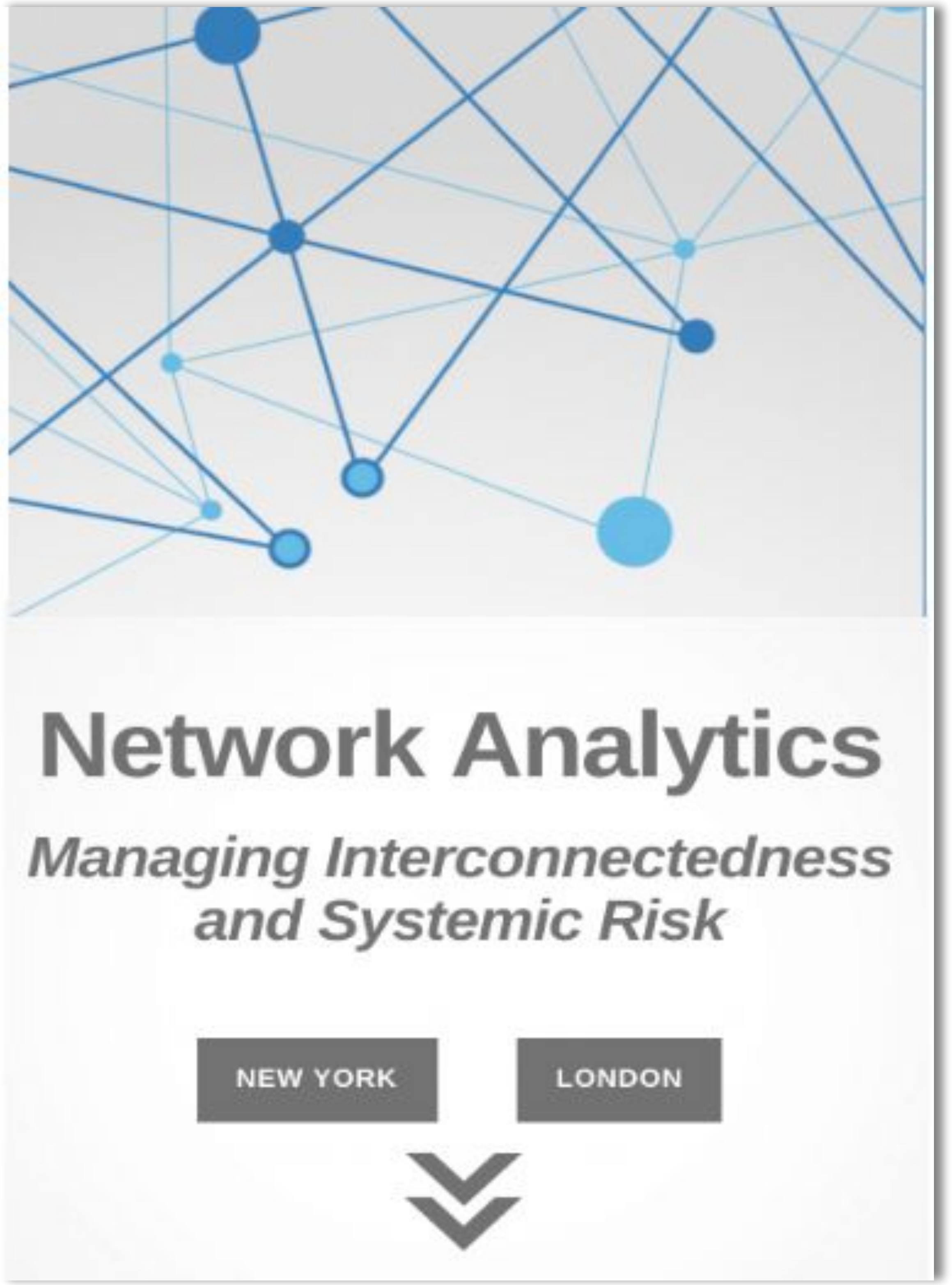
Further Resources on Network Analytics and Systemic Risk



Risk Journal founded by Kimmo Soramäki | link



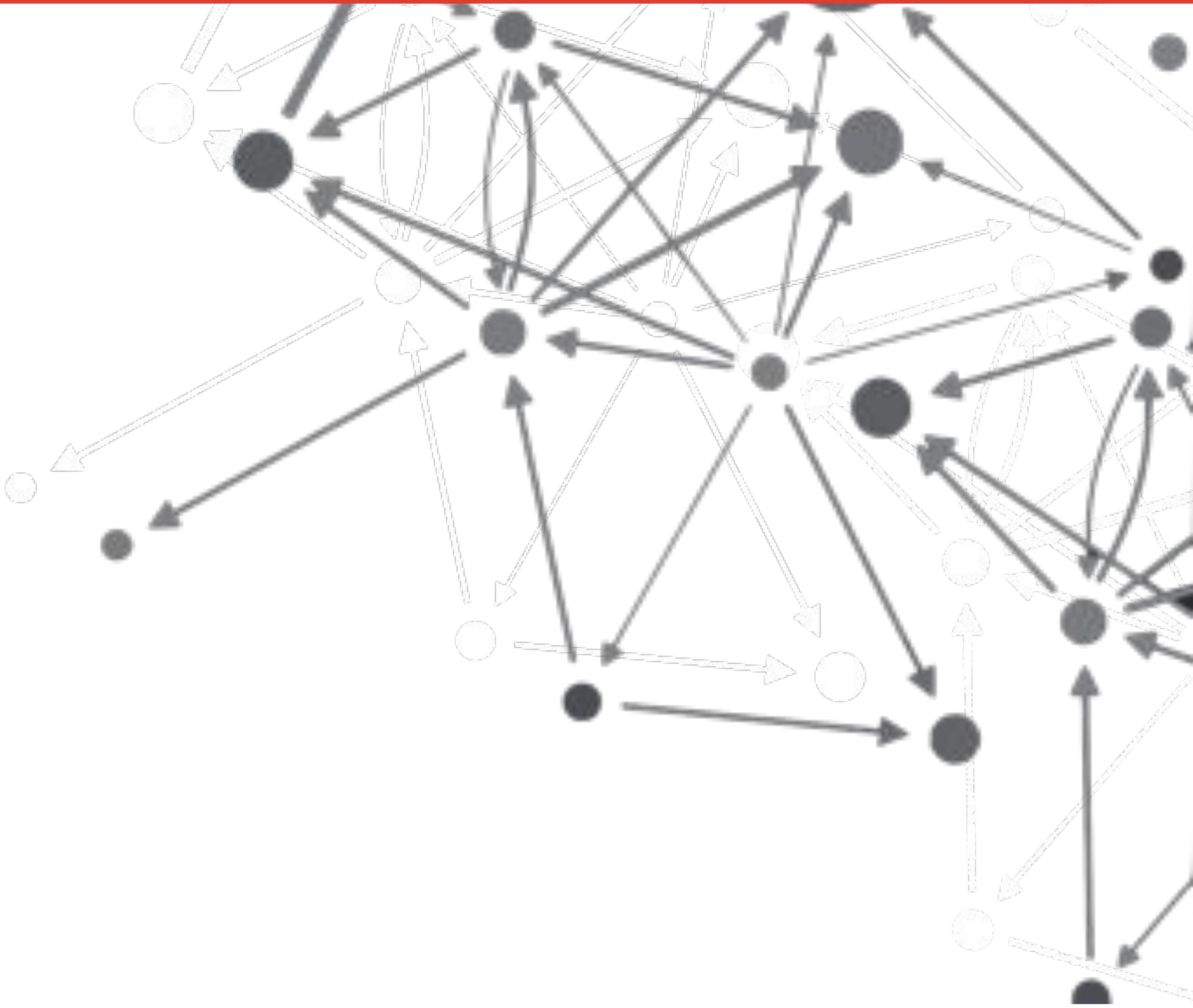
Risk Book by Kimmo Soramäki and Samantha Cook, FNA's Chief Scientist | link



Two-day Training course in London, New York and Singapore, instructed by Kimmo Soramäki | link

Network Theory is about

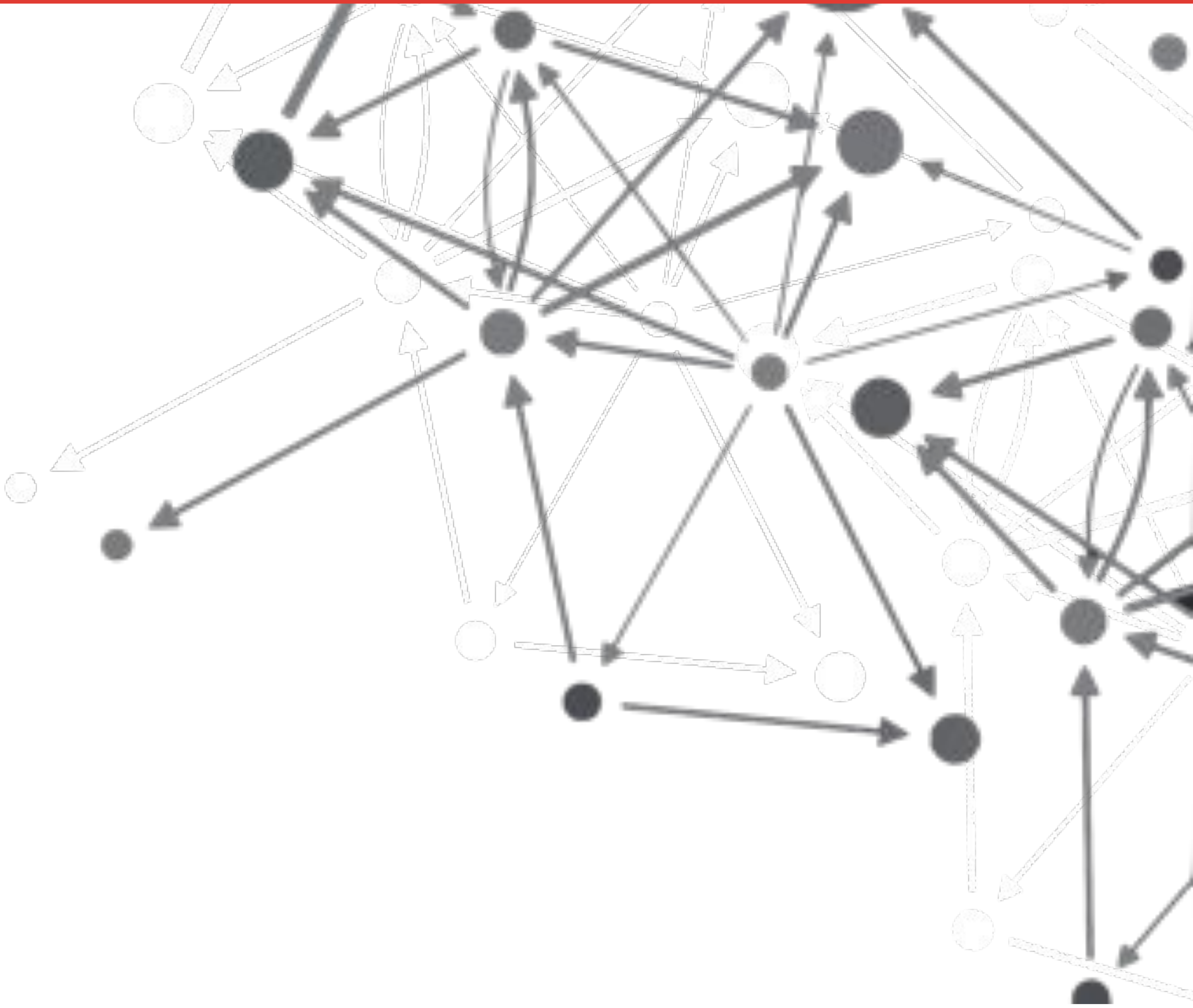
New Way of Looking at Data



- How is data connected with other data?
- How do these connections matter?
- How do complex systems move in time?

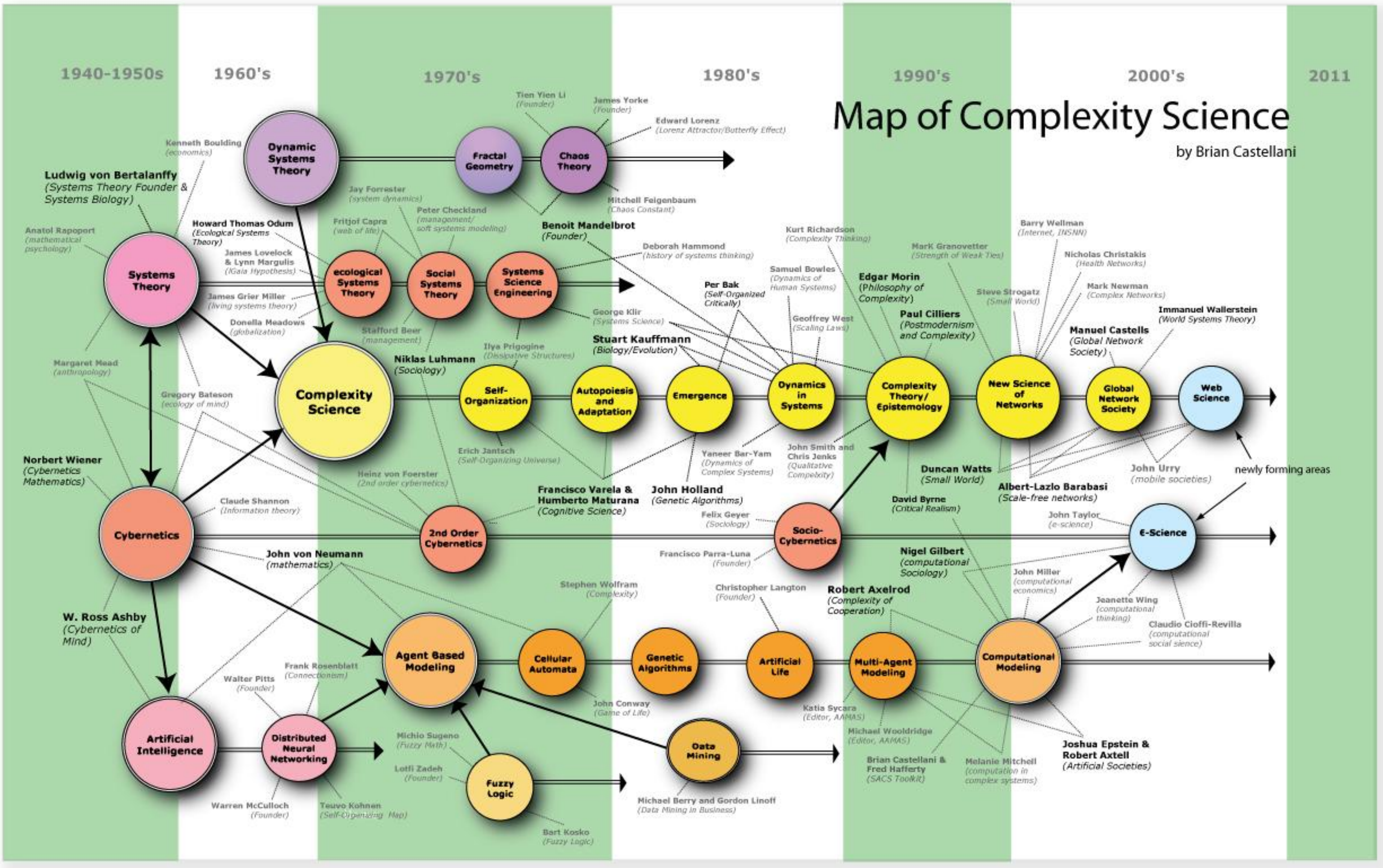
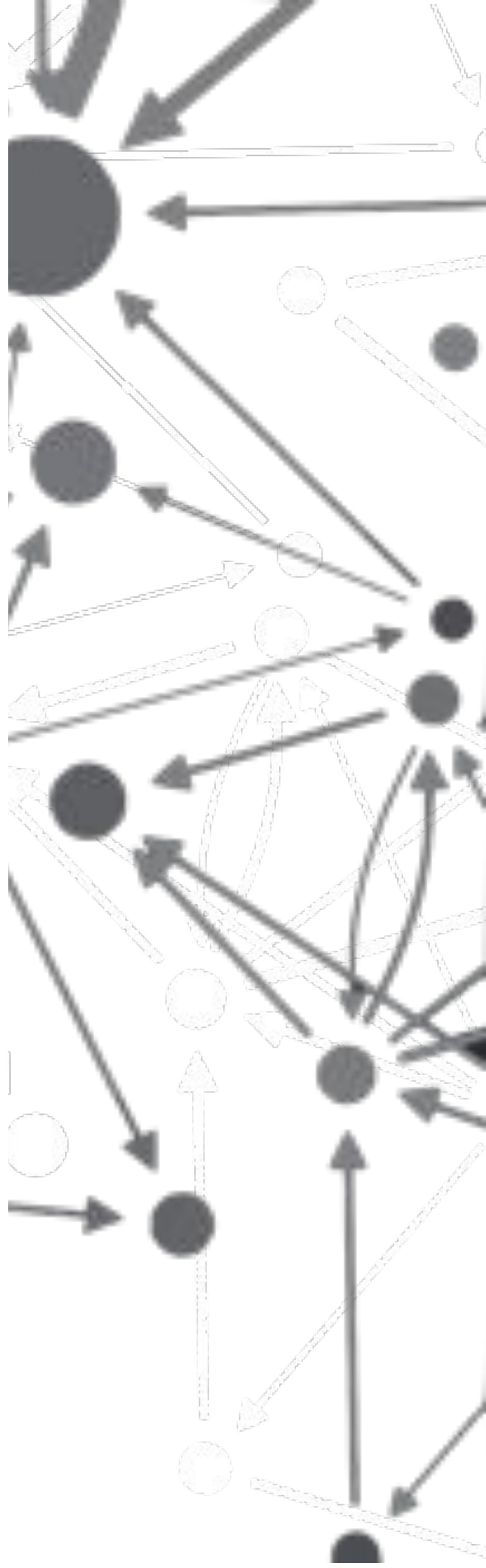
For the first time we are able to measure and model this!

Complex Systems

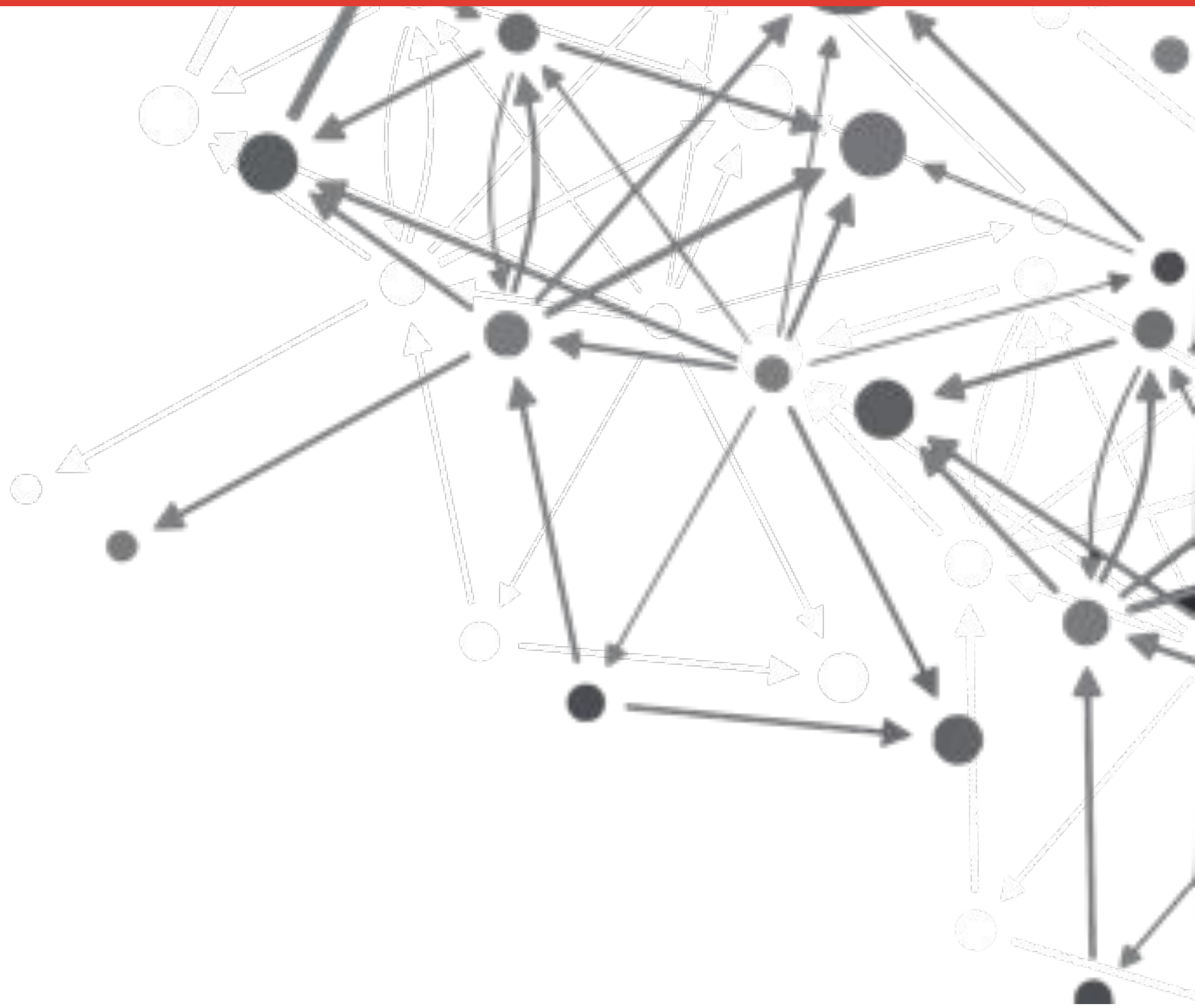


"Systems with rich interactions between the components of the system"

eg. financial markets, payment systems, road systems, friendship networks, ... almost **every** socio-economic system.

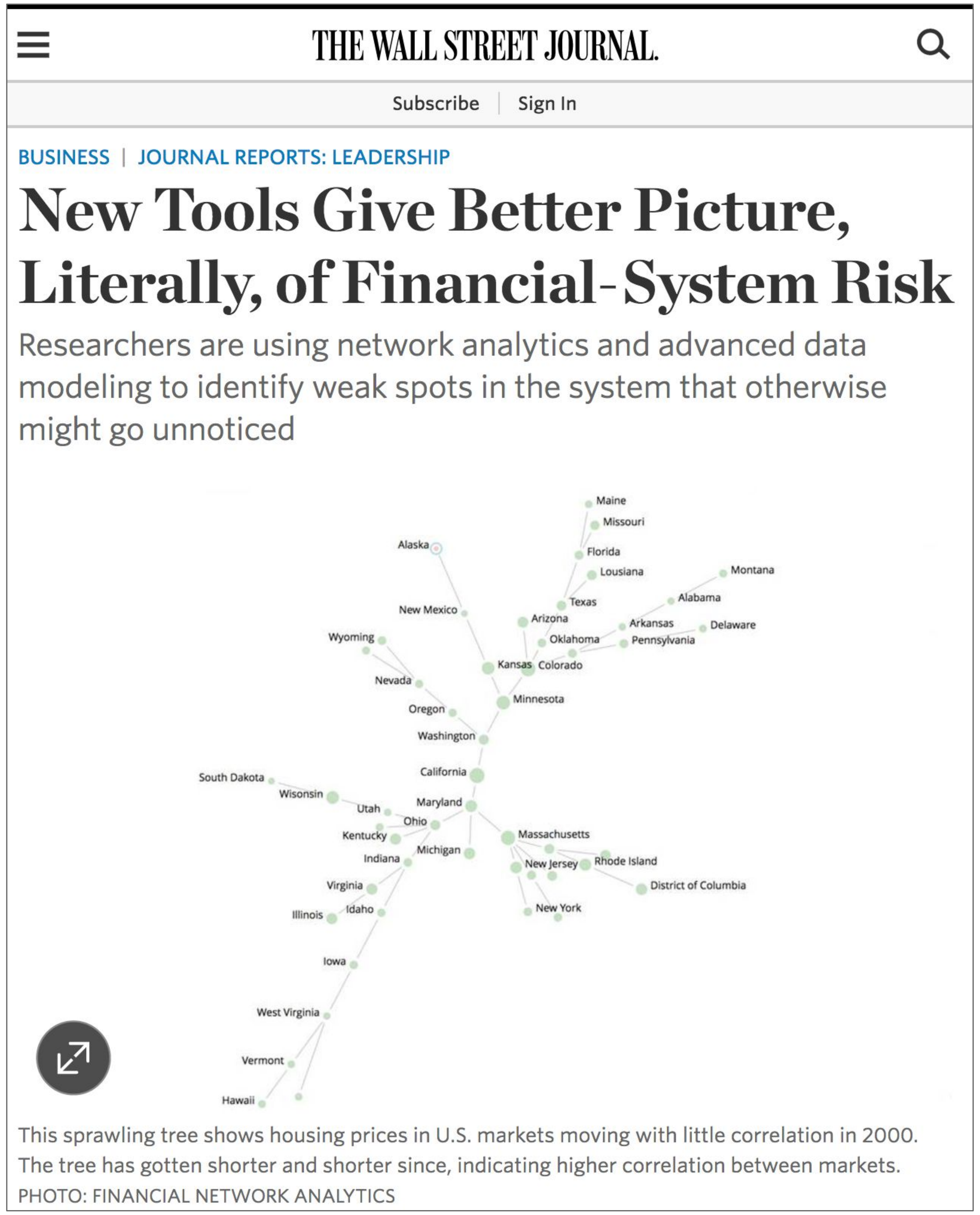

Map of Complexity Science
by Brian Castellani
1940-1950s
1960's
1970's
1980's
1990's
2000's
2011
Dynamic Systems Theory
Fractal Geometry
Chaos Theory
Systems Theory
ecological Systems Theory
Social Systems Theory
Systems Science Engineering
Complexity Science
Self-Organization
Autopoiesis and Adaptation
Emergence
Dynamics in Systems
Complexity Theory/ Epistemology
New Science of Networks
Global Network Society
Web Science
Cybernetics
2nd Order Cybernetics
Socio-Cybernetics
E-Science
Artificial Intelligence
Distributed Neural Networking
Agent Based Modeling
Cellular Automata
Genetic Algorithms
Artificial Life
Multi-Agent Modeling
Computational Modeling
Fuzzy Logic
Data Mining
newly forming areas
Ludwig von Bertalanffy (Systems Theory Founder & Systems Biology)
Kenneth Boulding (economics)
Anatol Rapoport (mathematical psychology)
Howard Thomas Odum (Ecological Systems Theory)
James Lovelock & Lynn Margulis (Gaia Hypothesis)
James Grier Miller (living systems theory)
Donella Meadows (globalization)
Margaret Mead (anthropology)
Gregory Bateson (ecology of mind)
Norbert Wiener (Cybernetics Mathematics)
Claude Shannon (information theory)
John von Neumann (mathematics)
W. Ross Ashby (Cybernetics of Mind)
Walter Pitts (Founder)
Warren McCulloch (Founder)
Frank Rosenblatt (Connectionism)
Teuvo Kohnen (Self-Organizing Map)
Jay Forrester (system dynamics)
Fritjof Capra (web of life)
Peter Checkland (management/ soft systems modeling)
Stafford Beer (management)
Niklas Luhmann (Sociology)
Ilya Prigogine (Dissipative Structures)
Erich Jantsch (Self-Organizing Universe)
Heinz von Foerster (2nd order cybernetics)
Tien Yien Li (Founder)
James Yorke (Founder)
Edward Lorenz (Lorenz Attractor/Butterfly Effect)
Mitchell Feigenbaum (Chaos Constant)
Benoit Mandelbrot (Founder)
Deborah Hammond (history of systems thinking)
George Klir (Systems Science)
Stuart Kauffmann (Biology/Evolution)
Francisco Varela & Humberto Maturana (Cognitive Science)
John Holland (Genetic Algorithms)
Stephen Wolfram (Complexity)
John Conway (Game of Life)
Michio Sugeno (Fuzzy Math)
Lotfi Zadeh (Founder)
Bart Kosko (Fuzzy Logic)
Michael Berry and Gordon Linoff (Data Mining in Business)
Per Bak (Self-Organized Critically)
Samuel Bowles (Dynamics of Human Systems)
Kurt Richardson (Complexity Thinking)
Geoffrey West (Scaling Laws)
Yaneer Bar-Yam (Dynamics of Complex Systems)
John Smith and Chris Jenks (Qualitative Complexity)
Felix Geyer (Sociology)
Francisco Parra-Luna (Founder)
Christopher Langton (Founder)
Robert Axelrod (Complexity of Cooperation)
Katia Sycara (Editor, AAMAS)
Michael Wooldridge (Editor, AAMAS)
Brian Castellani & Fred Hafferty (SACS Toolkit)
Melanie Mitchell (computation in complex systems)
Edgar Morin (Philosophy of Complexity)
Paul Cilliers (Postmodernism and Complexity)
Mark Granovetter (Strength of Weak Ties)
Steve Strogatz (Small World)
Duncan Watts (Small World)
David Byrne (Critical Realism)
Nigel Gilbert (computational Sociology)
John Miller (computational economics)
Barry Wellman (Internet, INSNN)
Nicholas Christakis (Health Networks)
Mark Newman (Complex Networks)
Manuel Castells (Global Network Society)
Immanuel Wallerstein (World Systems Theory)
Albert-Lazlo Barabasi (Scale-free networks)
John Urry (mobile societies)
John Taylor (e-science)
Jeanette Wing (computational thinking)
Claudio Cioffi-Revilla (computational social sience)
Joshua Epstein & Robert Axtell (Artificial Societies)


Main Modes of Analysis



- Top Down Analysis
- Bottom Up Analysis
- Features of Data
- Agent Based Models

Top Down Analysis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BUSINESS | JOURNAL REPORTS: LEADERSHIP

New Tools Give Better Picture, Literally, of Financial-System Risk

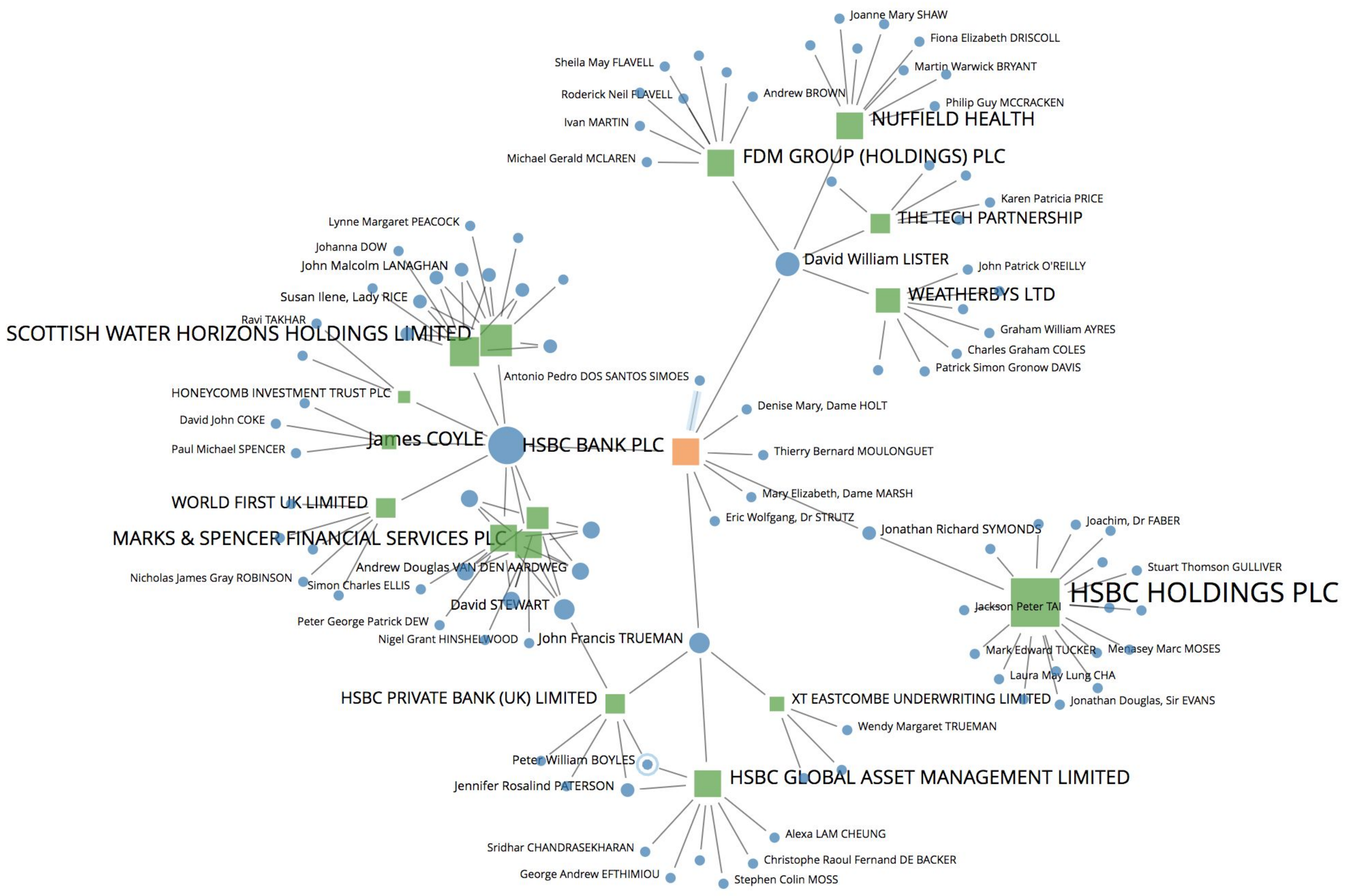
Researchers are using network analytics and advanced data modeling to identify weak spots in the system that otherwise might go unnoticed

This sprawling tree shows housing prices in U.S. markets moving with little correlation in 2000. The tree has gotten shorter and shorter since, indicating higher correlation between markets.
PHOTO: FINANCIAL NETWORK ANALYTICS

Typical use cases:

- Systemic risk analysis
- System monitoring
- System design
- System stress testing
- Clustering/Classification
- Early warning
- Anomaly detection

Bottom Up Analysis



Typical use cases:

- Criminal investigation
- Terrorist networks
- Money laundering
- KYC & KYCC
- Fundamental investment analysis
- Supply chain analysis

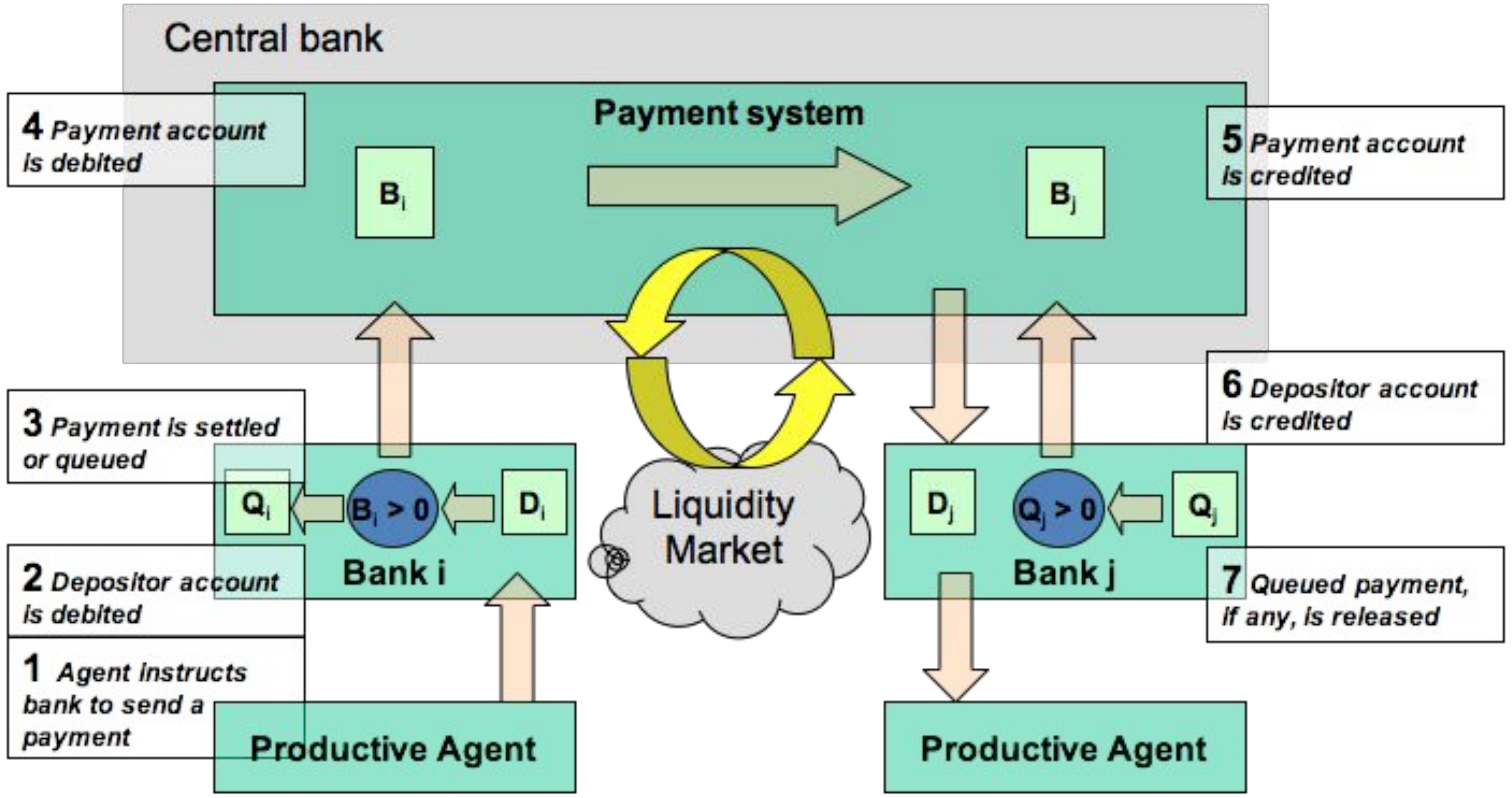
Network Features of Data

Typical use cases:

- AI/ML
- Fraud algorithms
- Recommendation engines
- Algorithmic investment

FNA Research: [Comparison of Graph Computing Platform Performance]()

Agent Based Models



Beyeler, Glass, Bech and Soramäki (2007), Physica A, 384-2, pp 693-718.

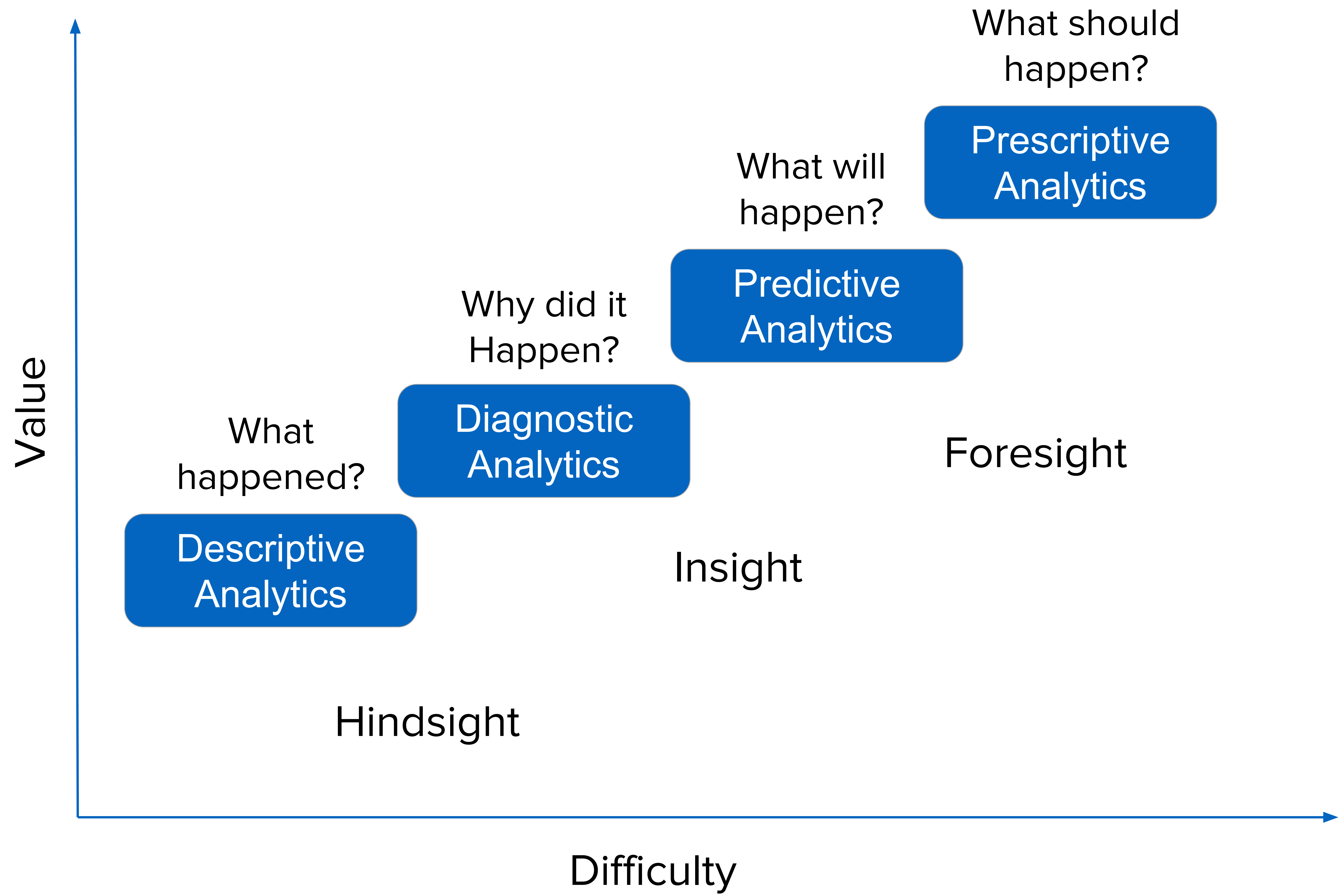
Typical use cases:

- Central Counterparty Clearing
- Payment Systems
- FX Settlement
- Financial Markets
- Housing Markets

Journey

Advanced Analytics	Monitoring	Simulation
1	2	3
Understand interconnectedness, data visualization	Detect risks and anomalies in real-time	What-if analysis, failure simulations & remediation scenarios
Identify Risks Concentrations	Provide Early Warning	Predict Outcomes

Analytical Framework



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Types of Networks

Network Concepts

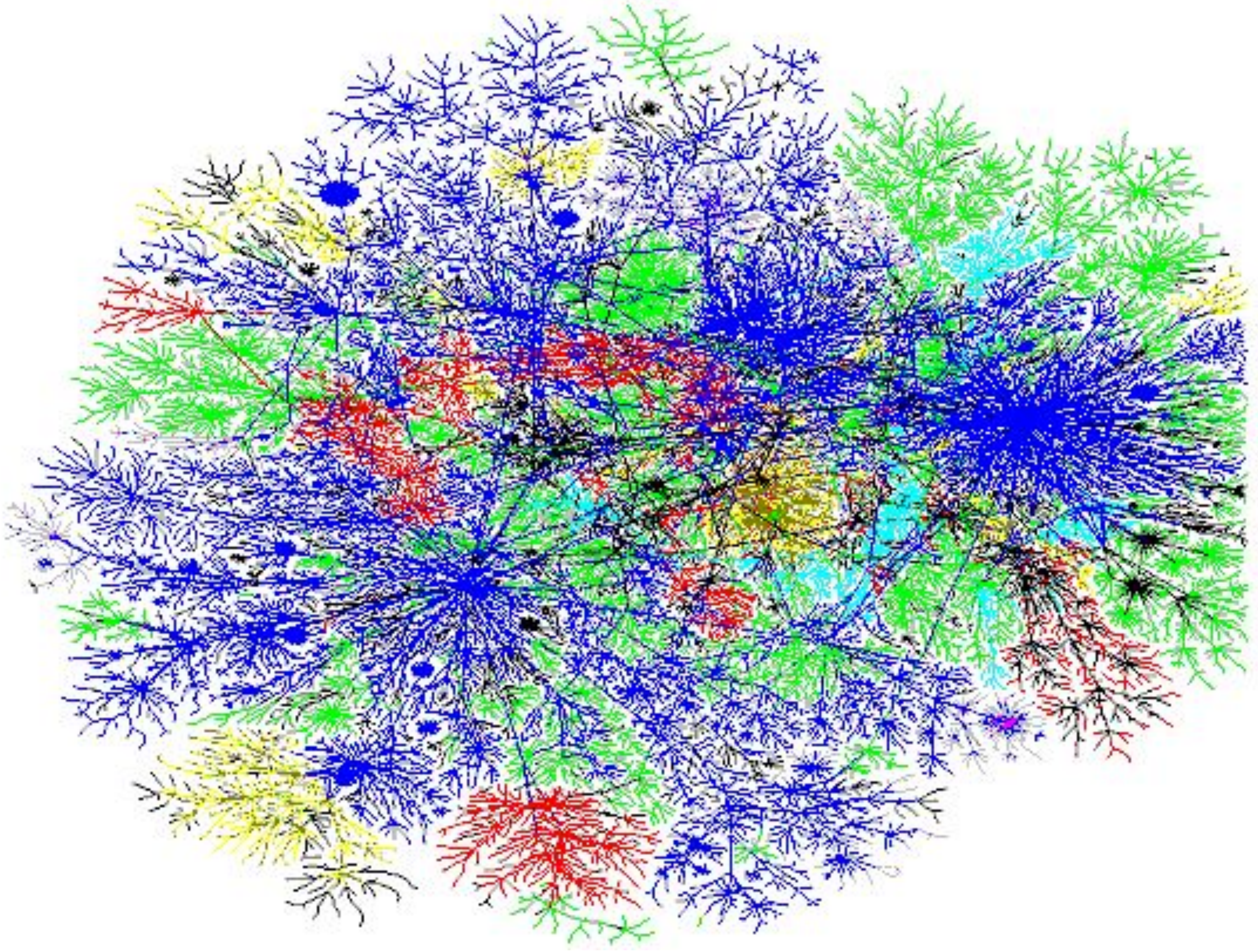
Constituents

- Networks (graphs)
- Nodes (vertices)
- Links (ties, edges or arcs)

Links can be

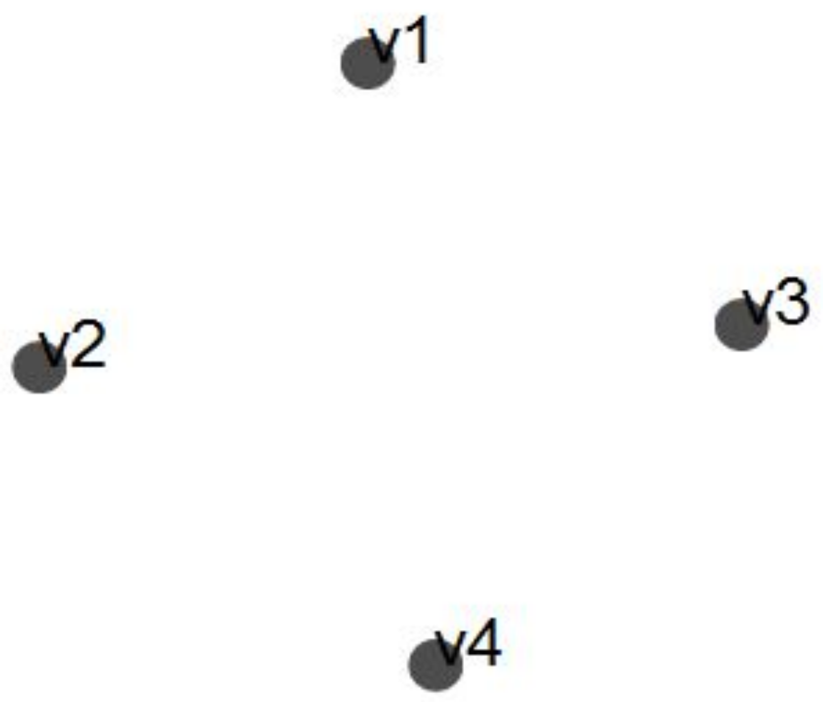
- Directed (arcs) vs undirected (edges, ties)
- Weighed vs unweighted

Graph + properties = Network

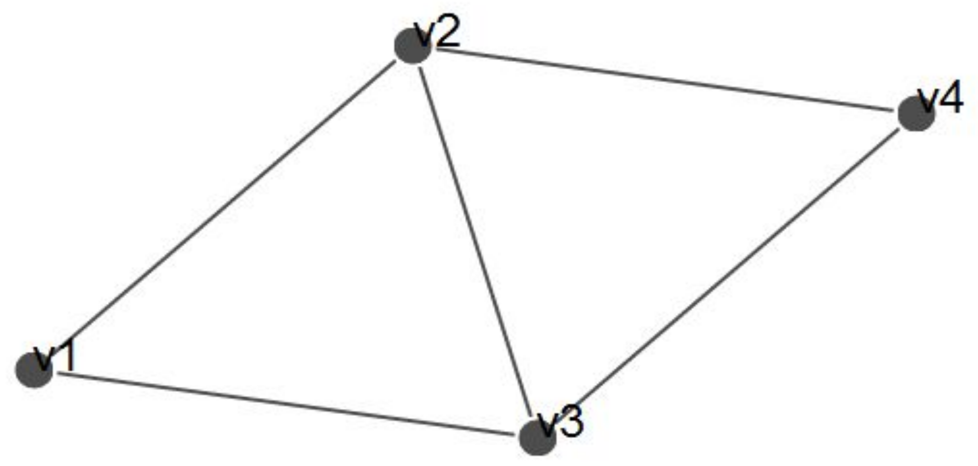


Some Graph Types

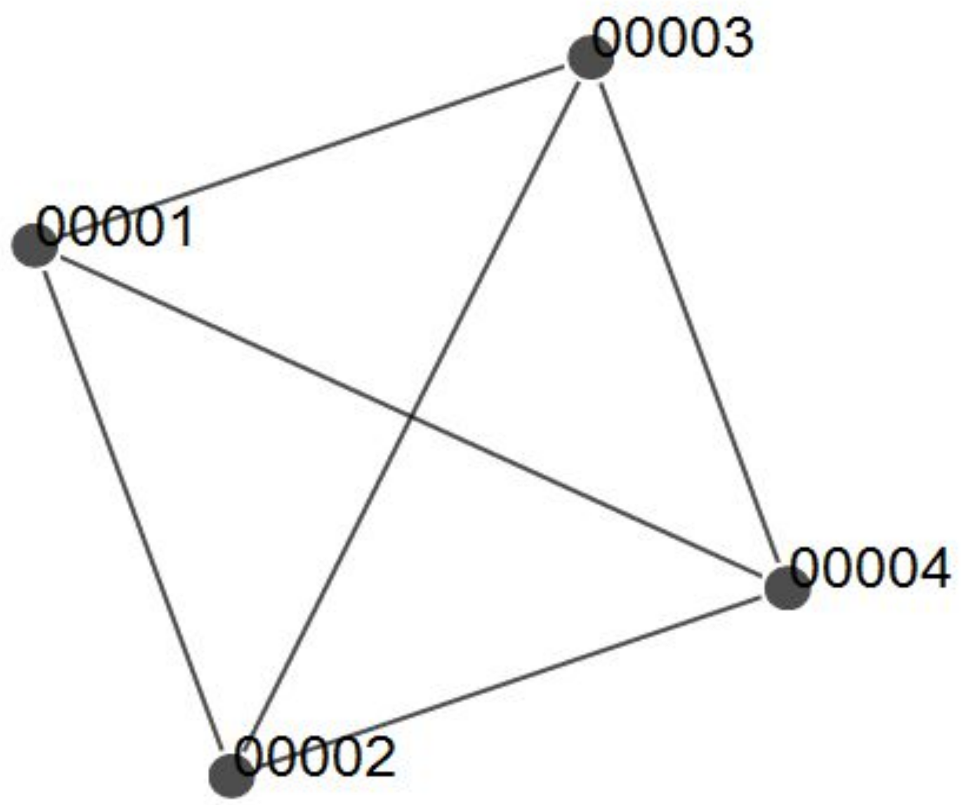
Trivial Graph



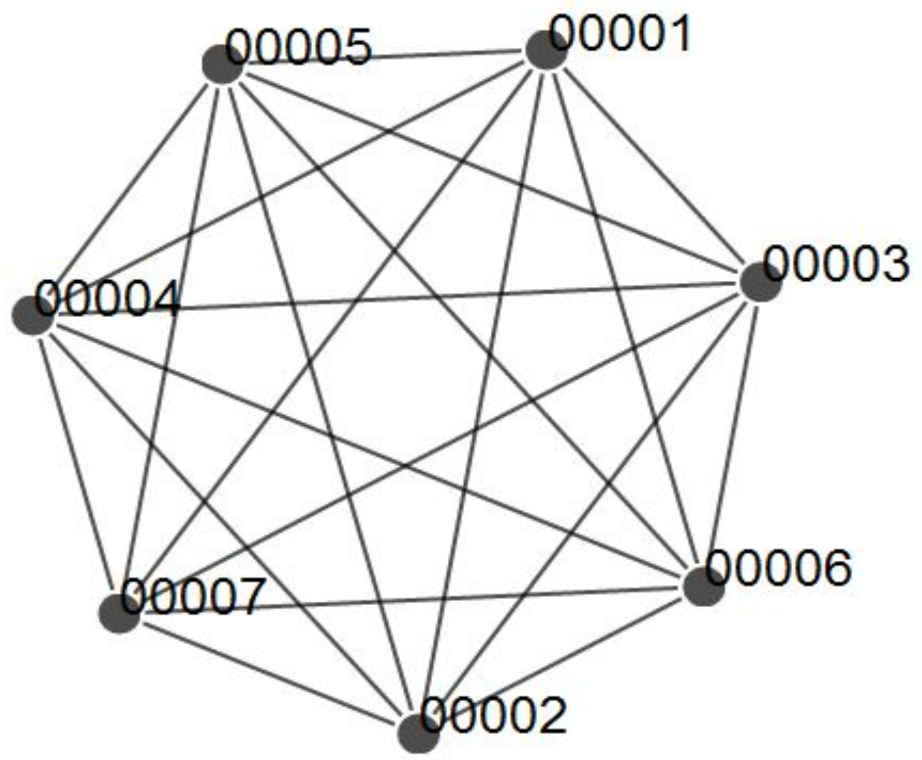
Empty Graph



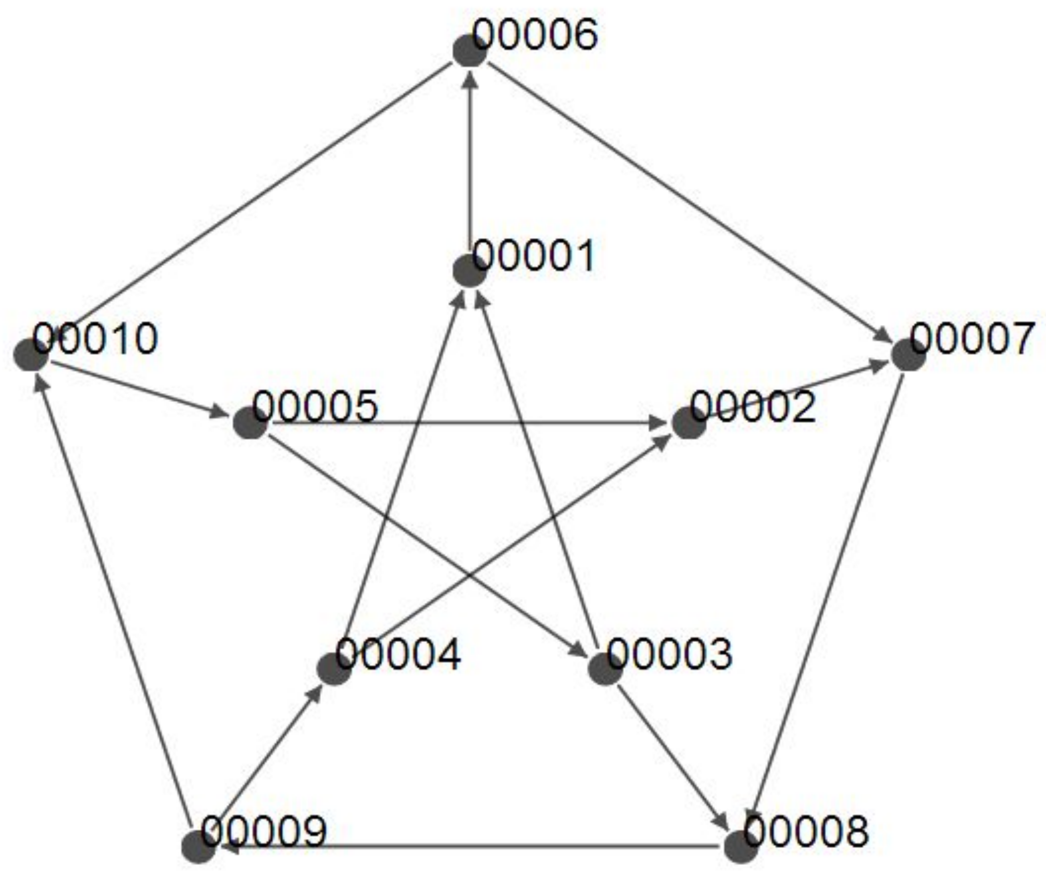
Undirected Graph



Complete graph, K4

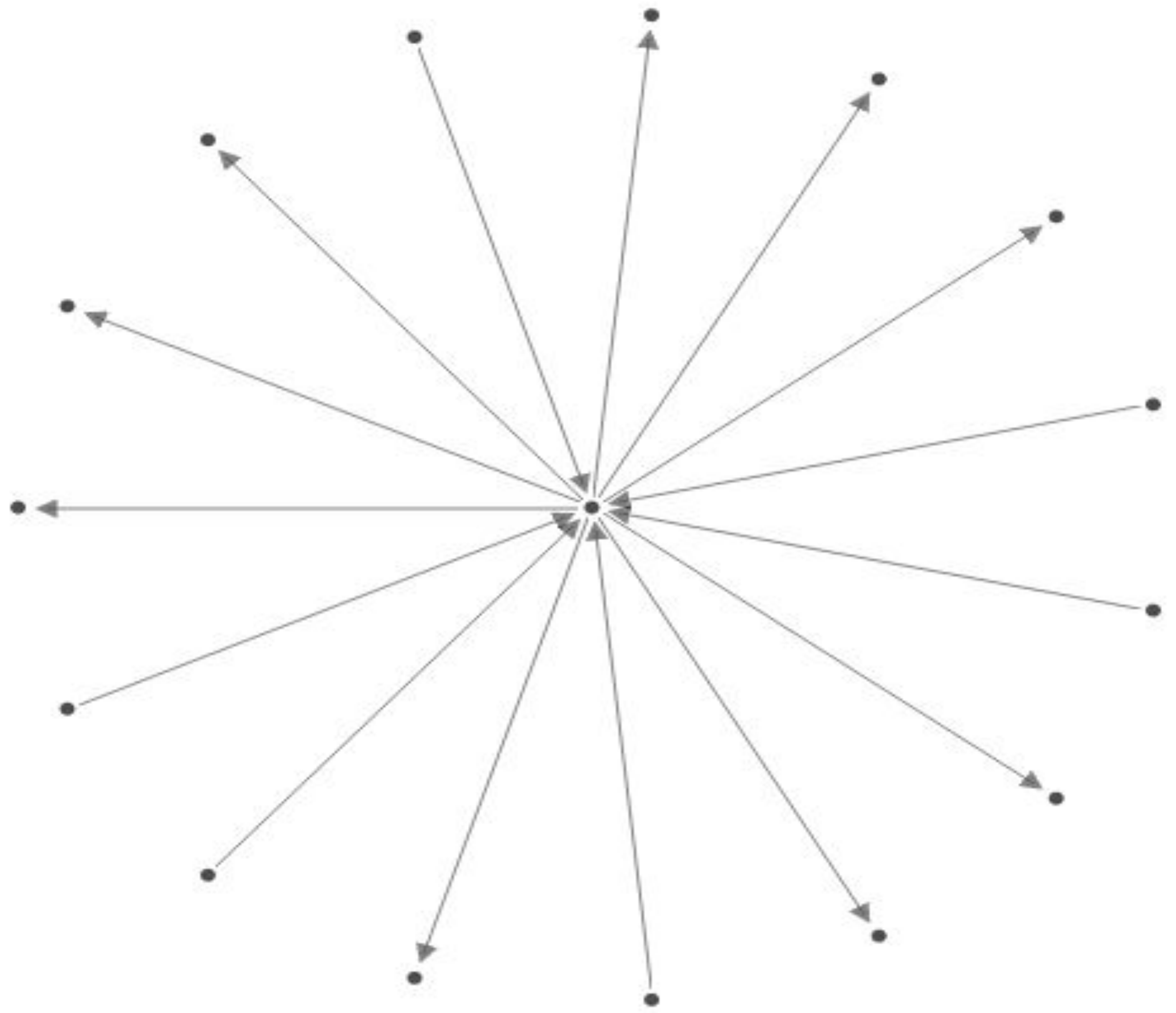


Complete graph, K7

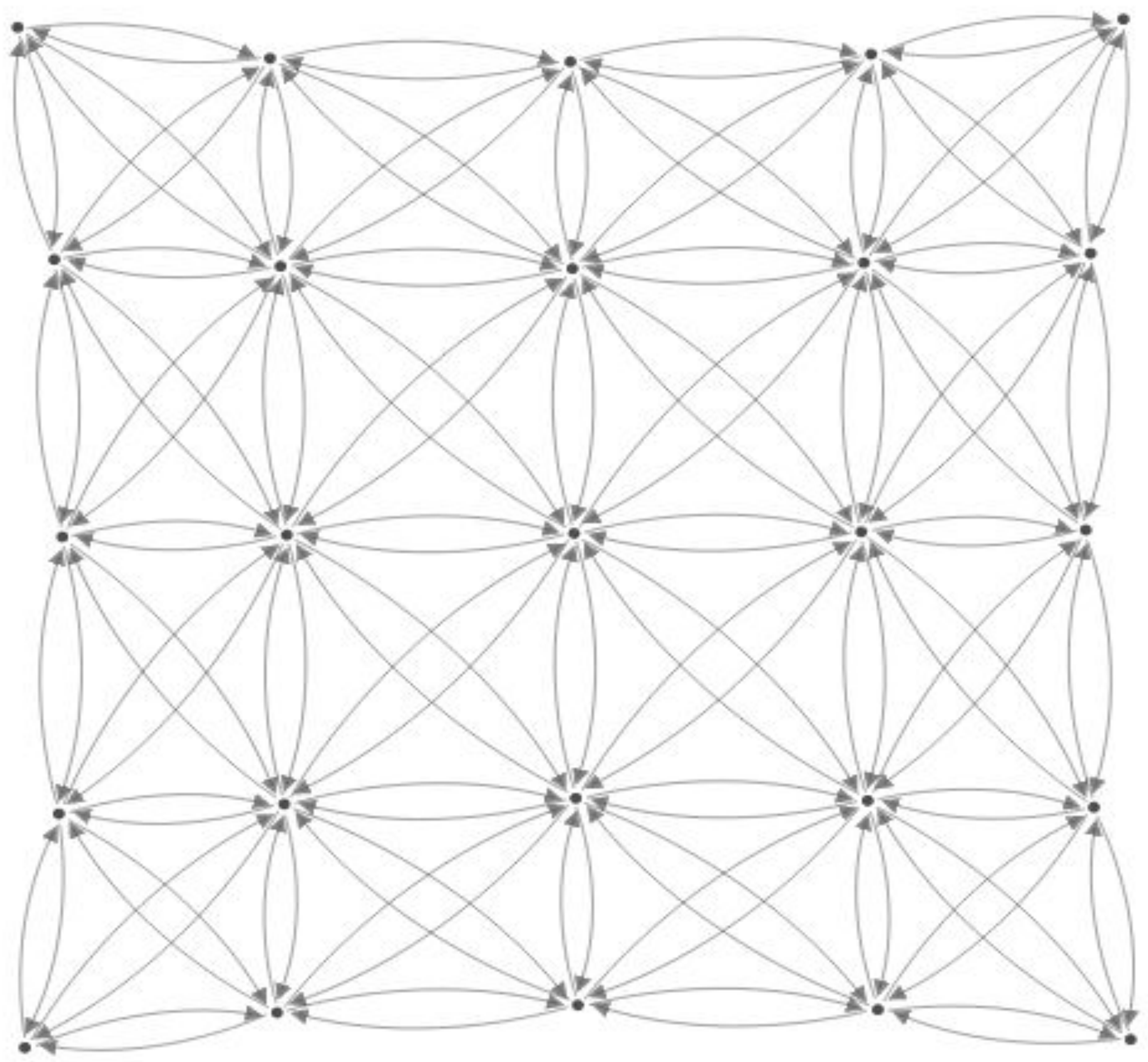


Directed Graph

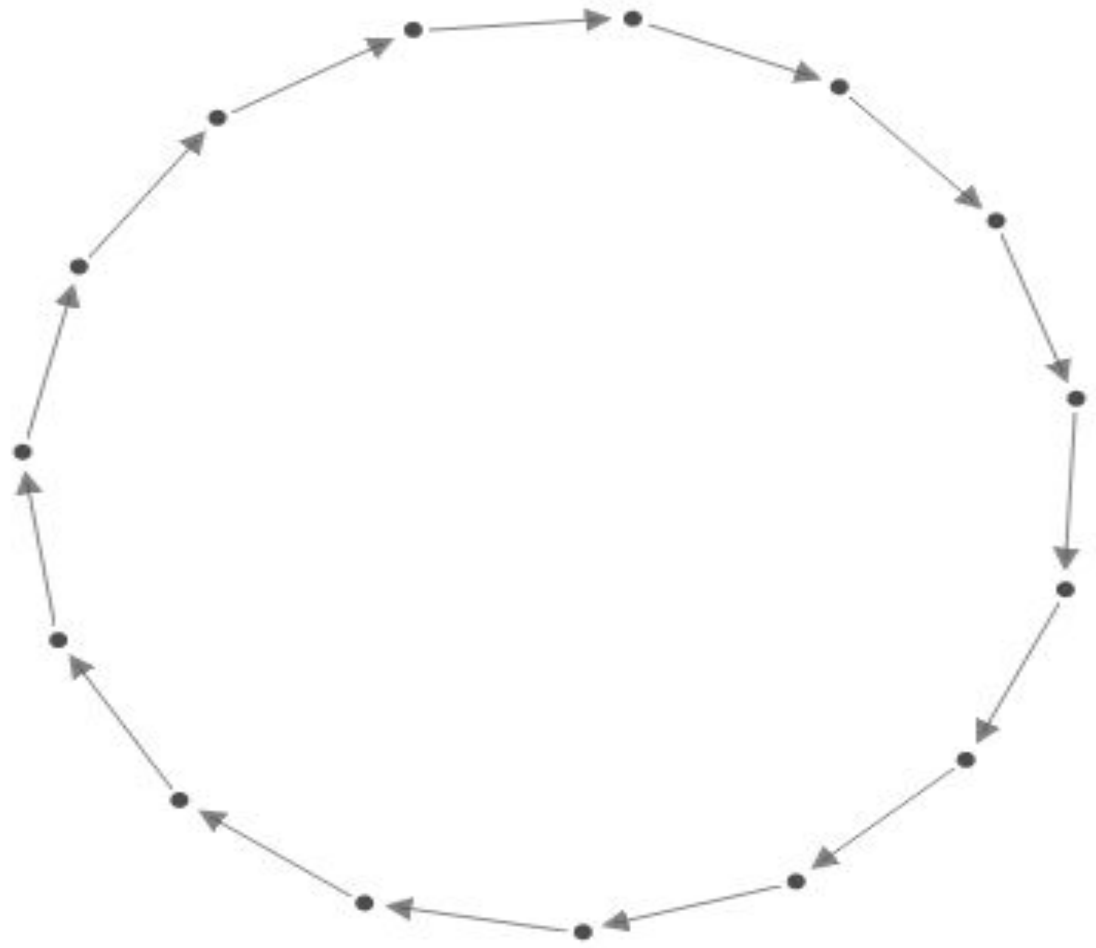
Simple Graphs / Non-random Graphs



Star

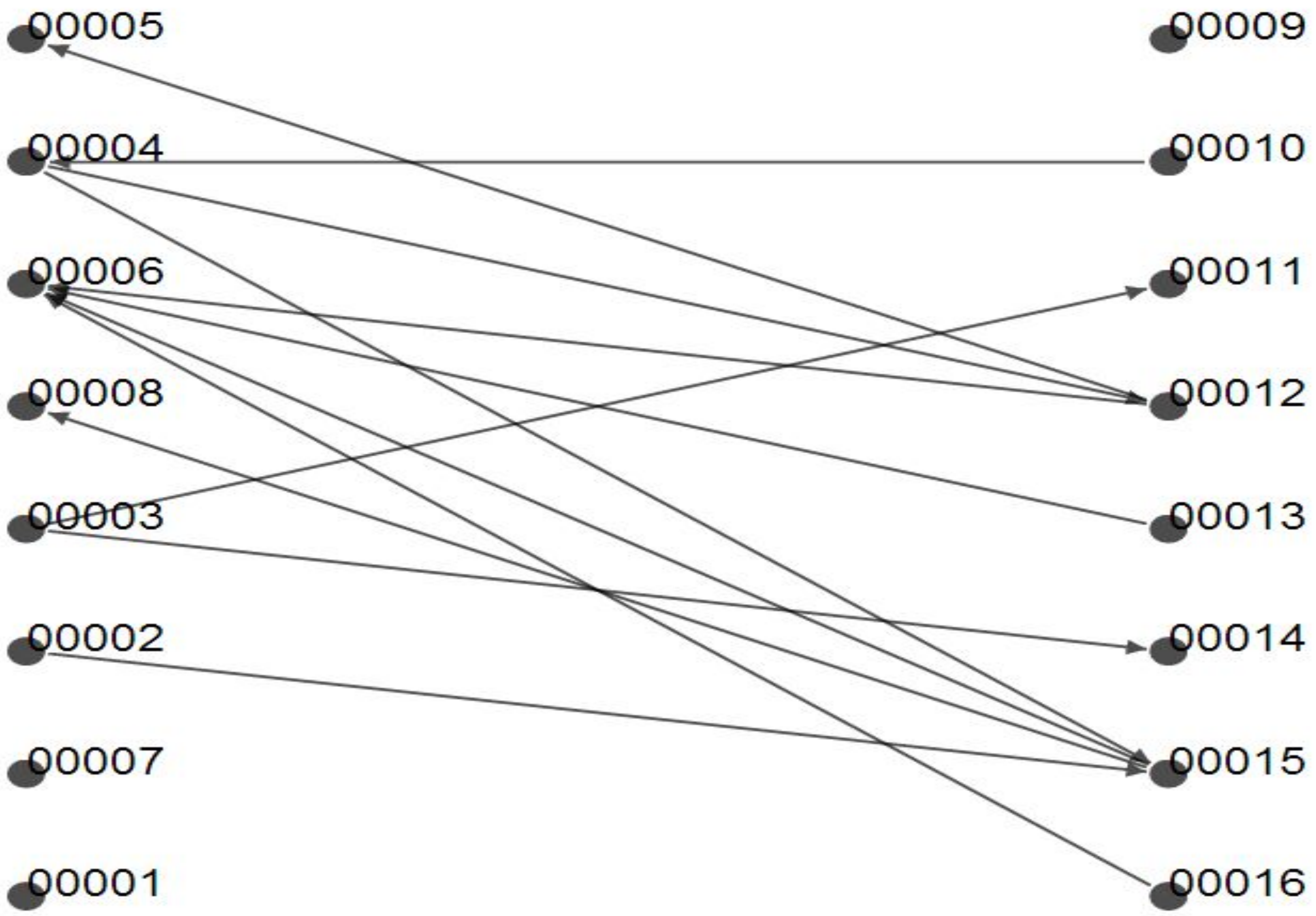


Lattice

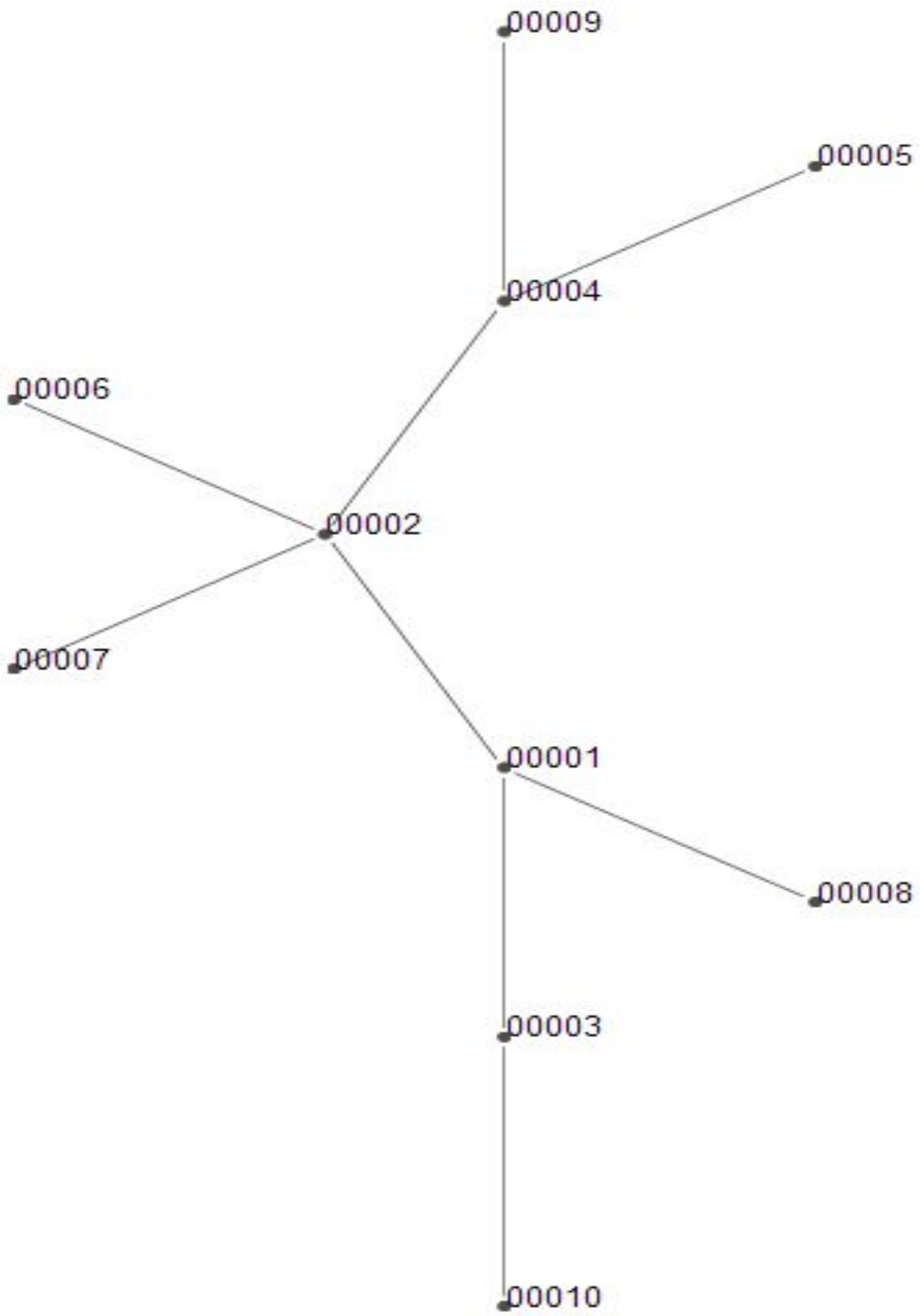


Ring

Simple Graphs / Non-random Graphs

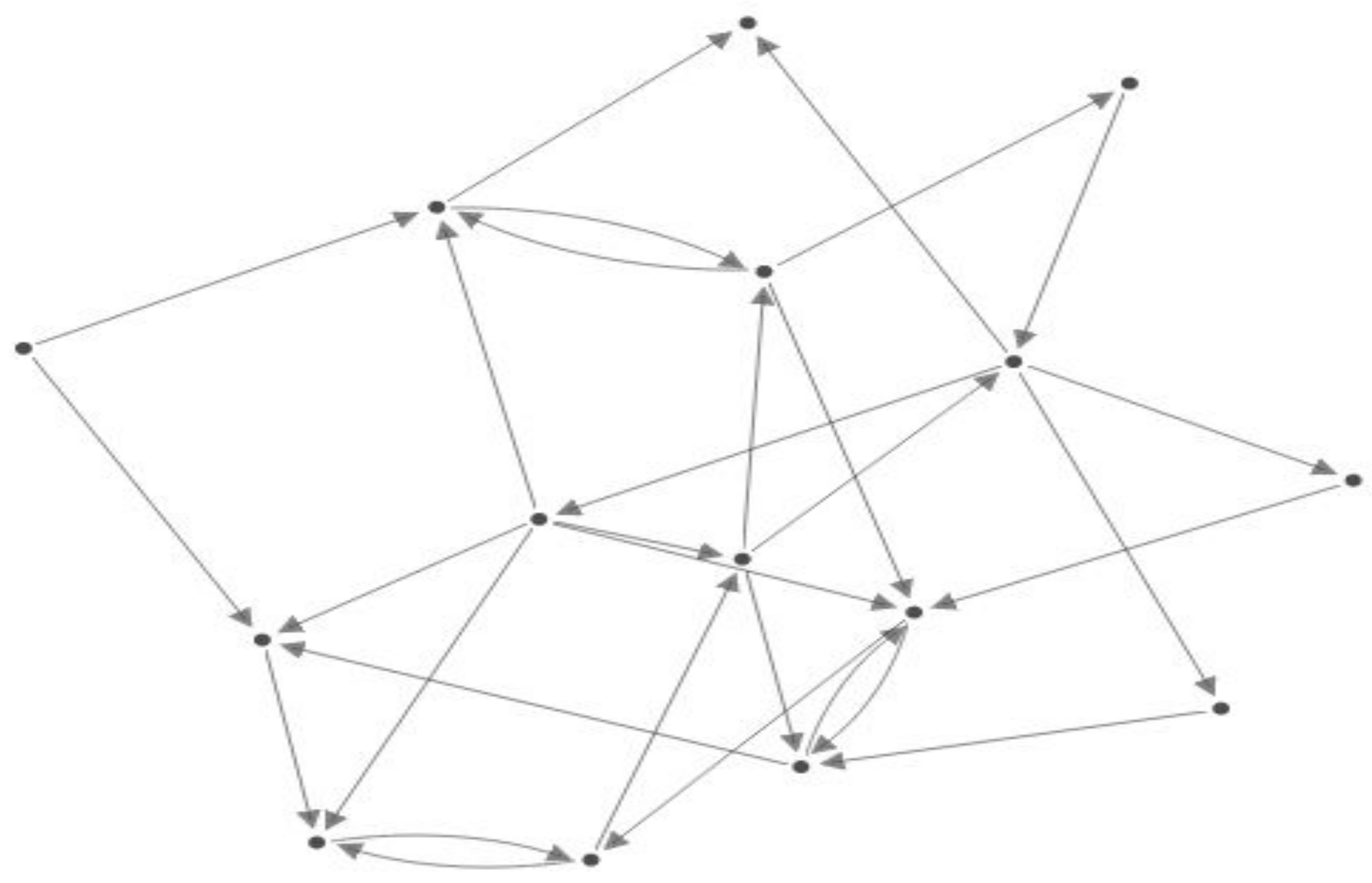


Bipartite

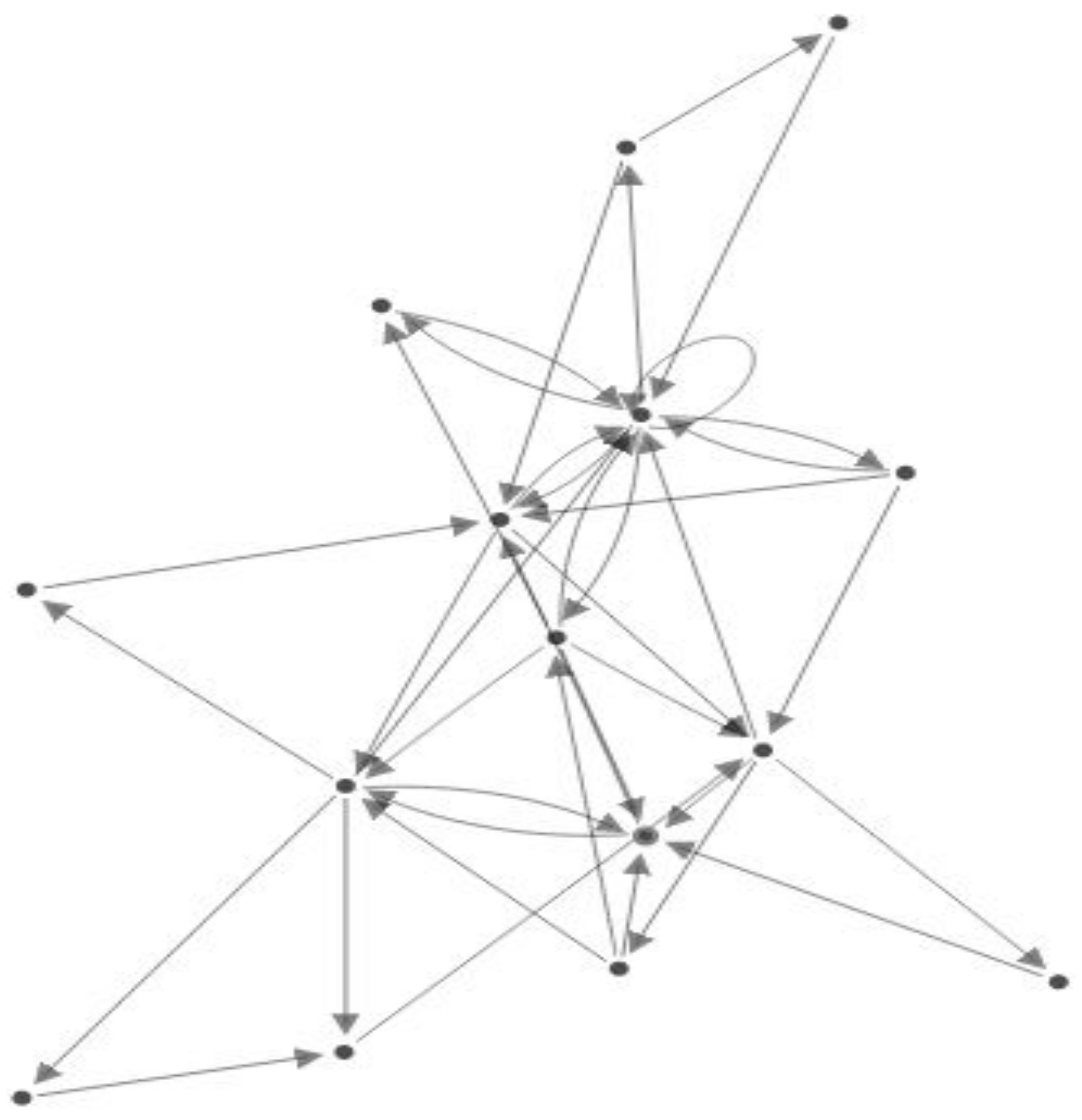


Tree

Random Graphs

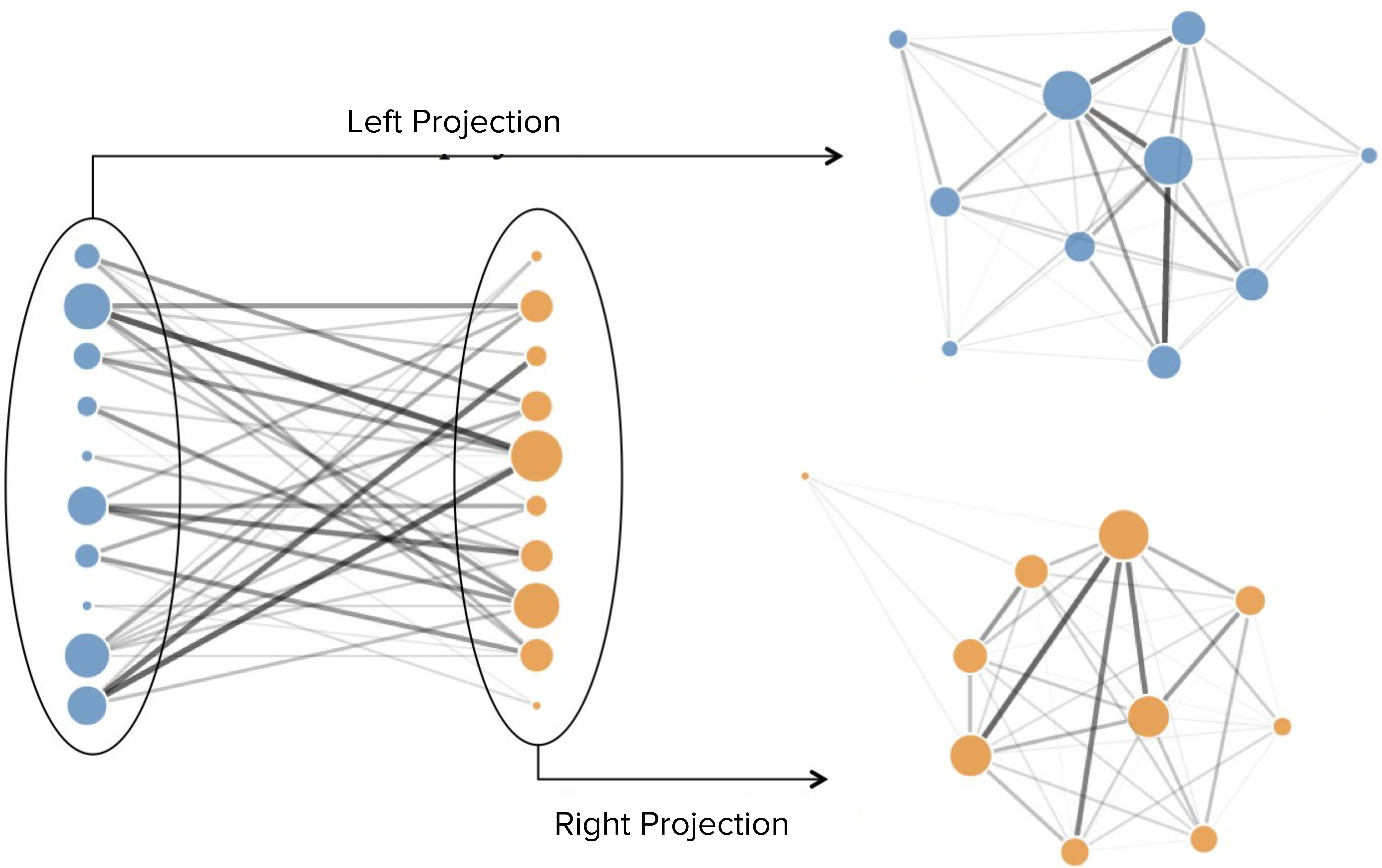


Random
(Erdos-Renyi)



Scale-free
(Barabasi-Albert)

Projection Networks



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Key Concept: Centrality

Centrality

Centrality measures importance of nodes (or links) in a network.

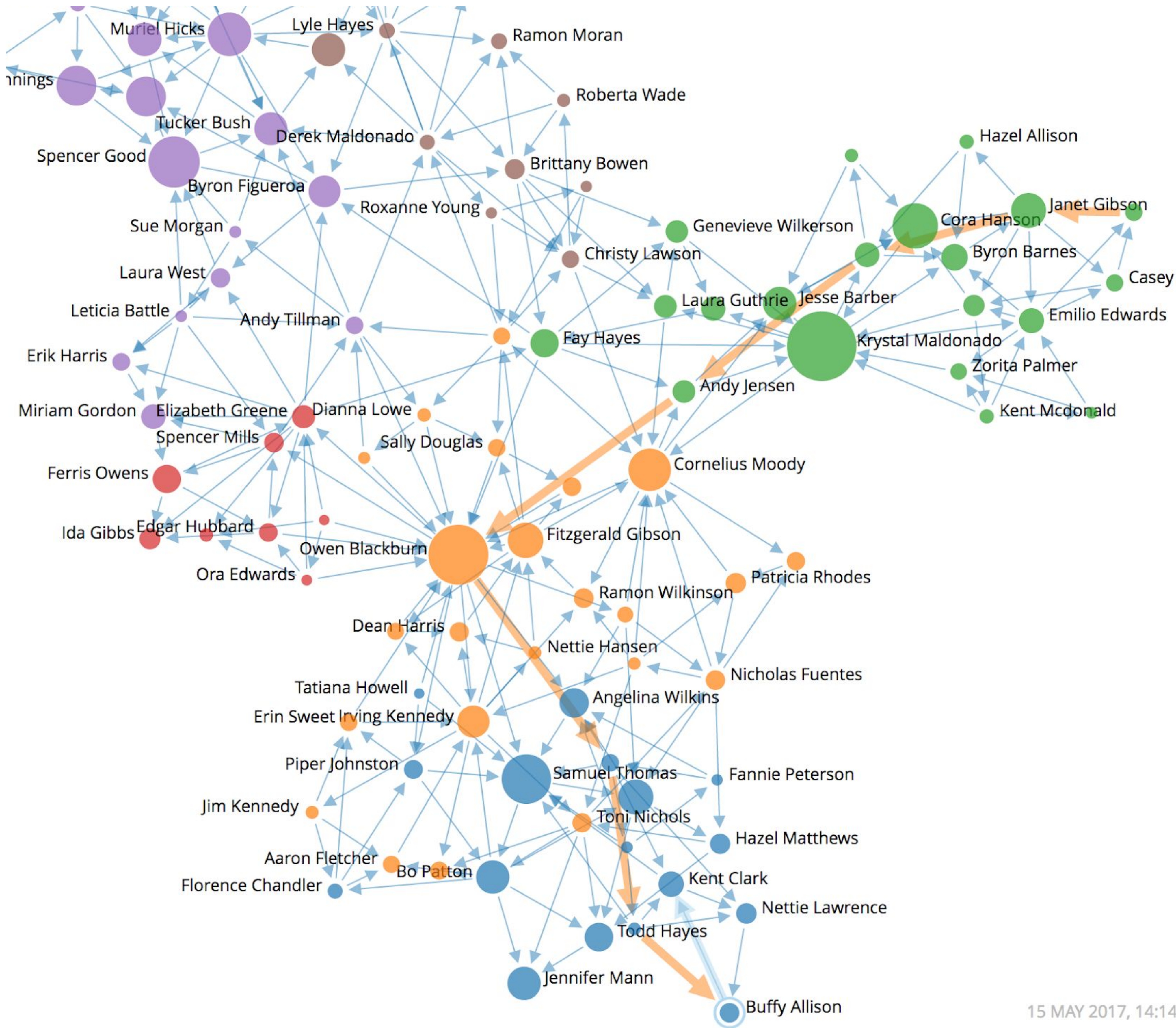
Depends on process that takes place in the network!

Trajectory

- Geodesic paths (shortest paths)
- Any path (visit no node twice)
- Trails (visit no link twice)
- Walks (free movement)

Transmission

- Parallel duplication
- Serial duplication
- Transfer

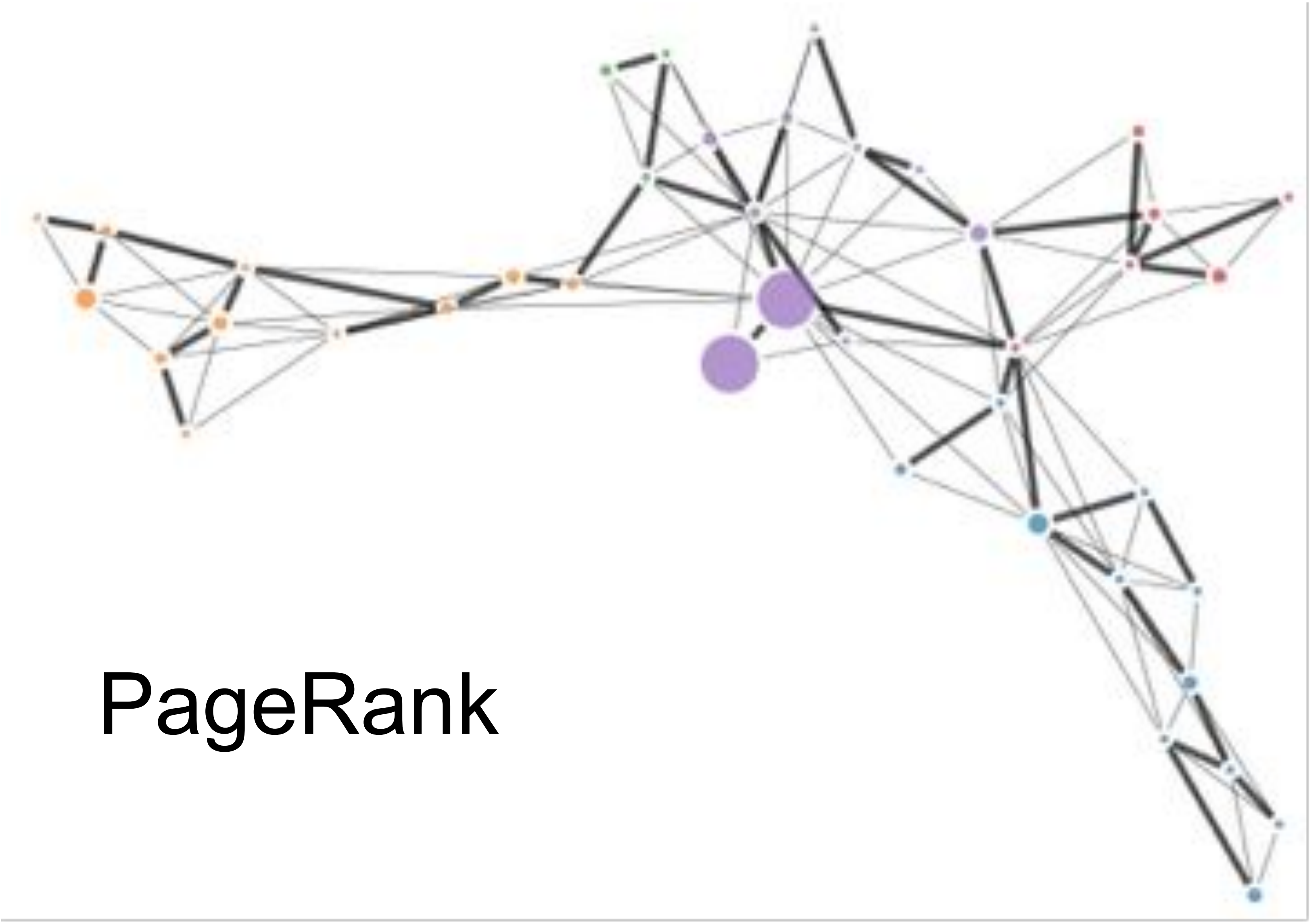


DHL Package = Transfer via shortest path
Money = Transfer via random walks
Virus = Serial duplication via paths

etc.

15 MAY 2017, 14:14

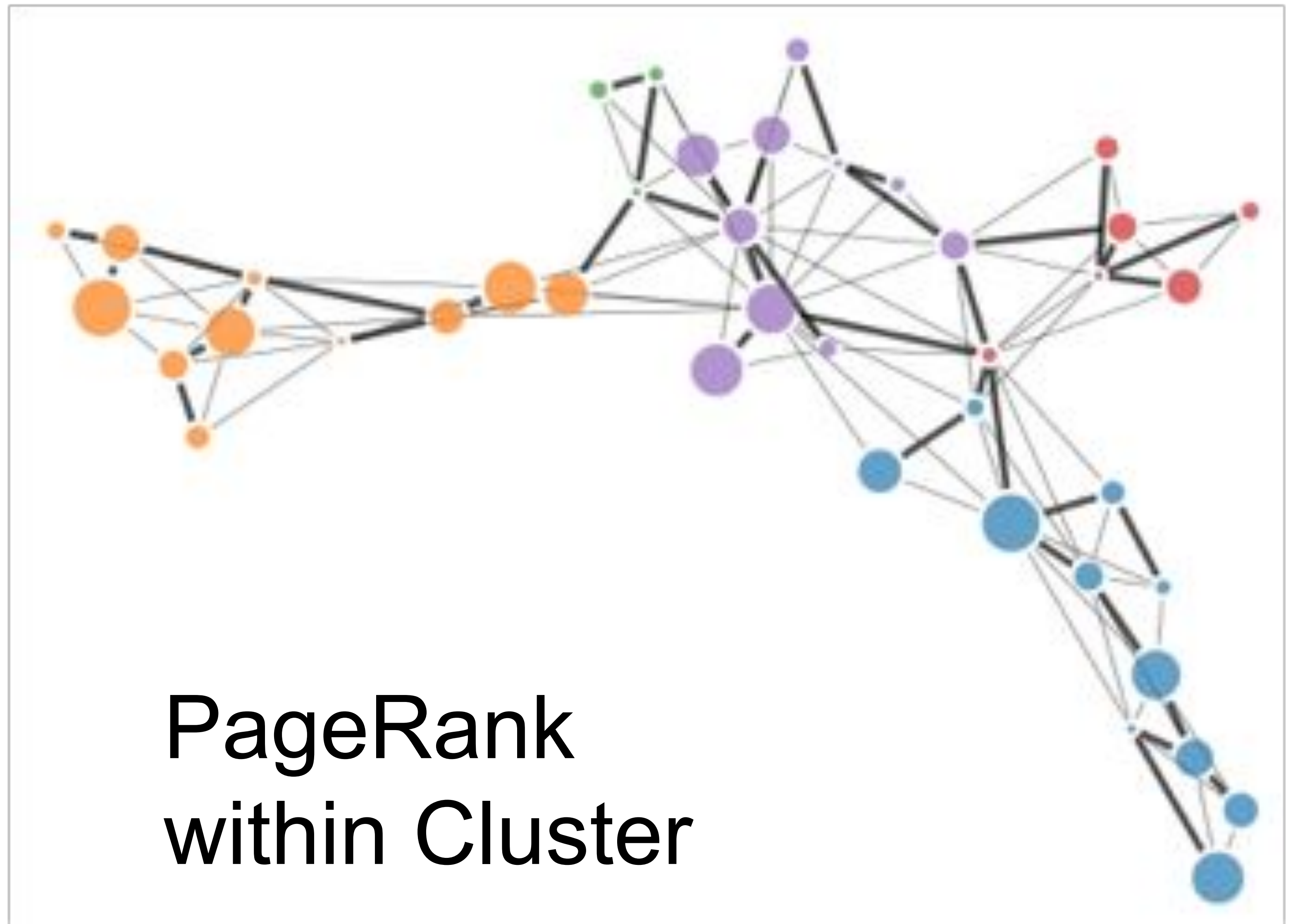
Common Centrality Metrics



PageRank

Betweenness

Closeness



PageRank
within Cluster

FNA

Communities

Community Detection

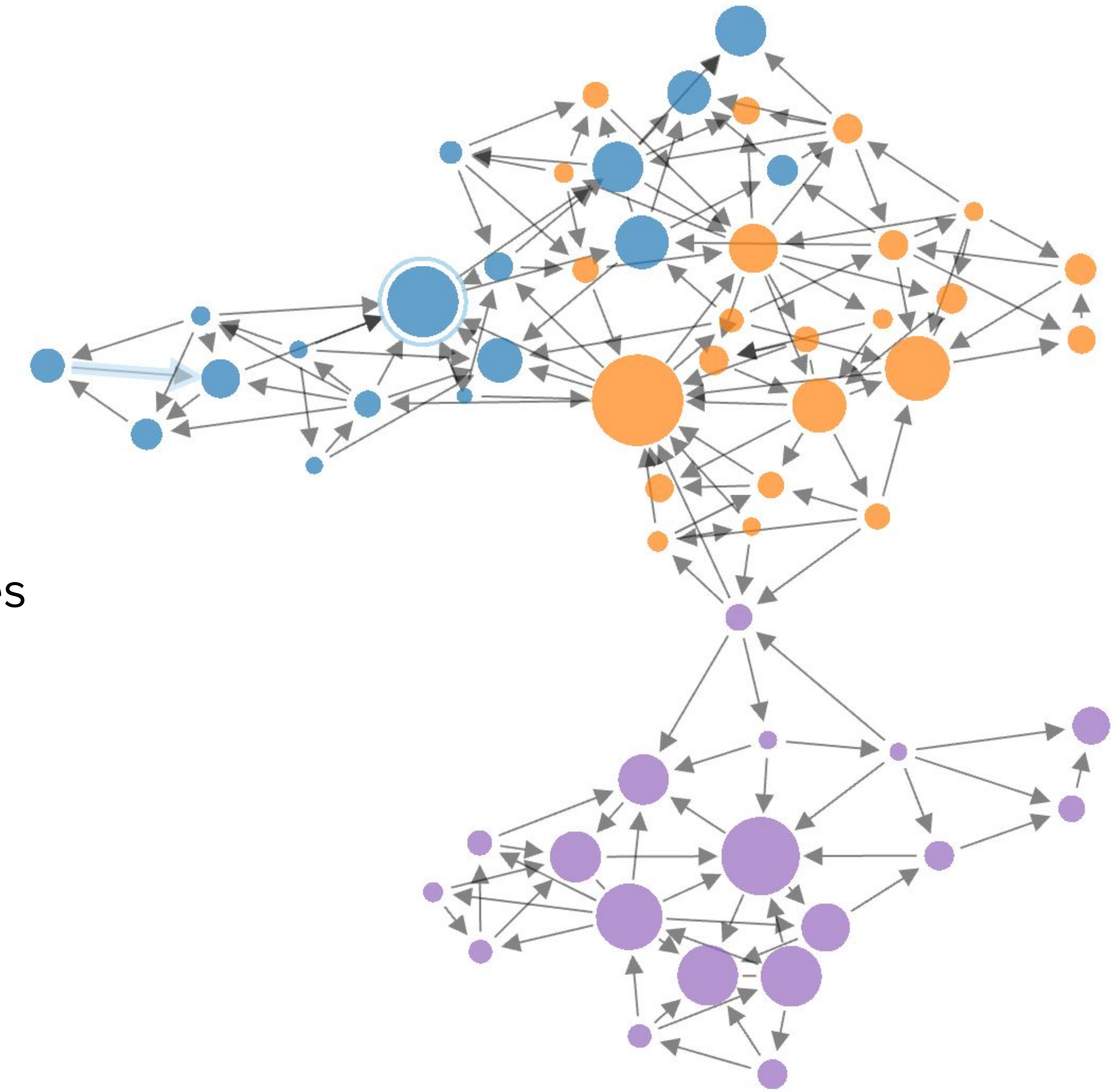
Often networks are large and complex and we want to simplify, categorize and label nodes into meaningful groups.

Community detection is an algorithmic way of doing this, and there are numerous methods available.

- Unsupervised learning, how do we know result is correct. What is correct?
- Which algorithm to choose?
- Some algorithms detect well large, but not small communities
- Is it a community or a cluster of several?
- What about overlapping communities?

Still more an art than a science. Try what works?

FNA Research: [Overview and Comparison of Community Detection Algorithms]



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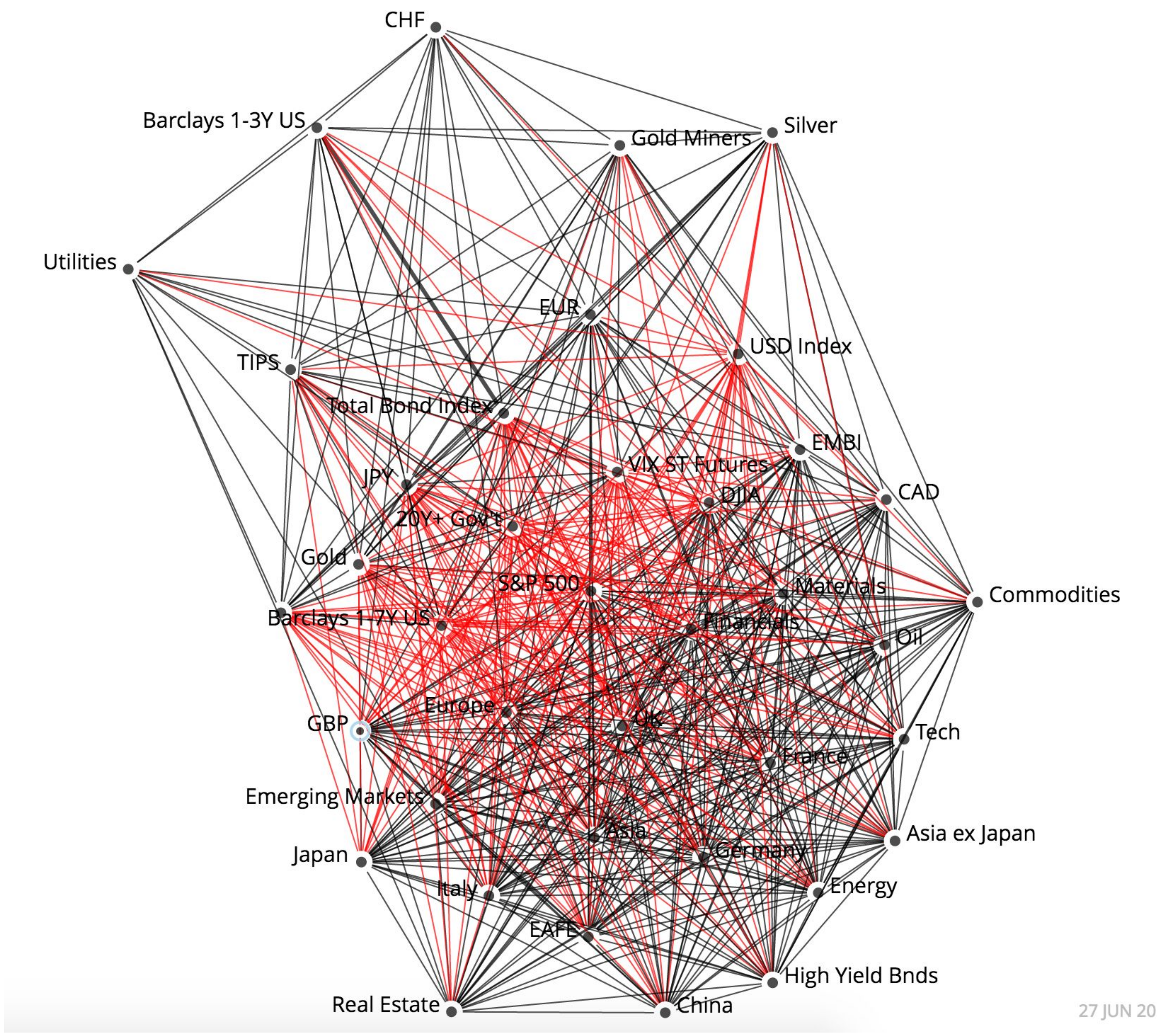
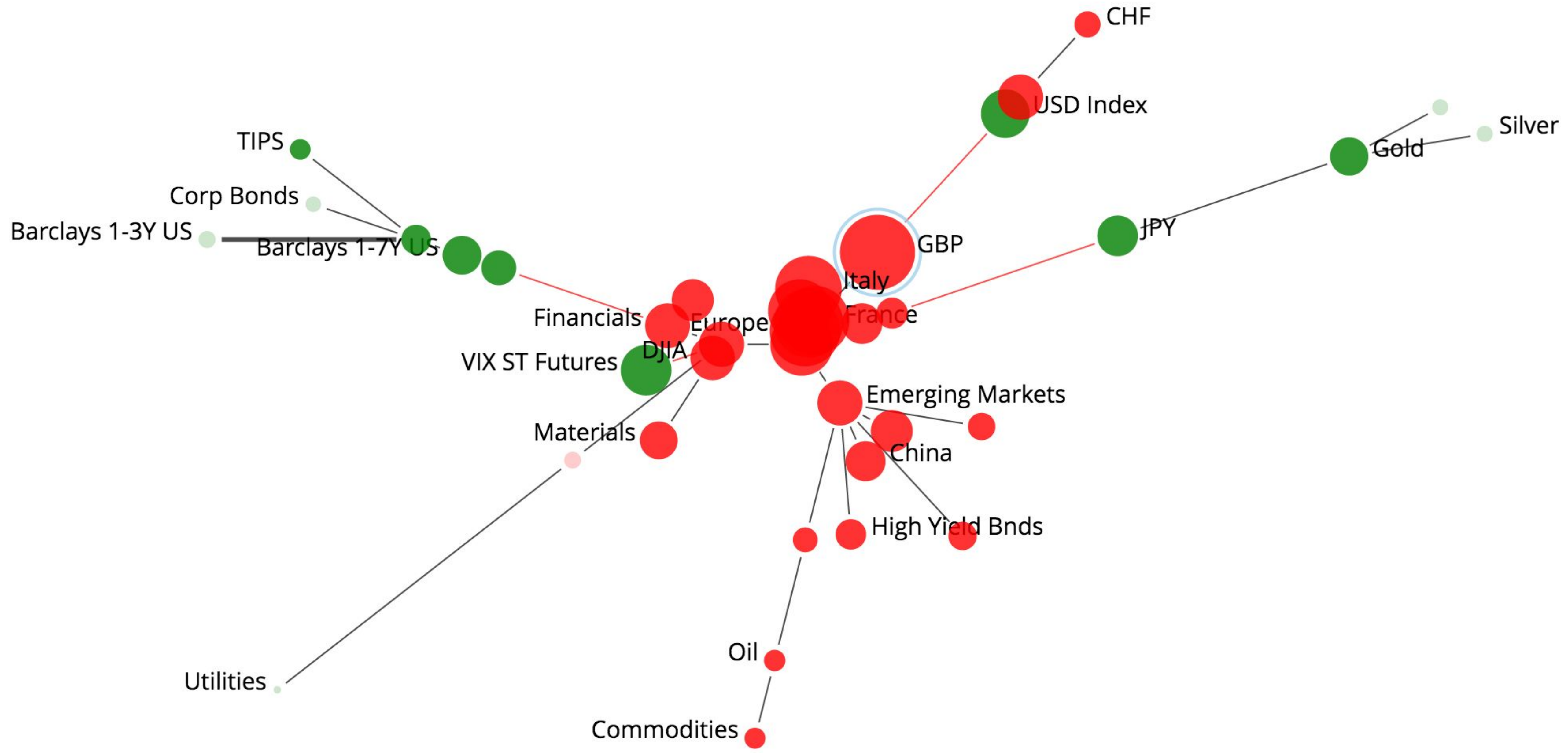
Filtering

Filtering

Often networks are large and complex and we want to filter out noise. Filtering techniques give solutions.

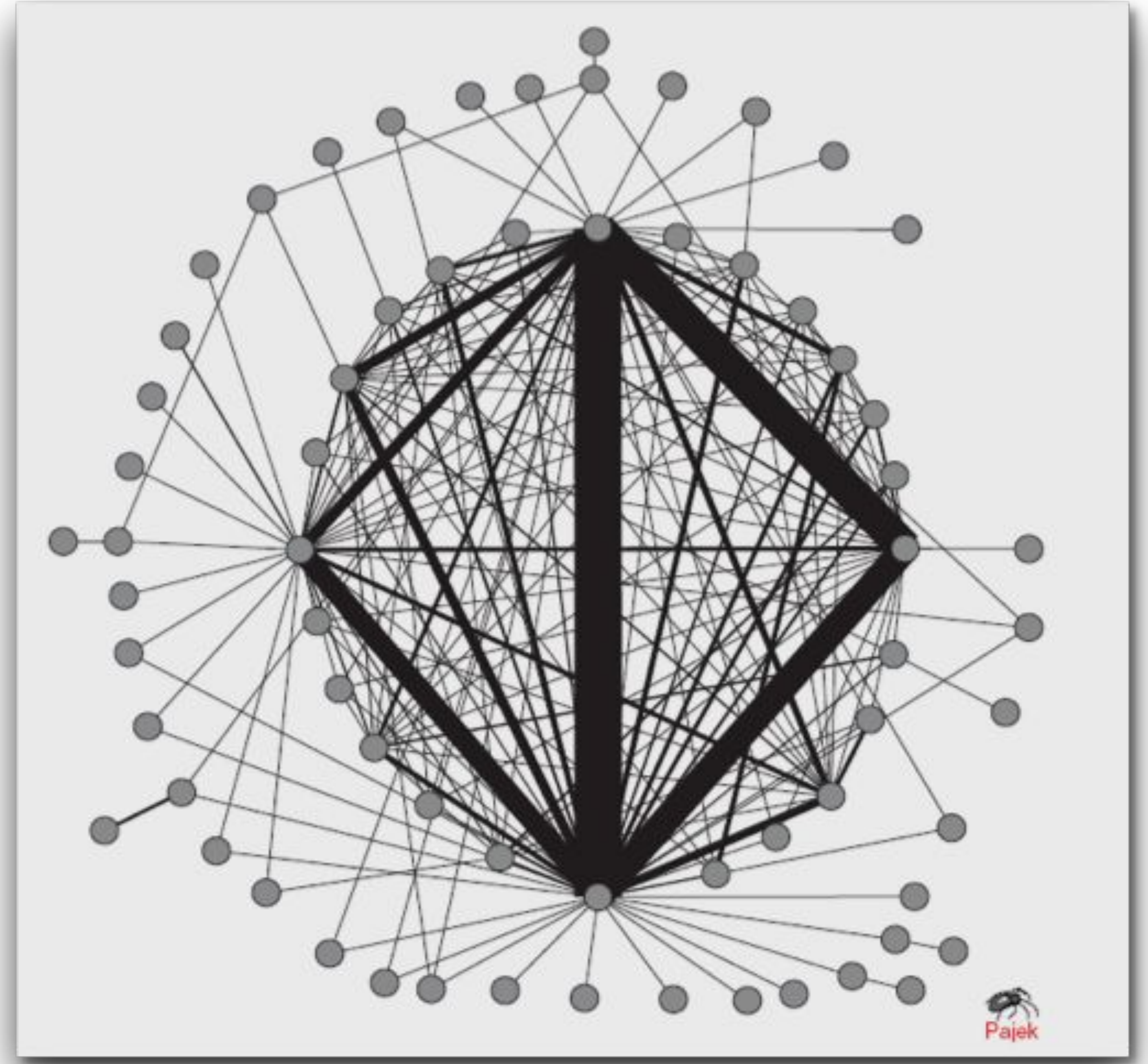




FNA

Top down analysis
Exposure Networks

First Financial Networks



Fedwire Interbank Payment Network (Fall 2001) was one of the first network views into any financial system.

Of a total of around 8000 banks, the 66 banks shown comprise 75% of total value. Of these, 25 banks completely connected

The research was subsequently used e.g. in congressional hearings to showcase the type of information that should be collected by financial institutions after the financial crisis.

Soramaki, K. M Bech, J. Arnold, R.J. Glass and W.E. Beyeler, The Topology of Interbank Payment Flows, Physica A, Vol. 379, pp 317-333, 2007.

Who pays whom?

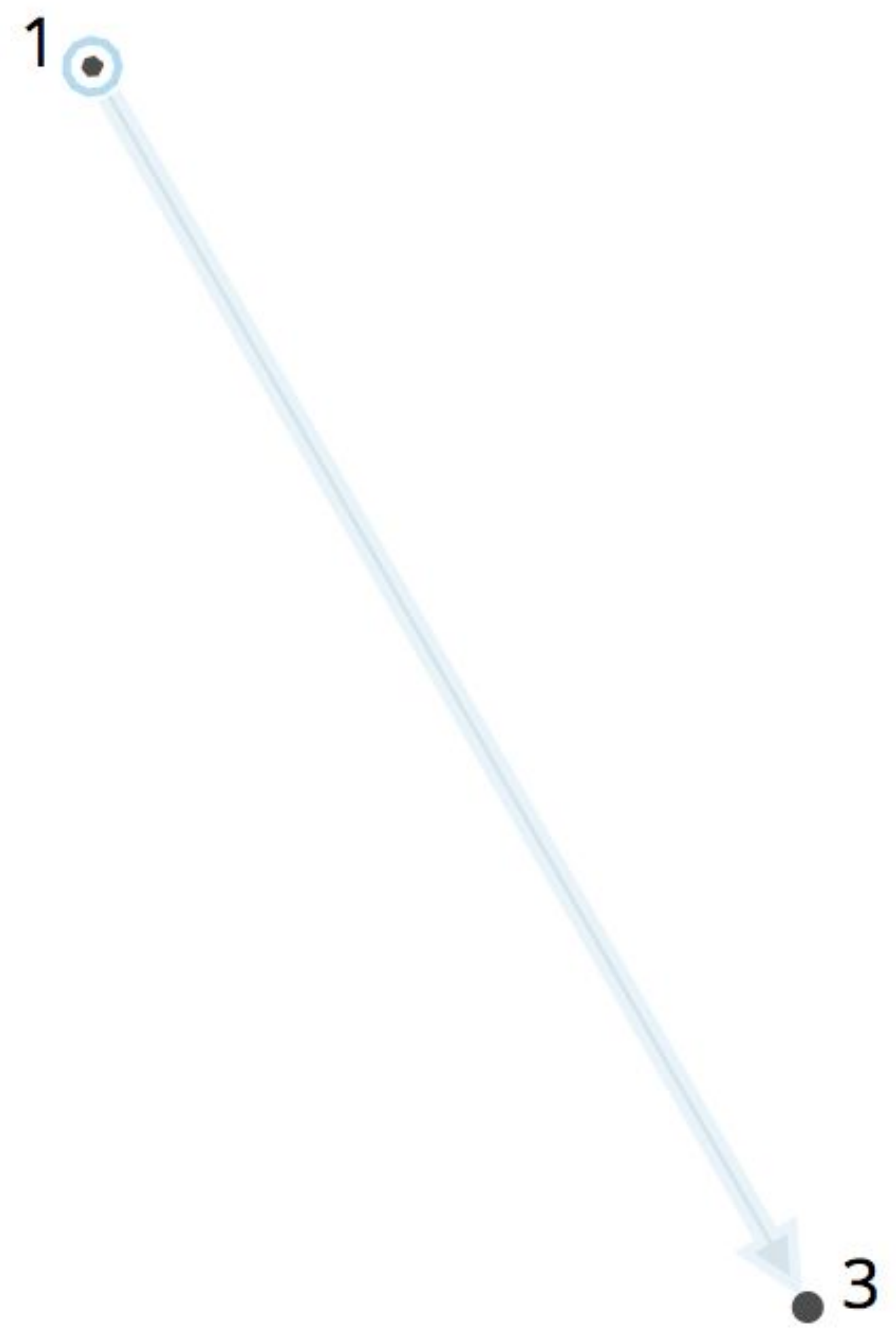
Our data contains:

date	buyer	seller	amount
26 July 2018	1	3	1
26 July 2018	3	5	1
26 July 2018	5	2	1
26 July 2018	3	4	1

…

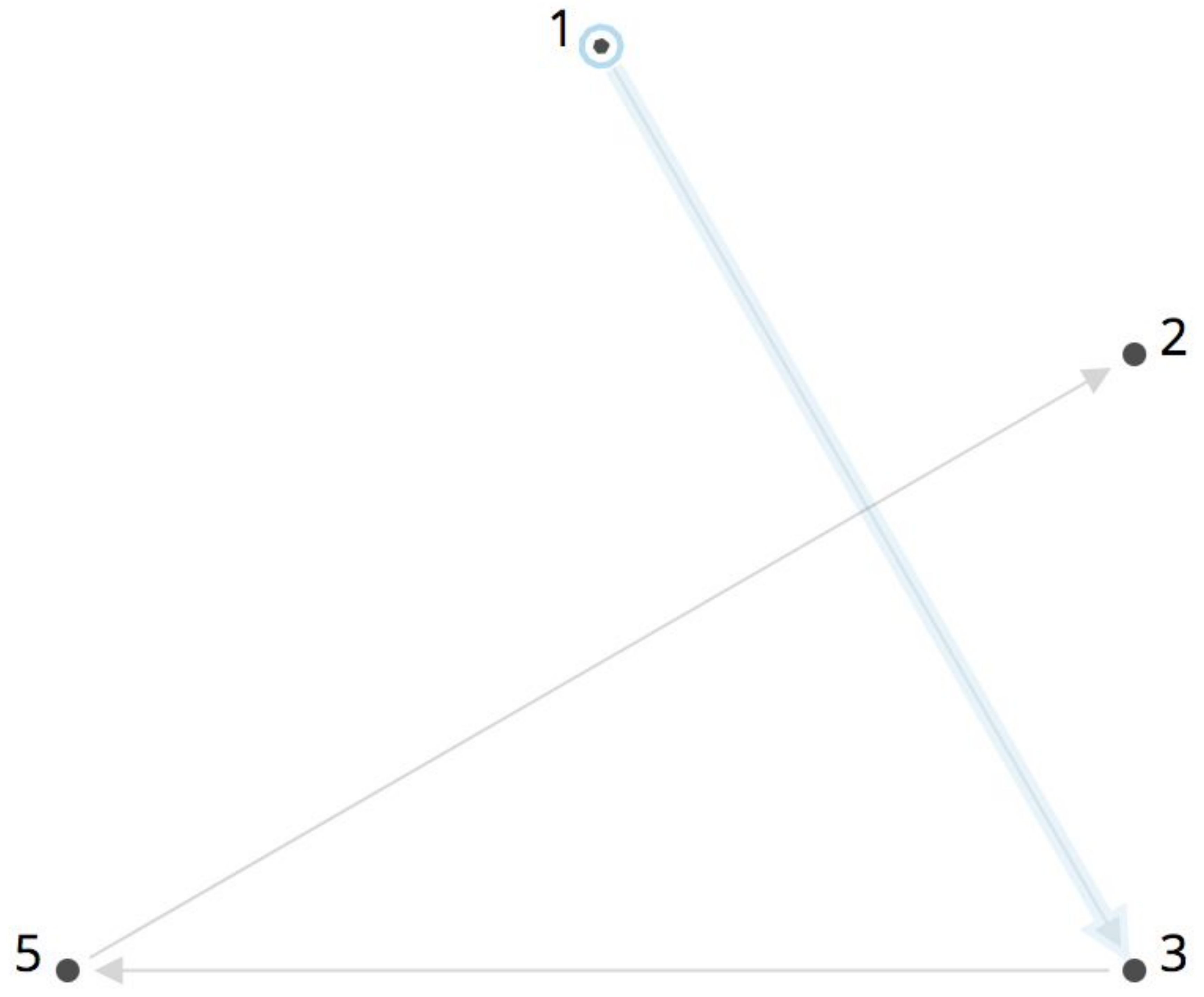
Who pays whom?

Payment from 1 to 3



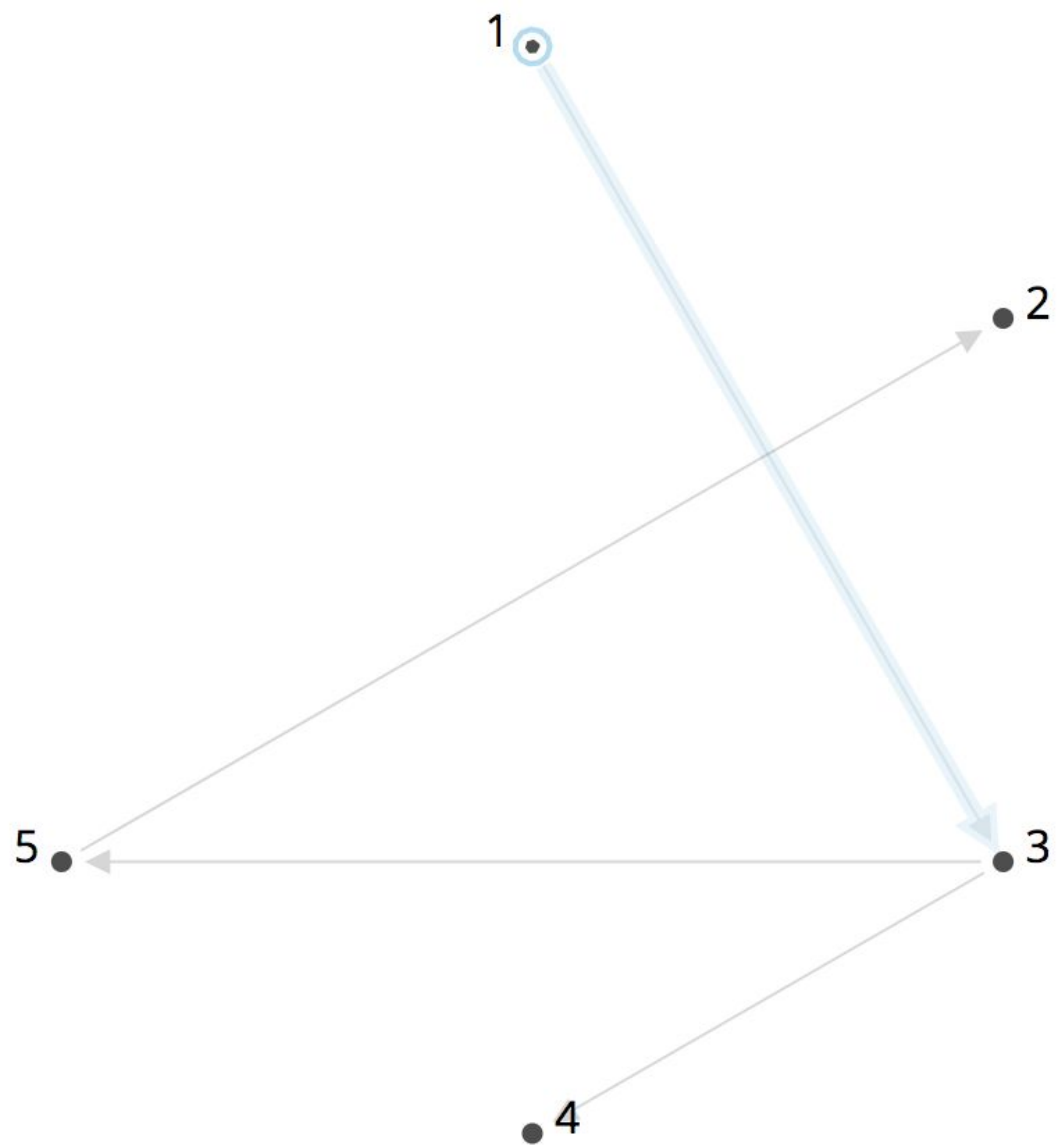
Who pays whom?

Payments from 3 to 4 and 5 to 2



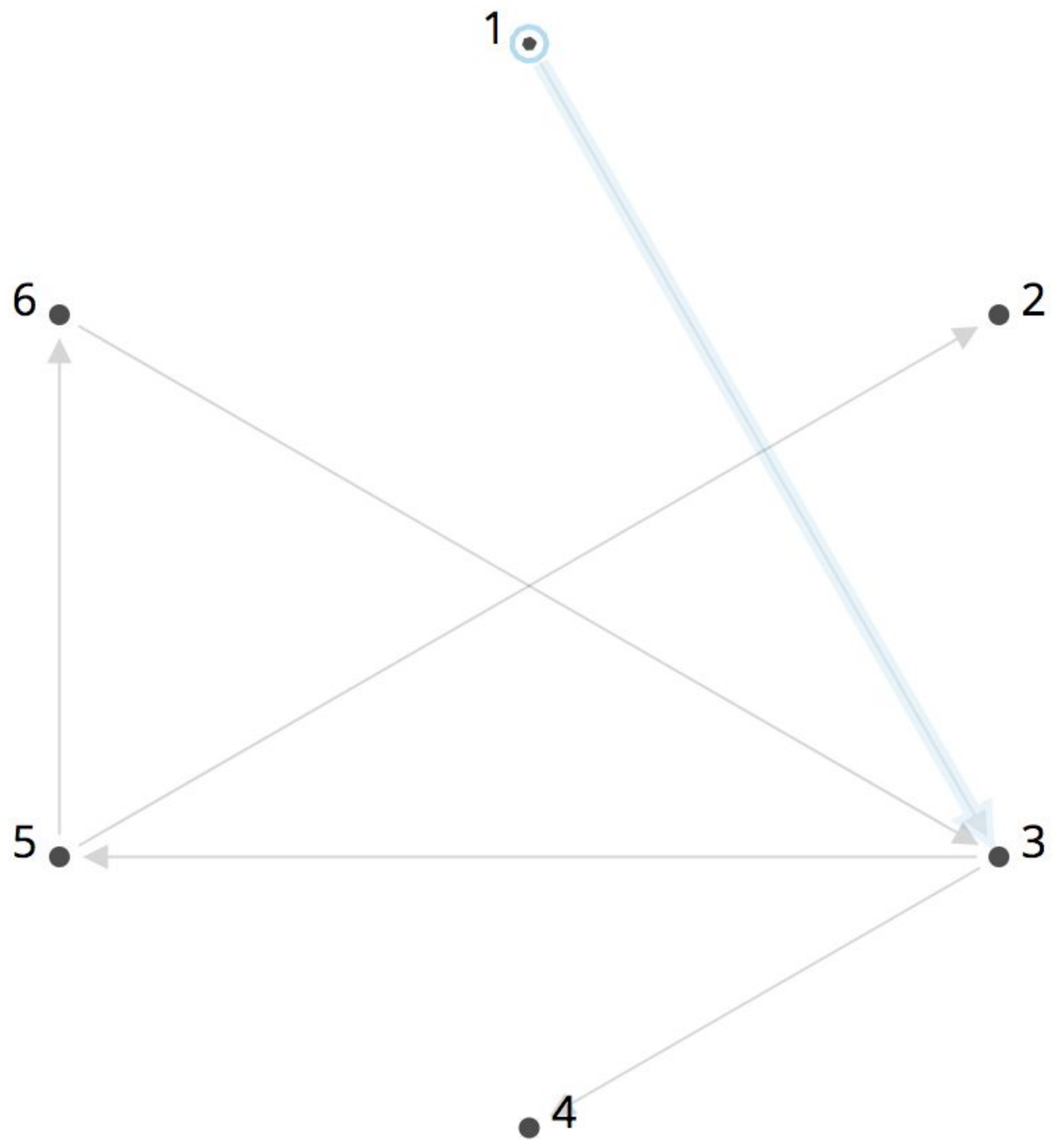
Who pays whom?

Payment from 3 to 4



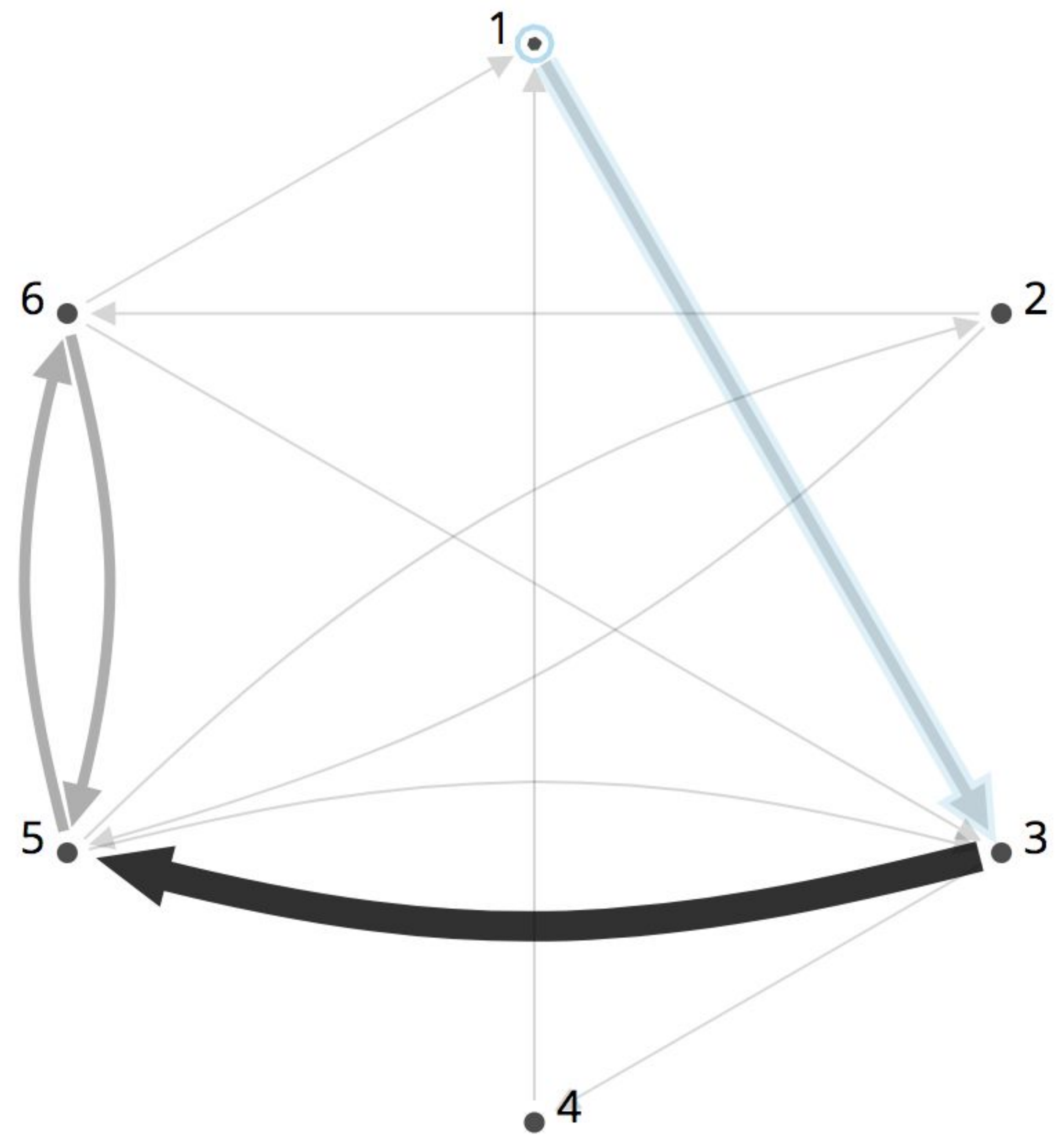
Who pays whom?

Payments from 5 to 6 and 6 to 3



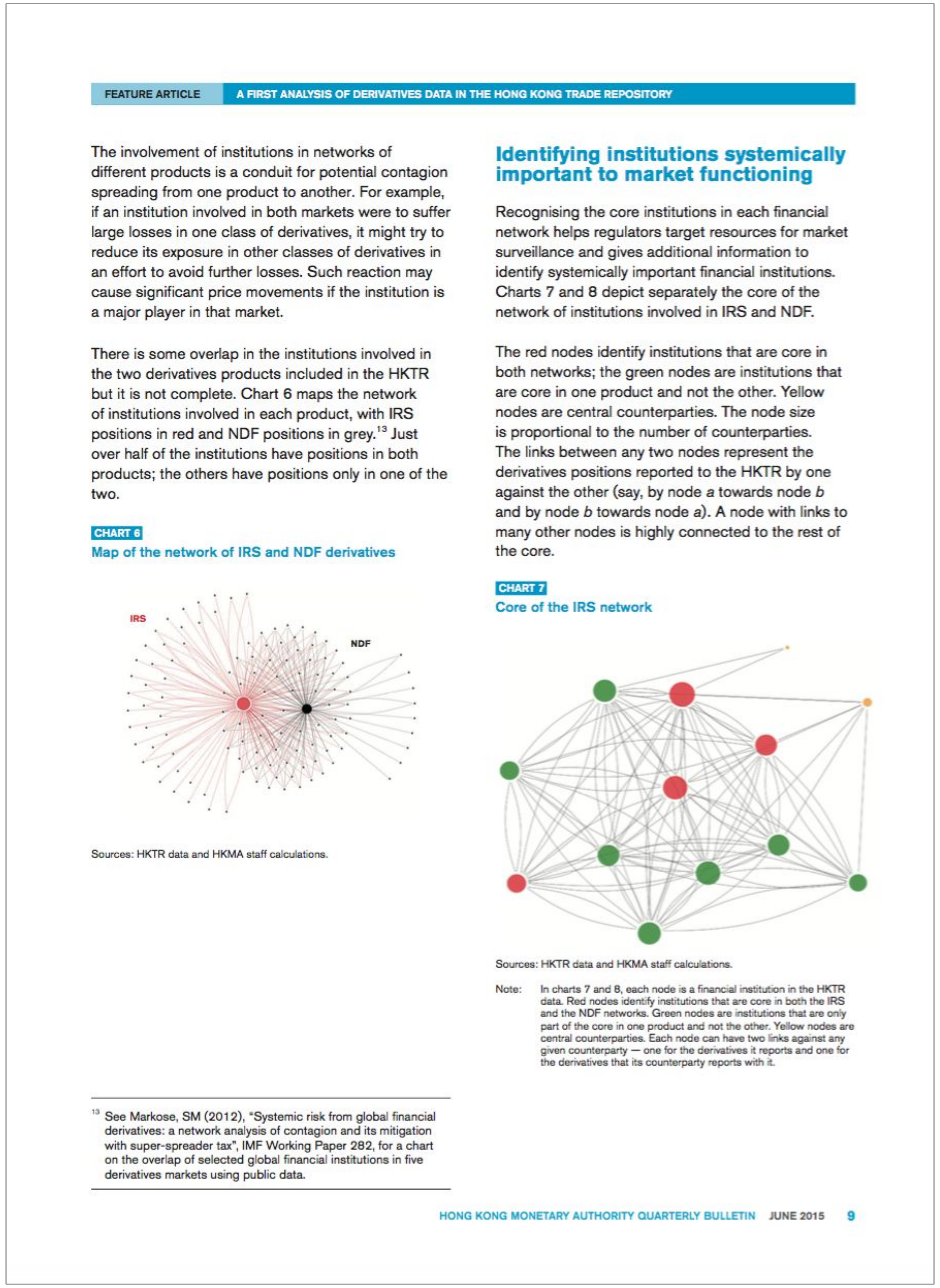
Who pays whom?

More payments ....



Thicker, darker links represent higher link weights, i.e., more payments

Use Case: Understanding Interconnectedness



FEATURE ARTICLE | A FIRST ANALYSIS OF DERIVATIVES DATA IN THE HONG KONG TRADE REPOSITORY

The involvement of institutions in networks of different products is a conduit for potential contagion spreading from one product to another. For example, if an institution involved in both markets were to suffer large losses in one class of derivatives, it might try to reduce its exposure in other classes of derivatives in an effort to avoid further losses. Such reaction may cause significant price movements if the institution is a major player in that market.

There is some overlap in the institutions involved in the two derivatives products included in the HKTR but it is not complete. Chart 6 maps the network of institutions involved in each product, with IRS positions in red and NDF positions in grey.[13] Just over half of the institutions have positions in both products; the others have positions only in one of the two.

CHART 6
Map of the network of IRS and NDF derivatives

IRS
NDF

Sources: HKTR data and HKMA staff calculations.

Identifying institutions systemically important to market functioning

Recognising the core institutions in each financial network helps regulators target resources for market surveillance and gives additional information to identify systemically important financial institutions. Charts 7 and 8 depict separately the core of the network of institutions involved in IRS and NDF.

The red nodes identify institutions that are core in both networks; the green nodes are institutions that are core in one product and not the other. Yellow nodes are central counterparties. The node size is proportional to the number of counterparties. The links between any two nodes represent the derivatives positions reported to the HKTR by one against the other (say, by node *a* towards node *b* and by node *b* towards node *a*). A node with links to many other nodes is highly connected to the rest of the core.

CHART 7
Core of the IRS network

Sources: HKTR data and HKMA staff calculations.

Note: In charts 7 and 8, each node is a financial institution in the HKTR data. Red nodes identify institutions that are core in both the IRS and the NDF networks. Green nodes are institutions that are only part of the core in one product and not the other. Yellow nodes are central counterparties. Each node can have two links against any given counterparty — one for the derivatives it reports and one for the derivatives that its counterparty reports with it.

[13] See Markose, SM (2012), "Systemic risk from global financial derivatives: a network analysis of contagion and its mitigation with super-spreader tax", IMF Working Paper 282, for a chart on the overlap of selected global financial institutions in five derivatives markets using public data.

HONG KONG MONETARY AUTHORITY QUARTERLY BULLETIN JUNE 2015 9

Background
As part of global regulatory reforms, the Hong Kong Monetary Authority (HKMA) started in 2013 to collect derivatives data through the Hong Kong Trade Repository.

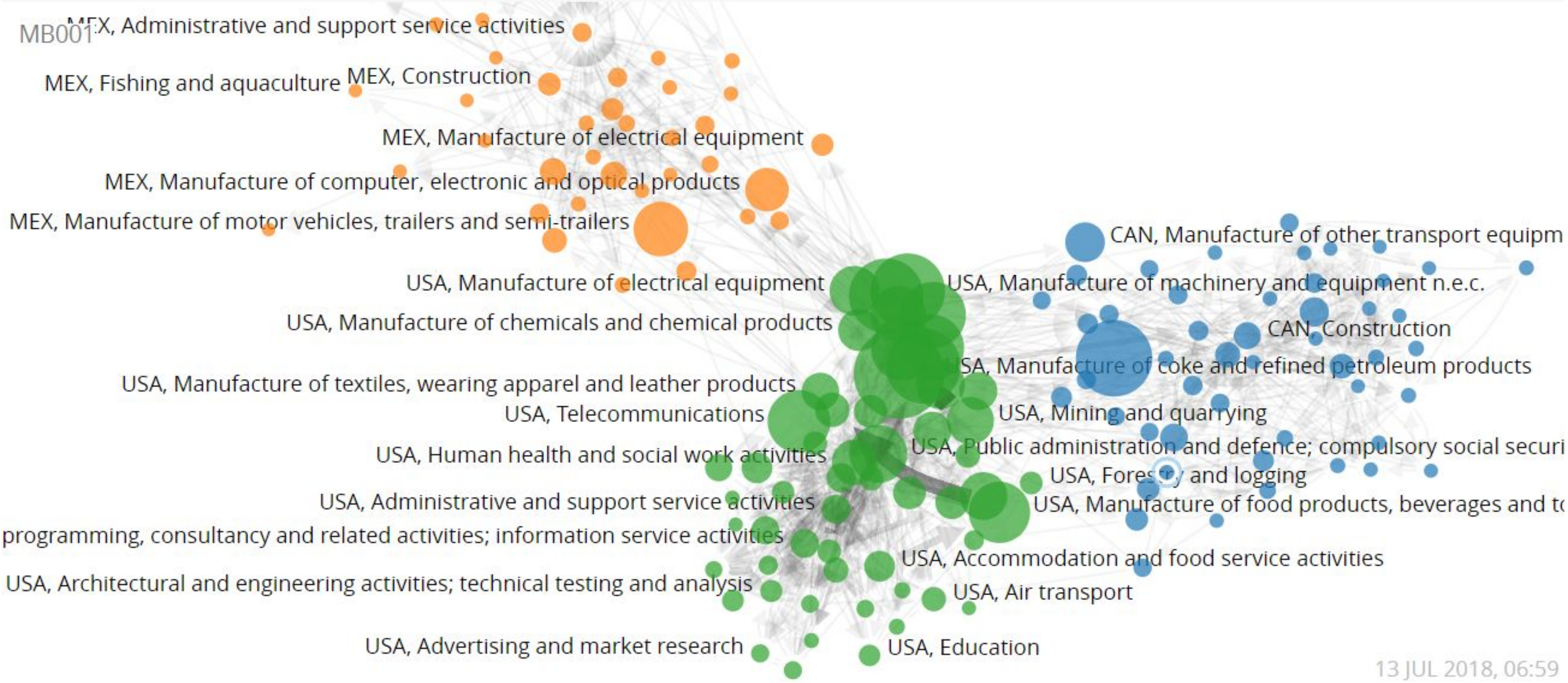
Objective
Bring more transparency to derivatives markets using the data collected by trade repositories.

Insights
Initial framework for analysing this new data source to assess the financial stability of the market and potential risks. This includes development of maps for the chain of exposures between institutions.

HKMA: A first analysis of derivatives data in the Hong Kong Trade Repository

World Trade Network

2014 WIOD NAFTA network



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Interconnectedness in the Global System of CCPs

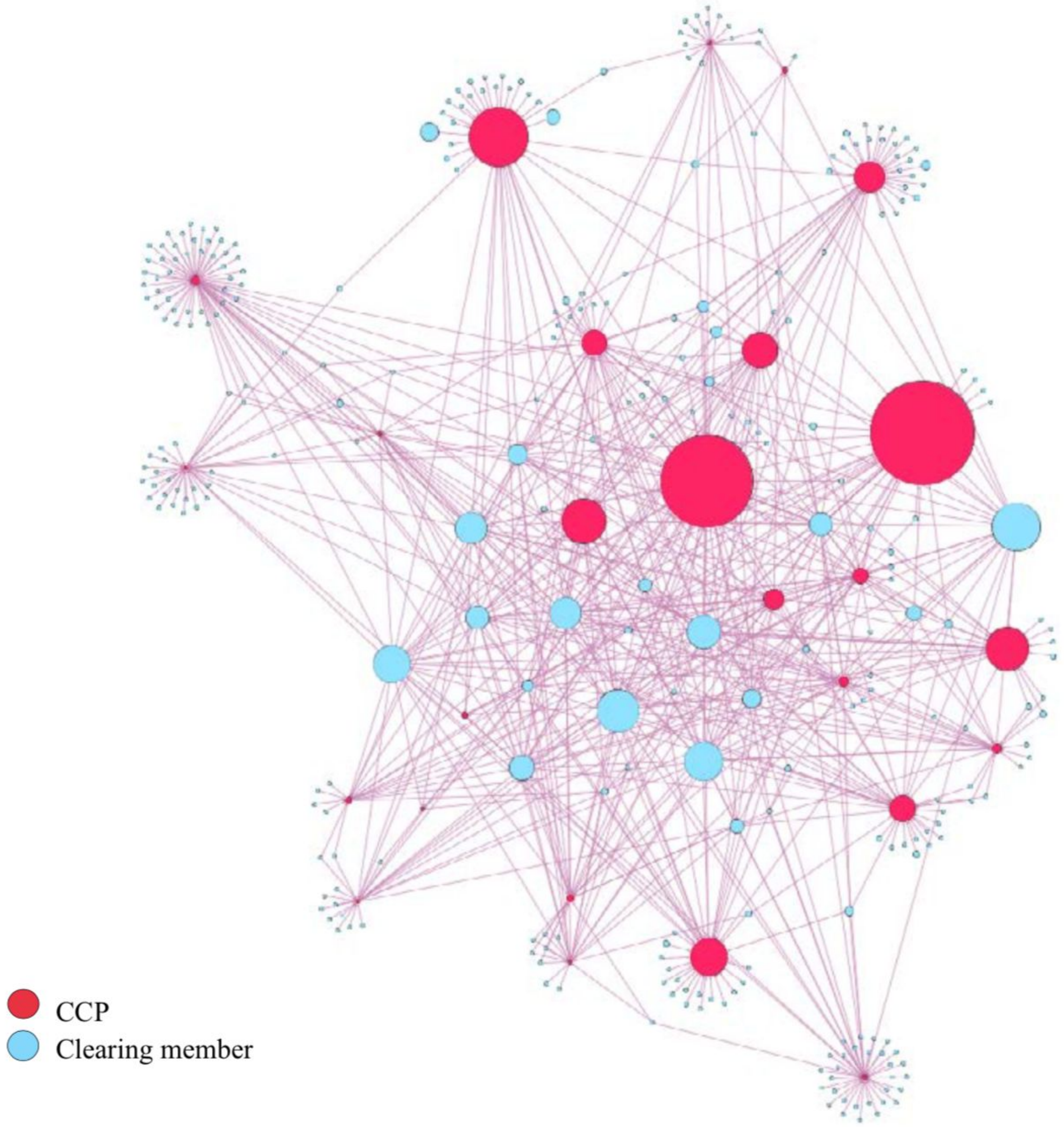
www.fna.fi

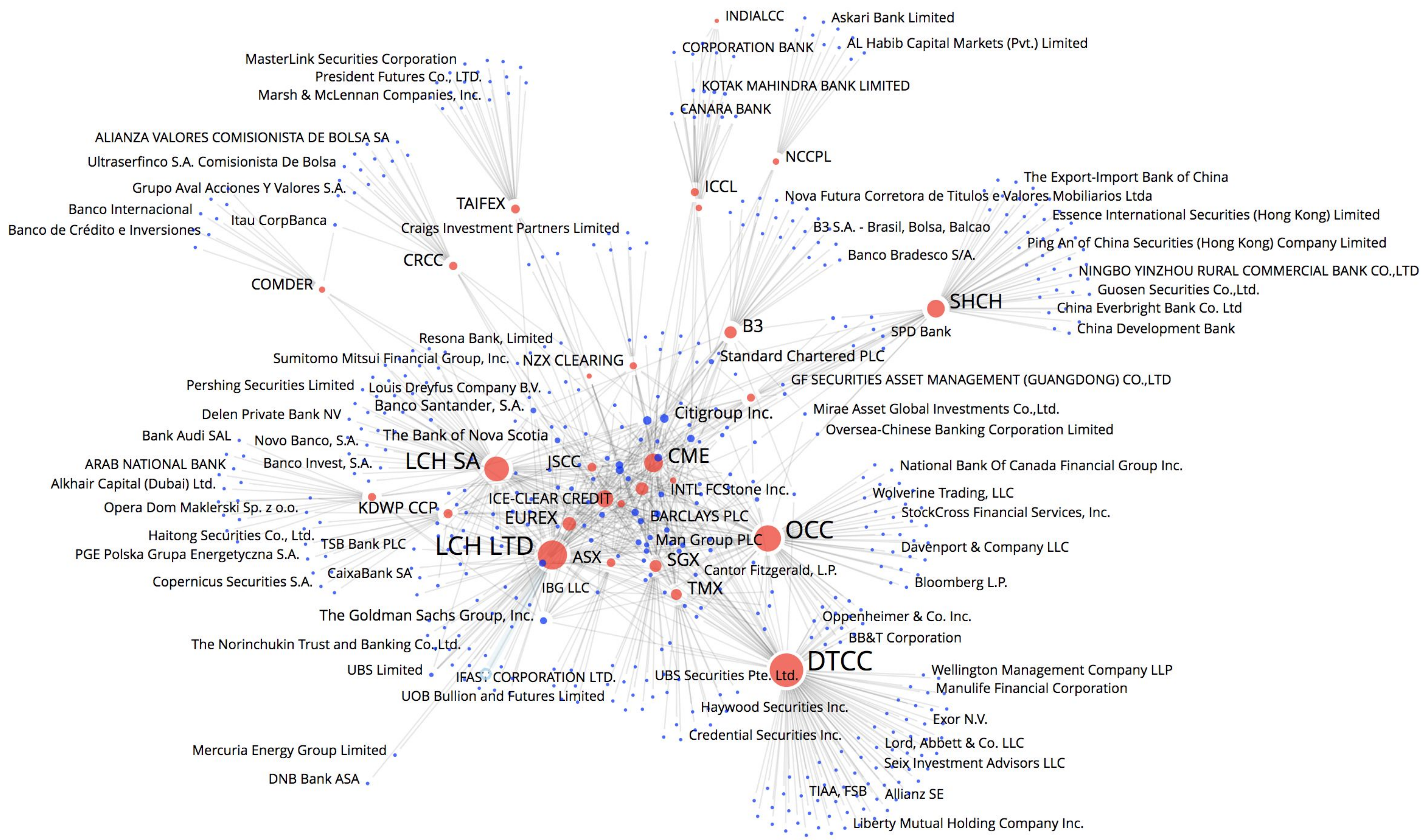
Scope of Analysis

Comparison with BIS "Analysis of Central Clearing Interdependencies" (2017)

	BIS (2017)	**FNA (2018)**
CCPs	26	29
Jurisdictions	20	25
Clearing Members	n/a	811
Parents Organizations	307	563
Roles	5 (member, settlement, LOC, ...)	1 (member)

Private vs Public Data





BIS (2017)

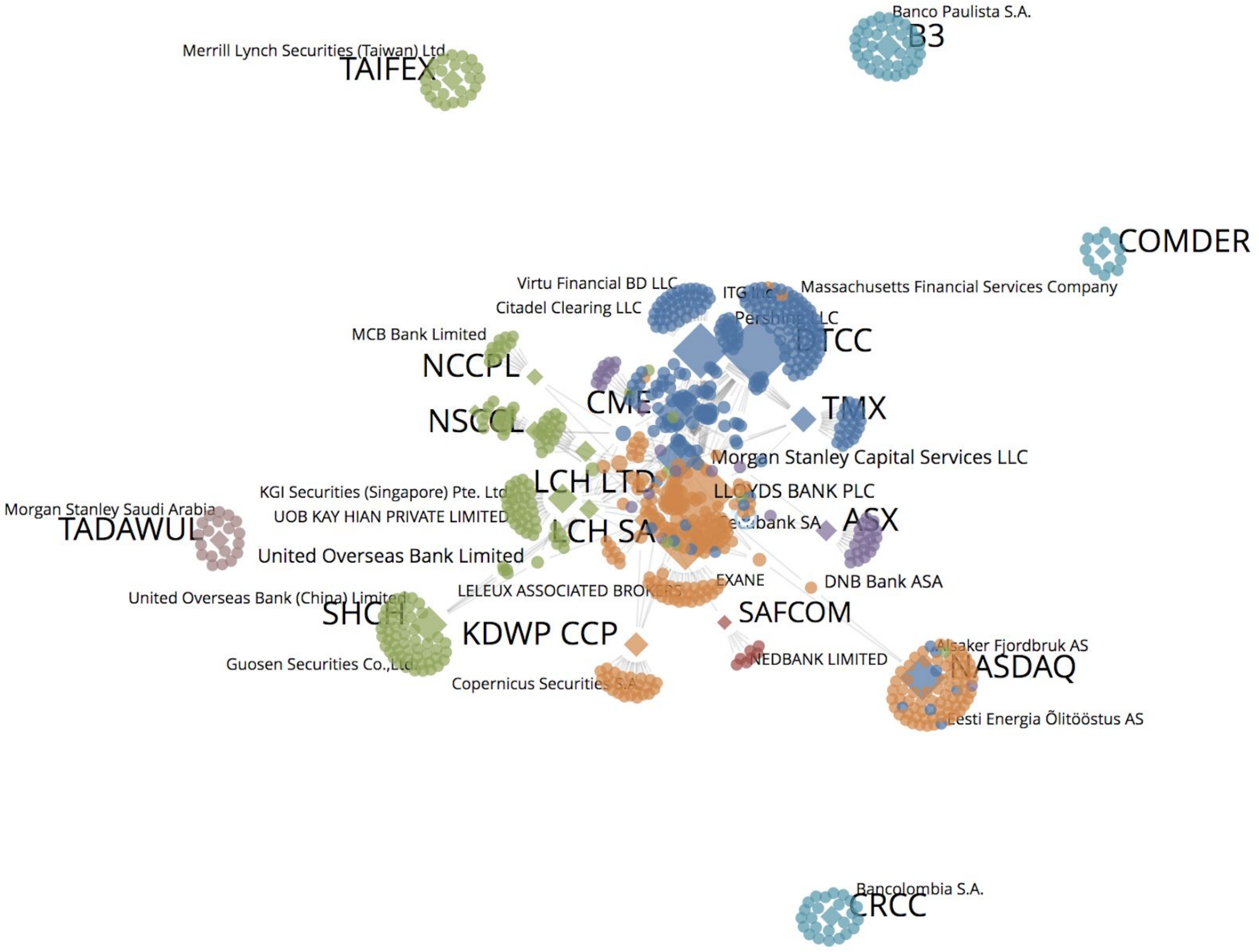
FNA (2018)

CCP Interconnectedness - Subsidiary Level

We see CCPs (diamonds) and their members (circles) from different regions:

- North America (blue)
- Europe (Yellow)
- Asia (green)
- Middle East (brown)
- Latin America (blue)
- Australia & Oceania (purple)

On subsidiary level, we see a tight core with peripheral CCPs and a number of completely disconnected CCPs from Latin America and Middle East.

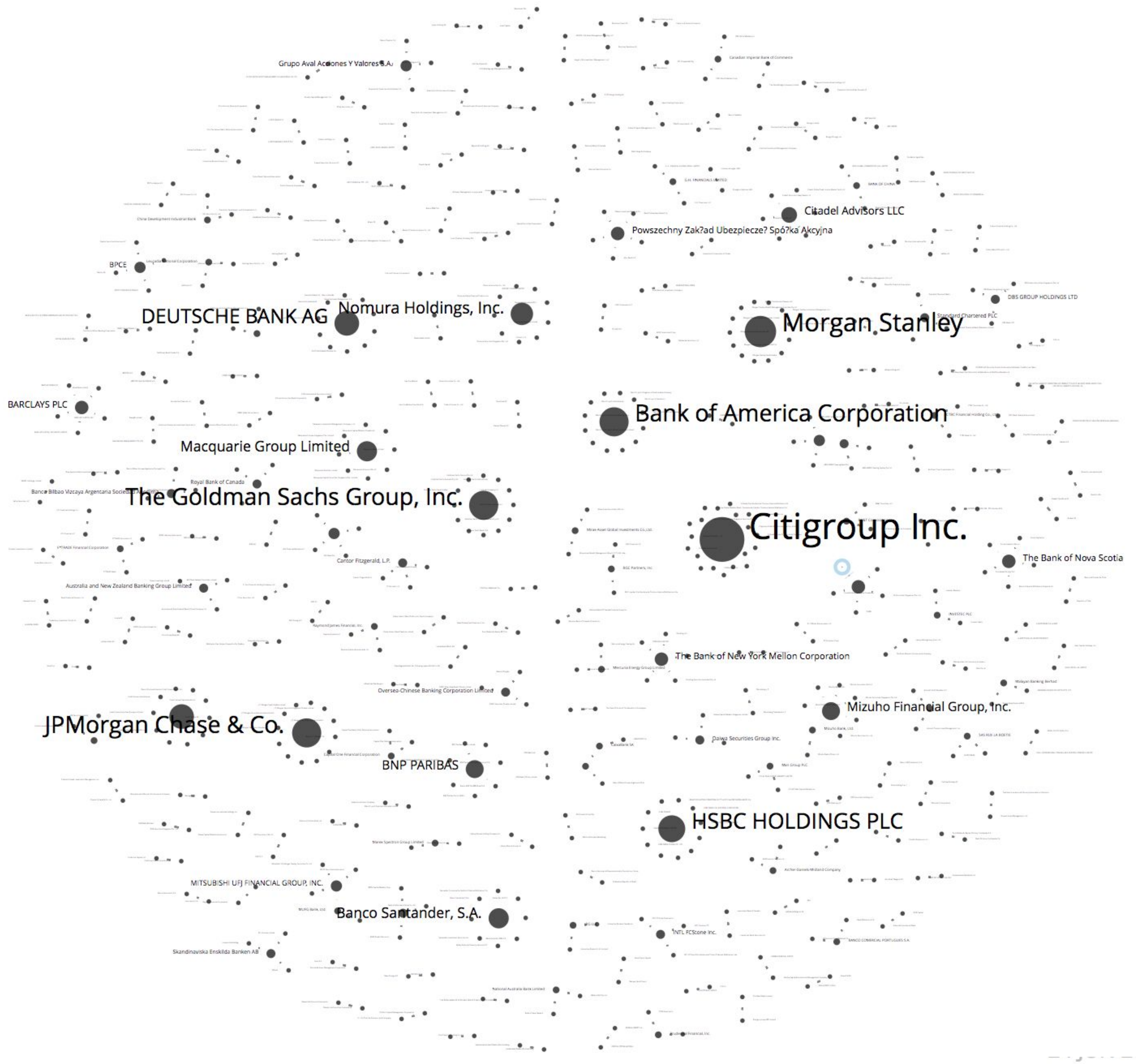


Banking Groups

210 Banking Groups

Largest (# of entities):

1. Citigroup (19)
2. Morgan Stanley (13)
3. Goldman Sachs (12)
4. JPMorgan Chase (12)
5. Bank of America (12)
6. HSBC (11)
7. Credit Suisse (10)
8. Deutsche Bank (10)
9. Nomura (9)
10. Banco Santander (8)

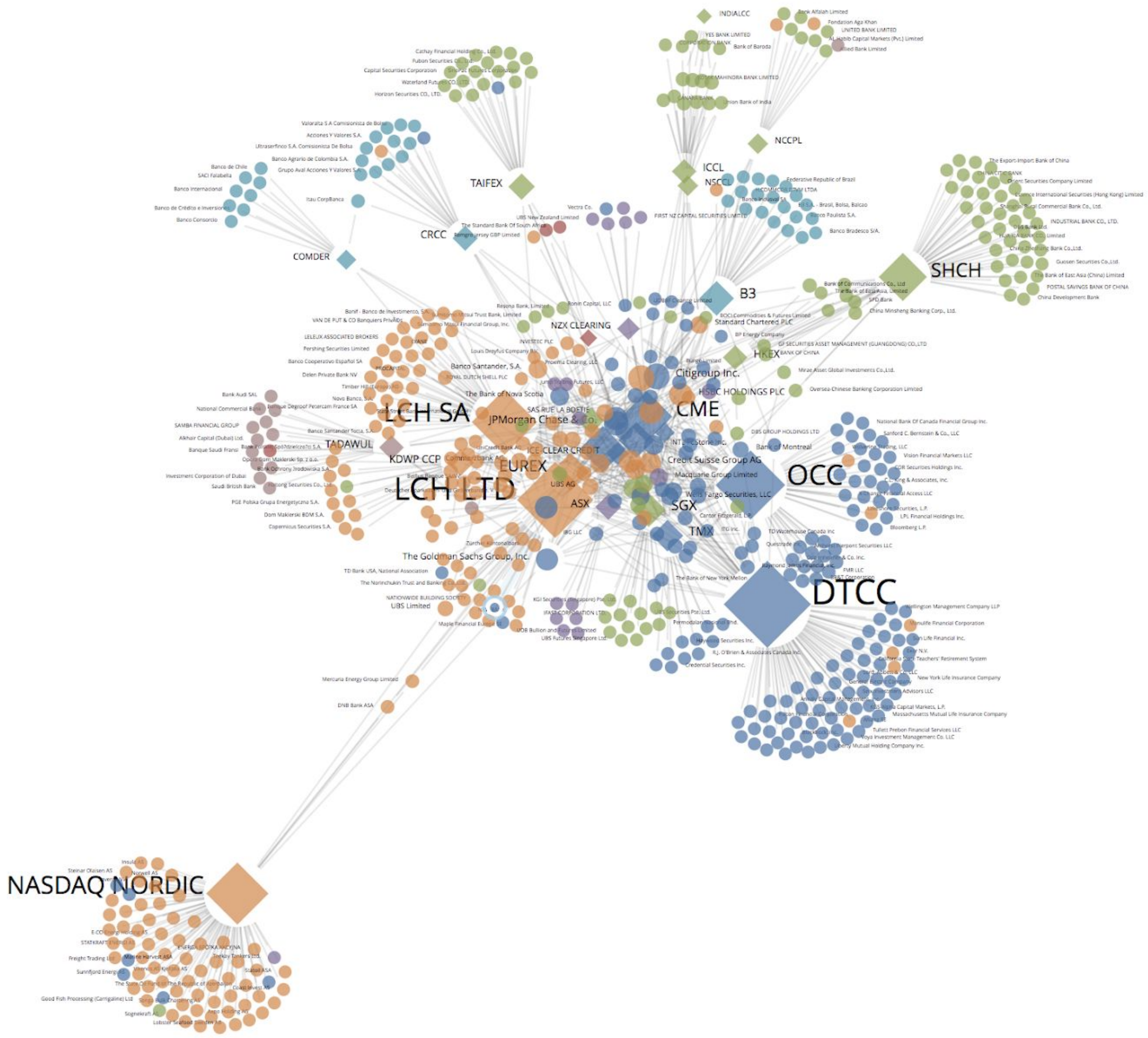


CCP Interconnectedness on Parent Level

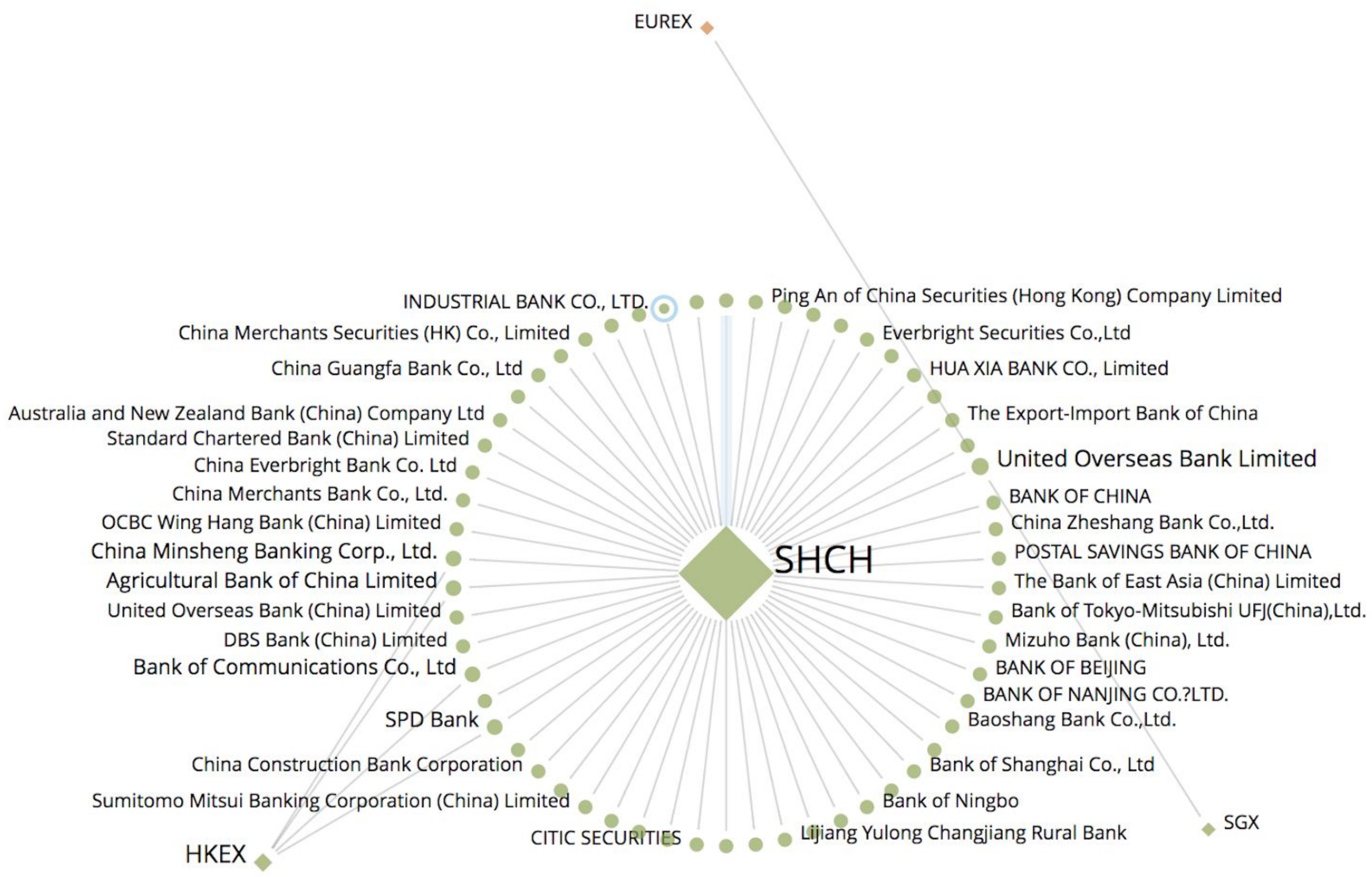
We see CCPs (diamonds) and their members (circles) from different regions:

- North America (blue)
- Europe (Yellow)
- Asia (green)
- Middle East (brown)
- Latin America (blue)
- Australia & Oceania (purple)

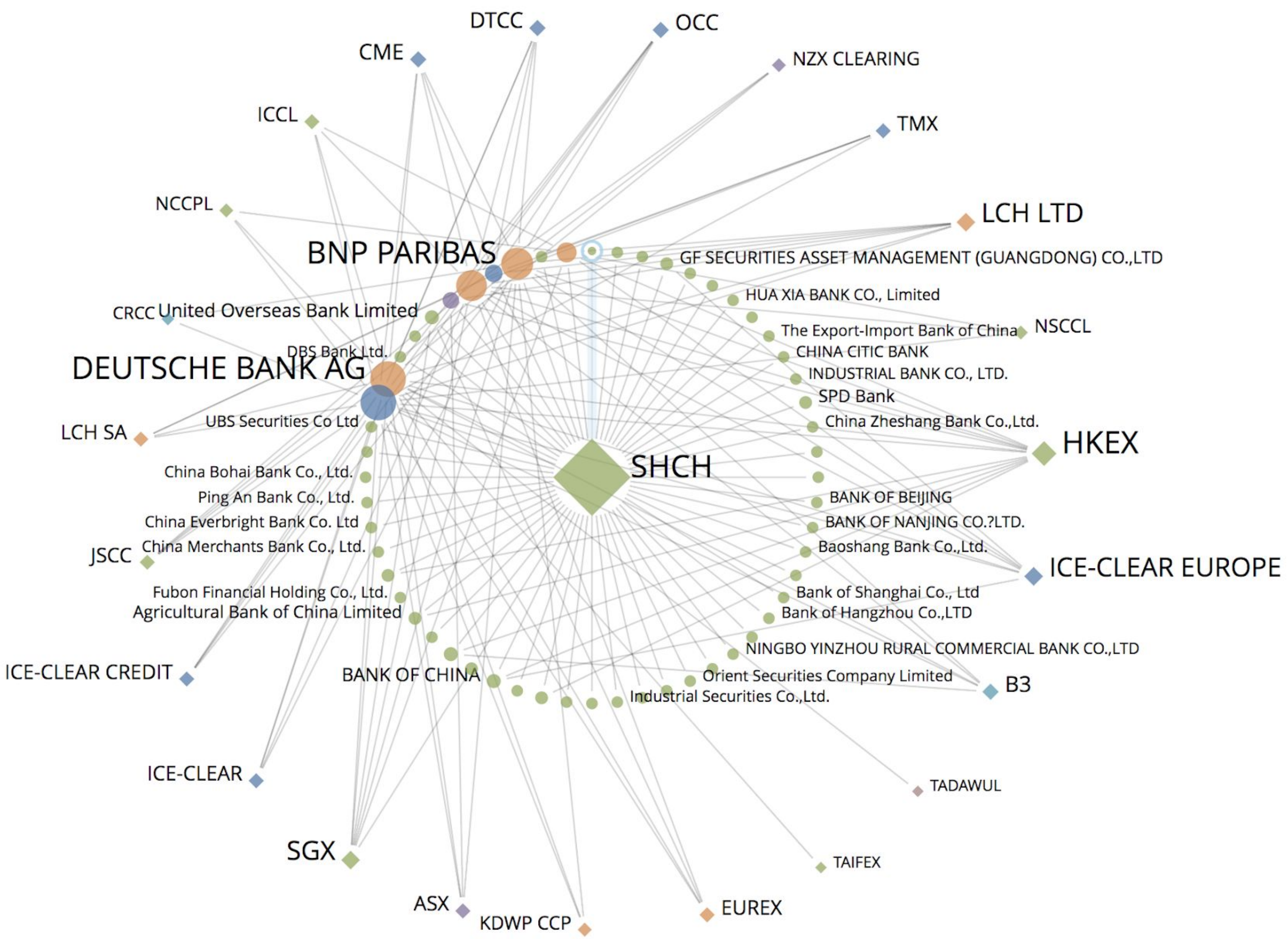
On parent level we see a completely connected network dominated by a core consisting of CCPs from North America and Europe and global banks.



CCP Interconnectedness on Subsidiary vs Parent Level - Example



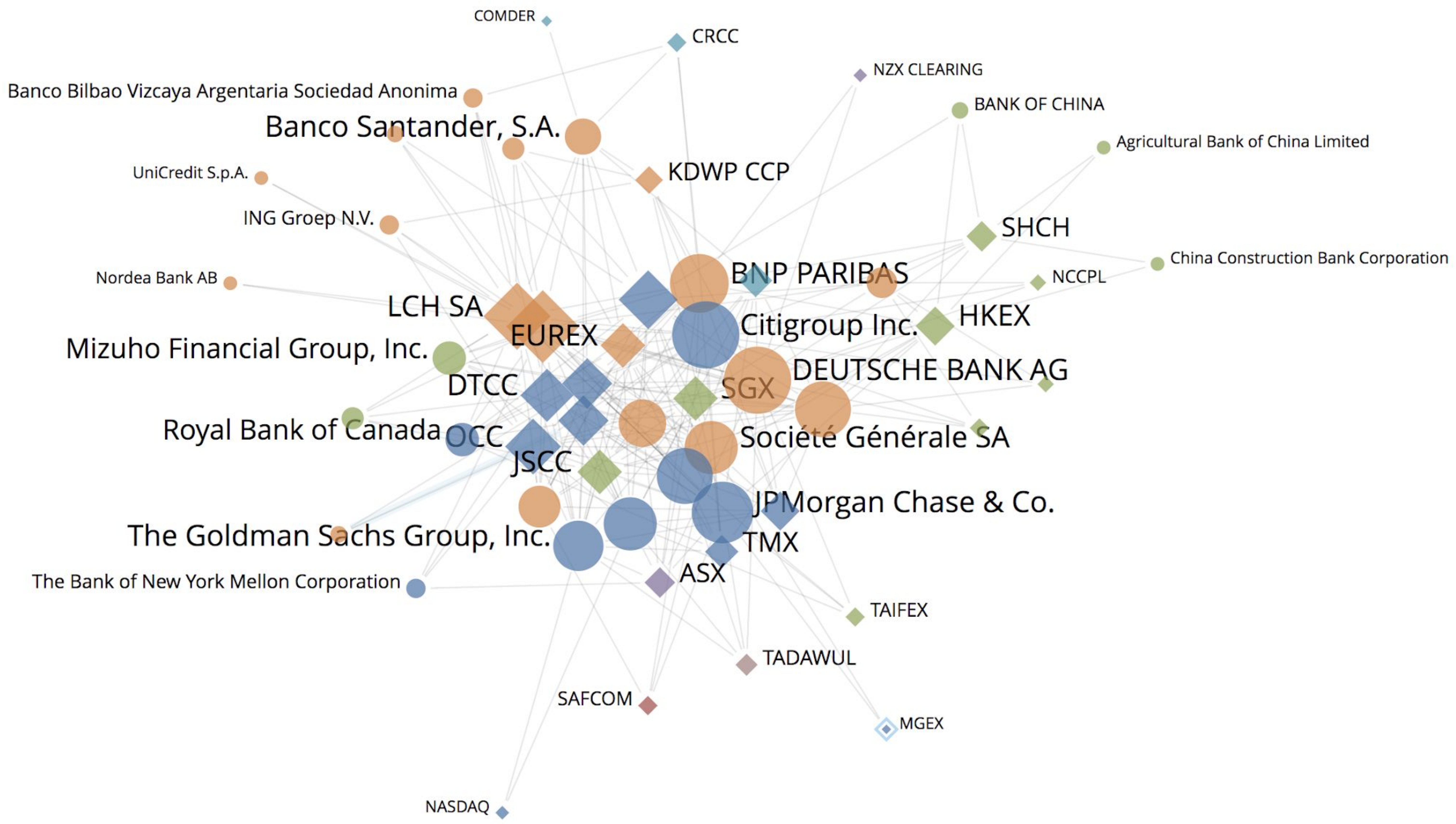
Subsidiary Level
(Connected to 3 CCPs)



Parent Level
(Connected to 23 CCPs)

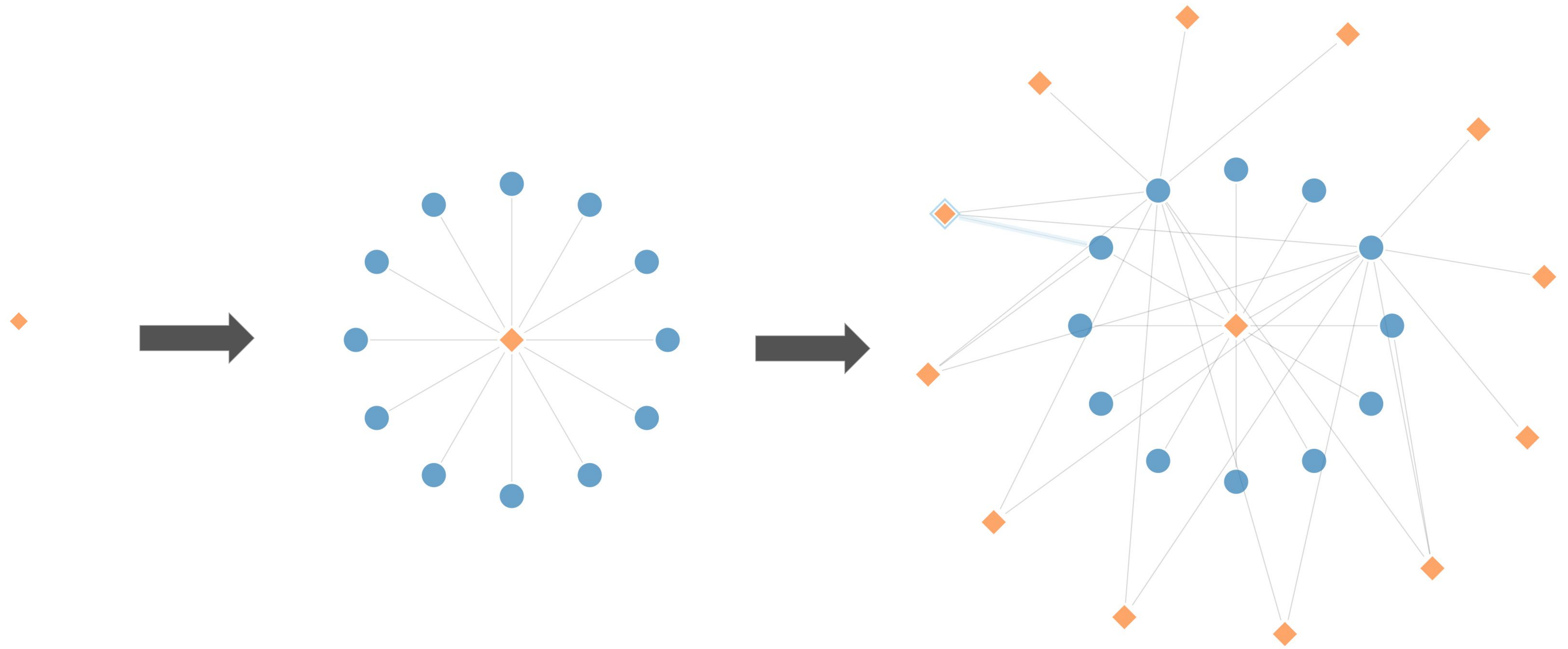
CCP Interconnectedness on GSIB Level

Bank (Parent)	# of FMIs
Citigroup	21
DEUTSCHE BANK	21
JPMorgan Chase & Co.	19
BNP PARIBAS	18
Bank of America	17
HSBC	17
Morgan Stanley	16
Societe Generale	16
The Goldman Sachs	15
Credit Suisse	14



Contagion - CCP Disruption

A disruption in a CCP would affect all of that CCP's clearing members, thereby affecting the other CCP's to which the affected CCP's members belong, possibly creating a cascading cycle as disruption is propagated across members and CCPs



CCP disruption

Propagates to all members

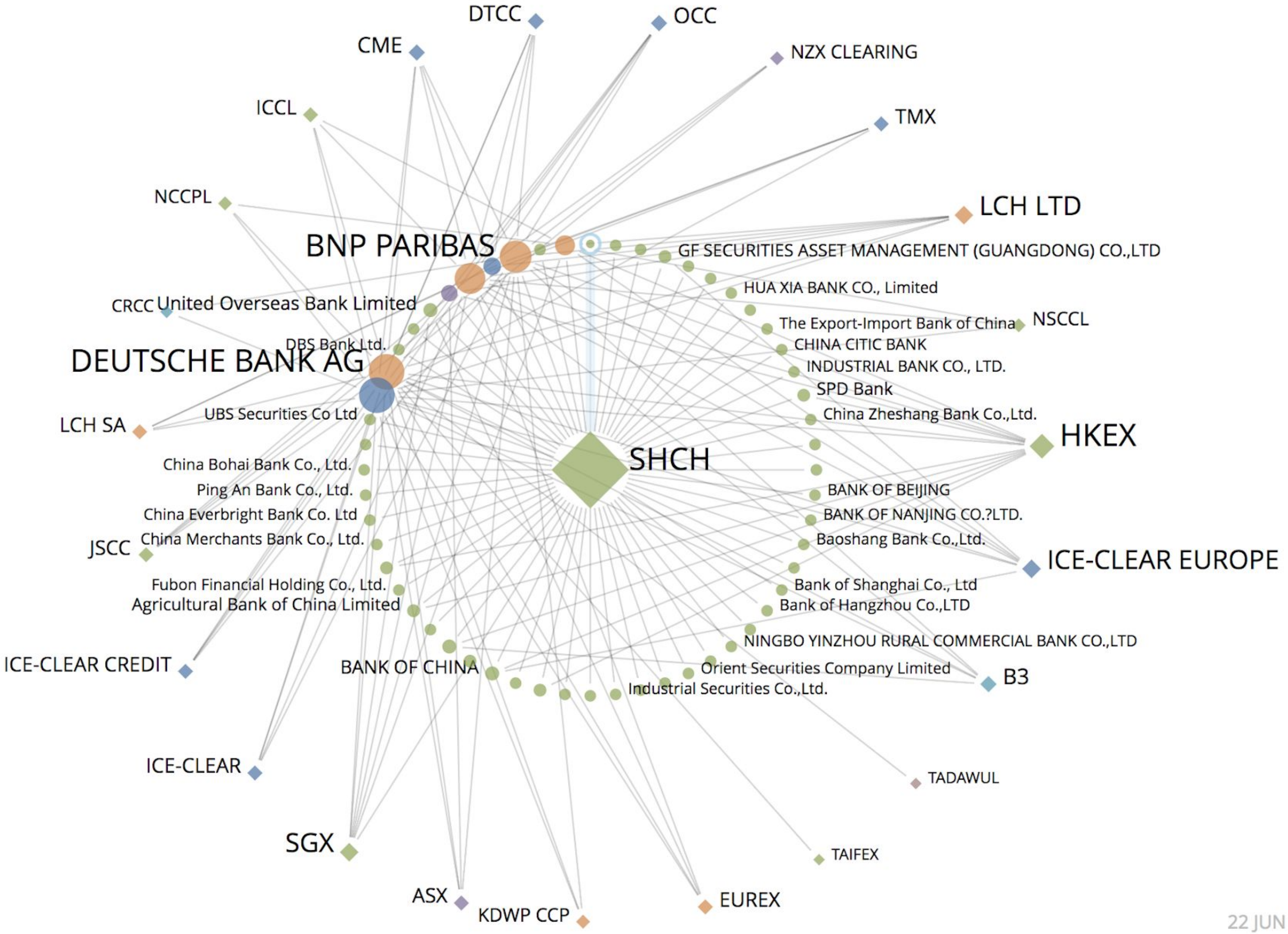
Propagates to other CCPs

Footprint of CCPs - SHCL

SHCL's 56 members are connected to 23 other CCPs

Most members are domestic with a few large global banks based in EU & US.

The most connected CCP is HKEx.

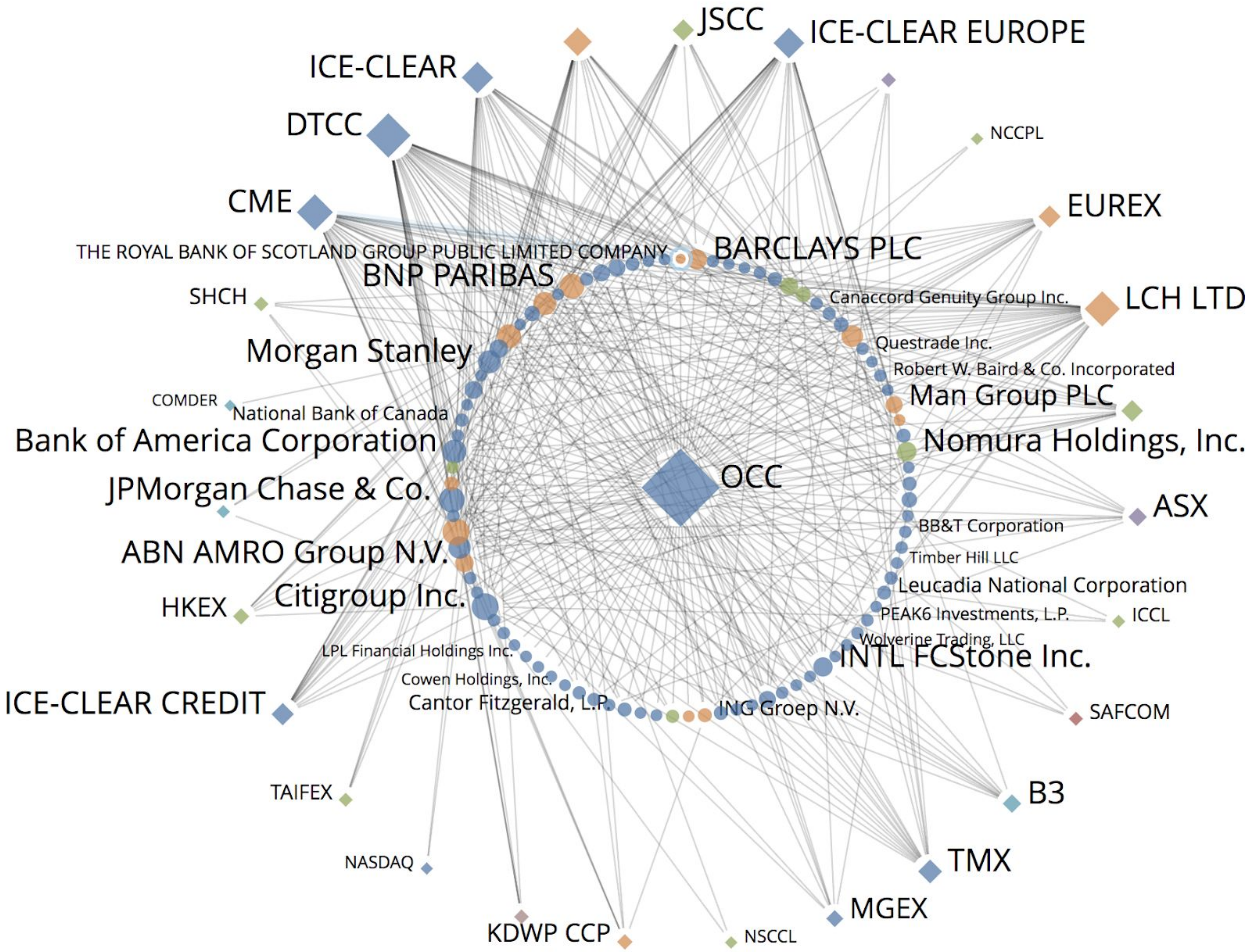


Footprint of CCPs - OCC

OCC's 89 members are connected to 27 other CCPs

The membership is mostly US with a significant EU base.

The most connected CCP's are DTCC and CME.

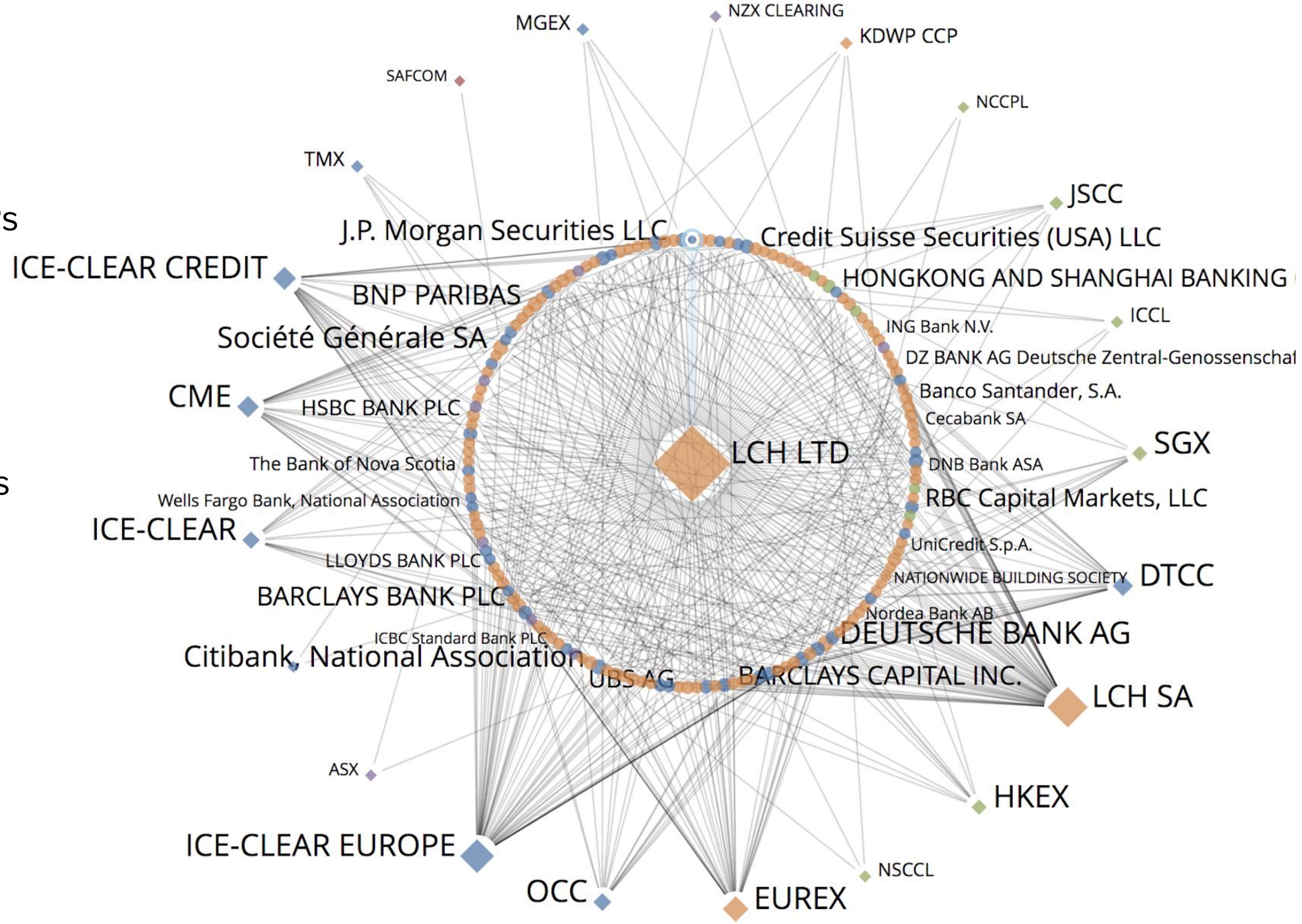


Footprint of CCPs - LCH Ltd

LCH Ltd 100 members are connected to 27 other CCPs

The membership is mostly European with a significant US base.

The most connected CCP is LCH SA and ICE-CLEAR EUROPE.



Contagion – Member Disruption

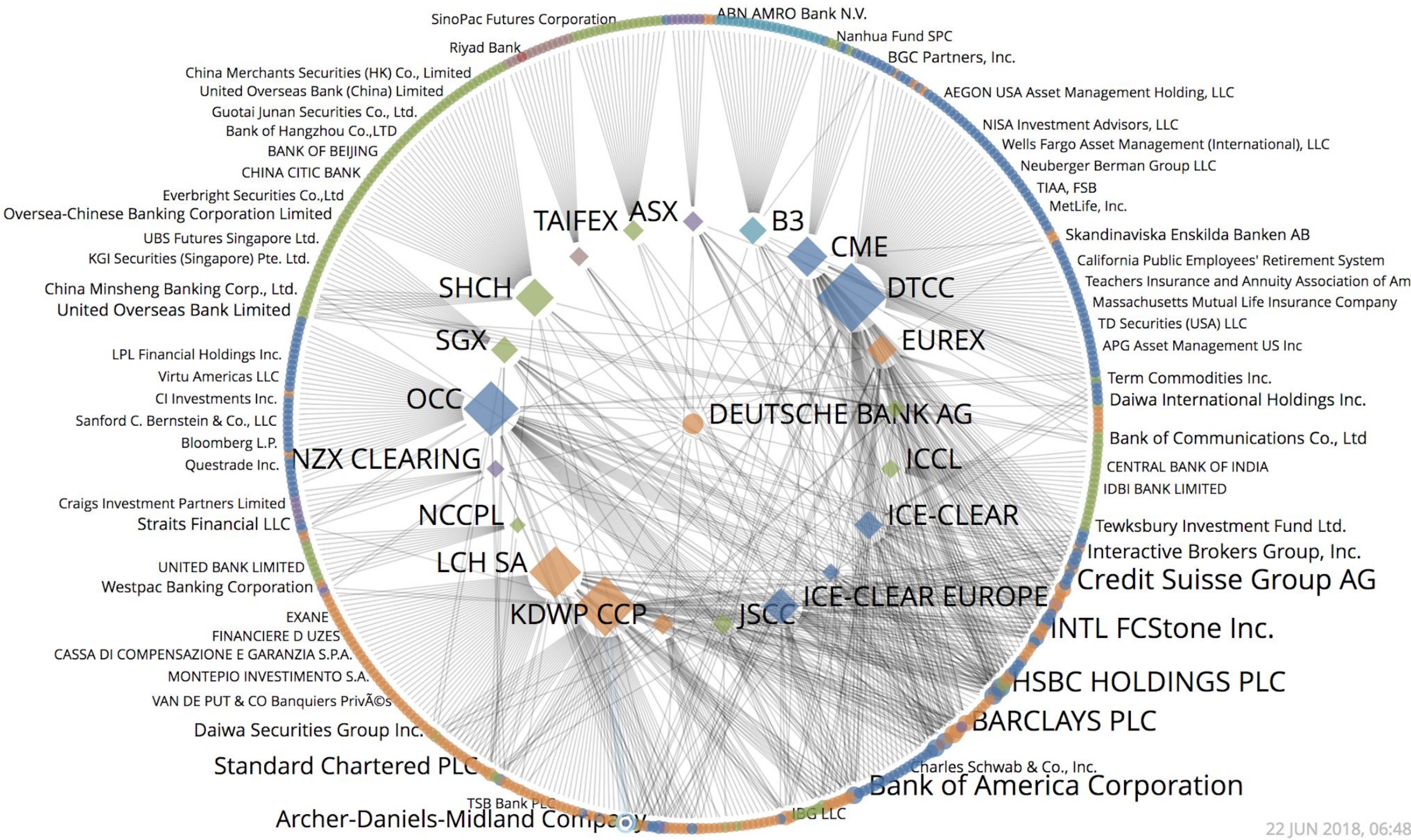
A member disruption can be felt by up to **458** banking groups or banks (of total of 563, or 80%) that are members of the same CCP as the stricken group.

Banking Group	# banking groups connected via a CCP
Deutsche Bank	458
Citigroup	446
Morgan Stanley	442
BNP Paribas	423
Goldman Sachs	412
HSBC Holdings	402
JPMorgan Chase	388
Bank of America	382
Credit Suisse	348
Société Générale	340

Contagion – Member Disruption

Deutsche Bank Group participates in 21 CCPs (of 29 mapped).

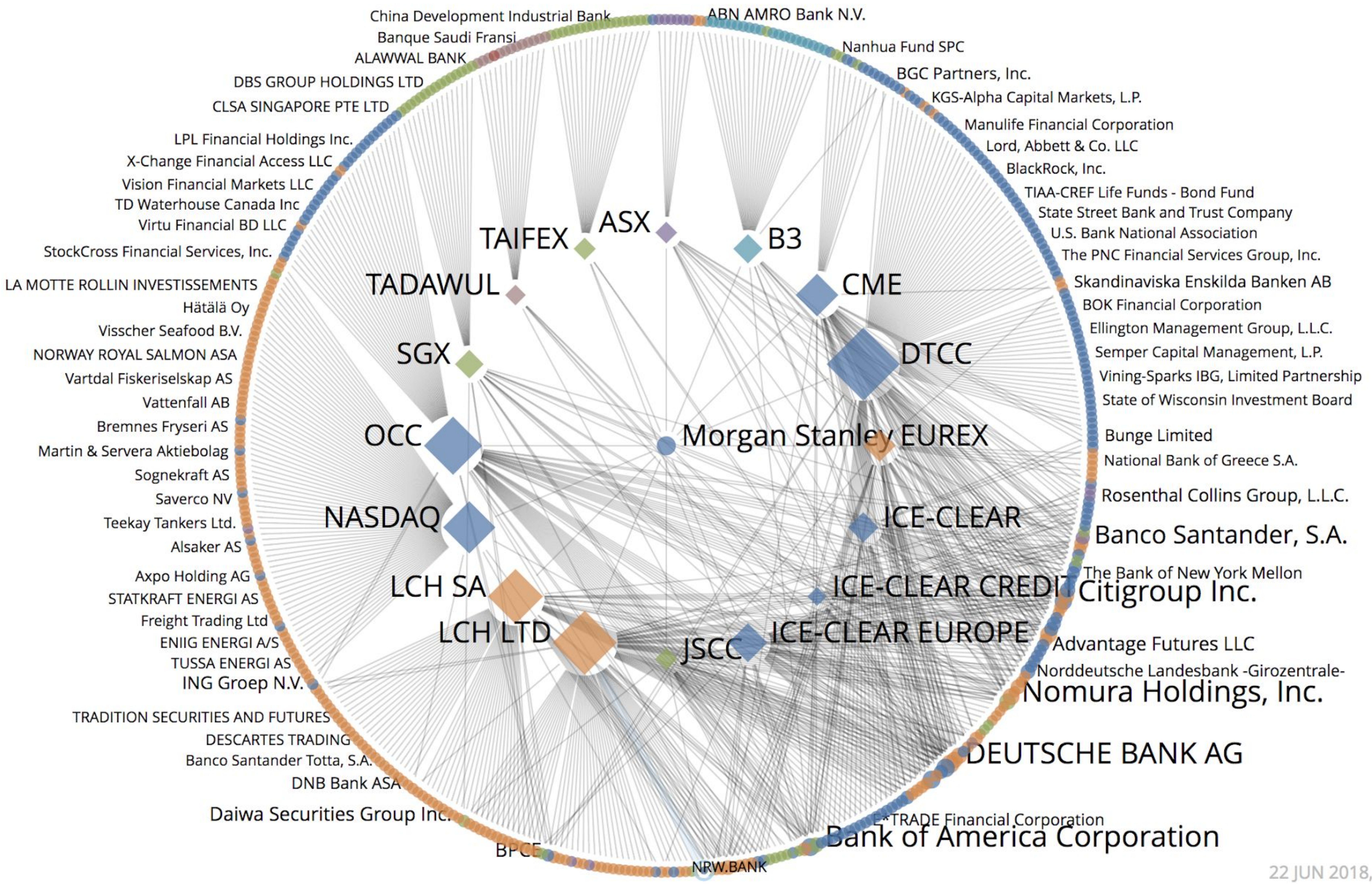
458 other banking groups or banks are members of these CCPs.



Contagion – Member Disruption

Morgan Stanley participates in 16 CCPs (of 29 mapped).

442 other banking groups or banks are members of these CCPs.



FNA

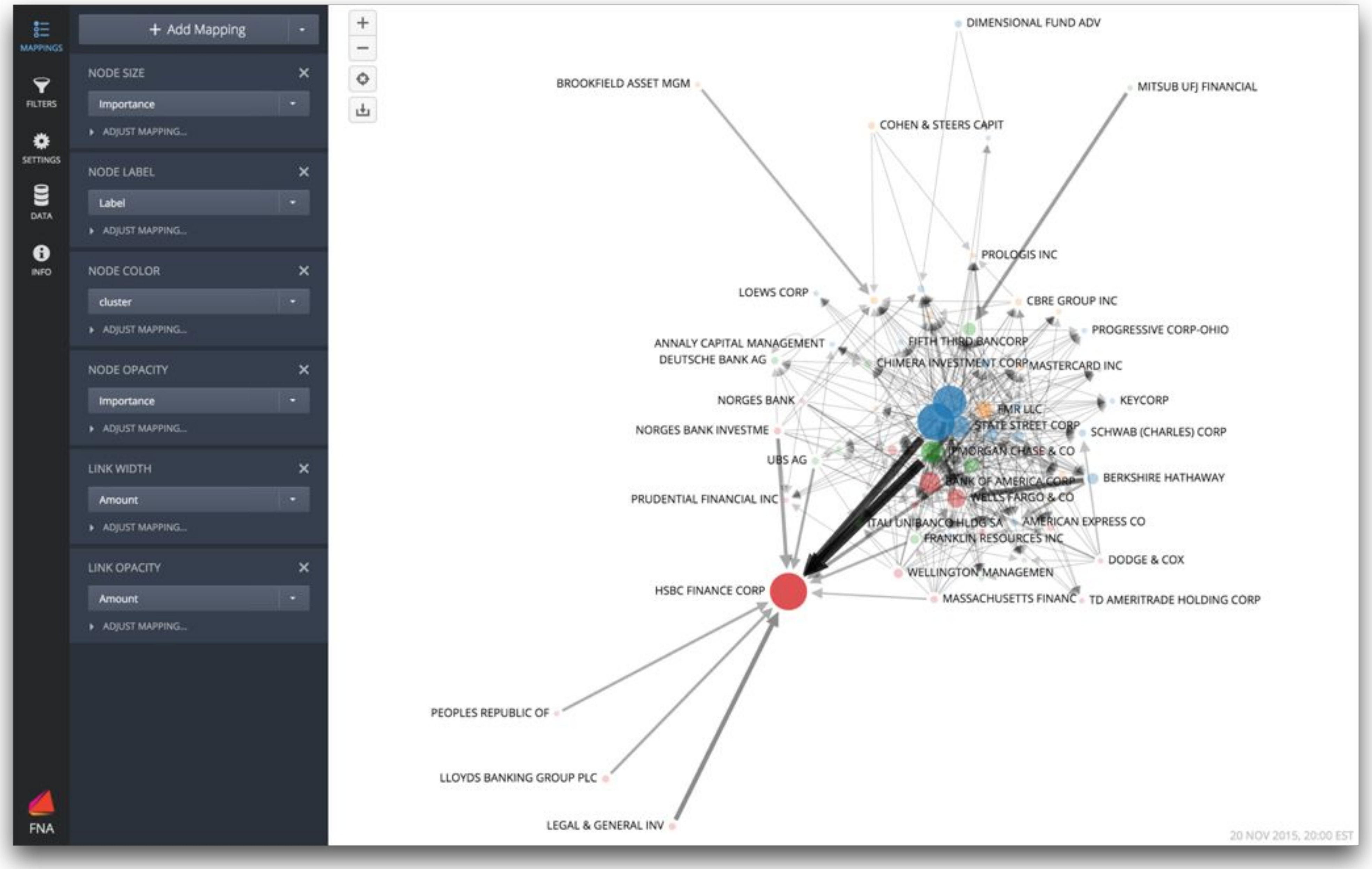
Top Down Analysis
Correlation Networks

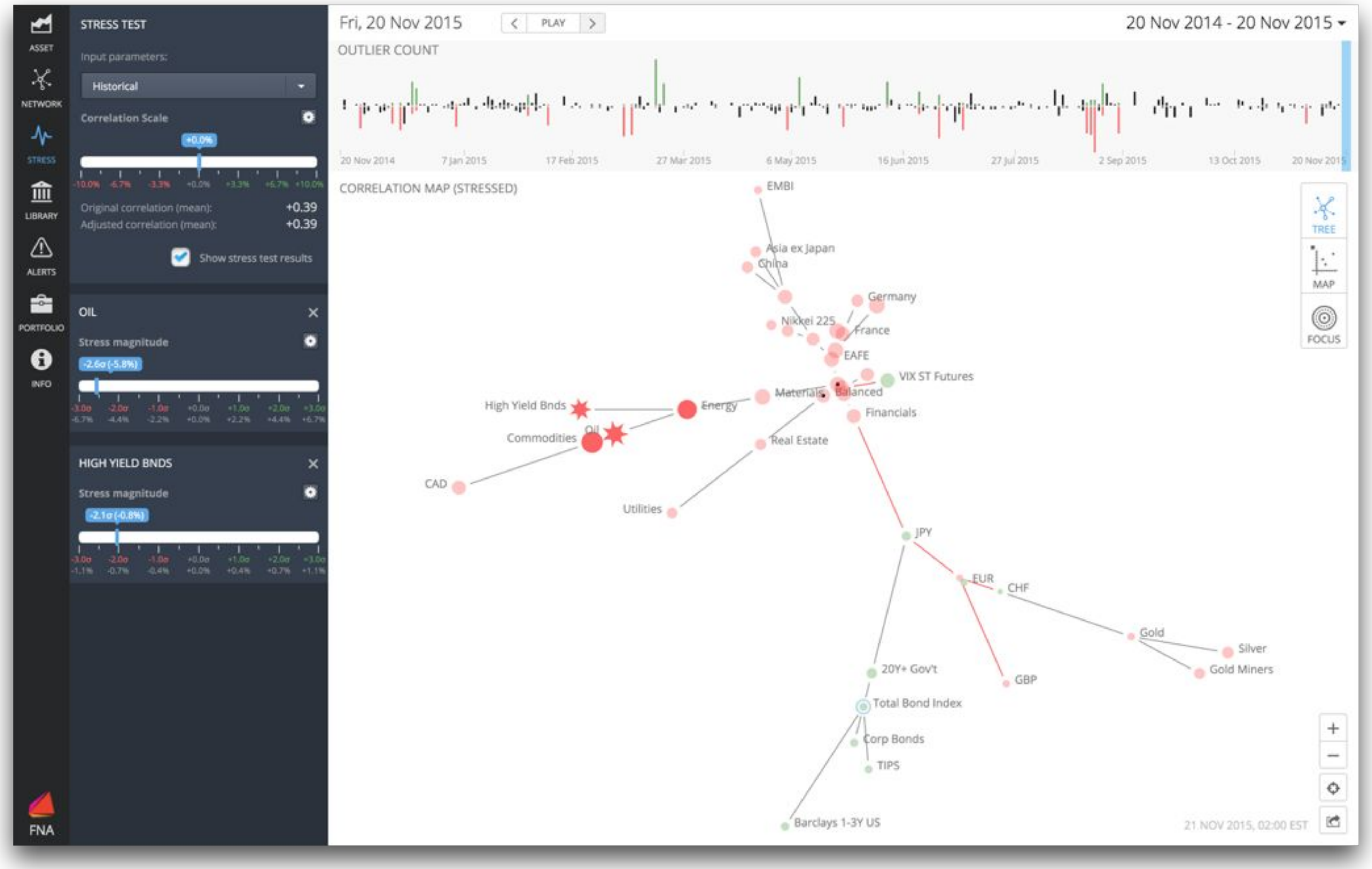
www.fna.fi

Transactions & Similarity Based Networks

Transaction: payment, trade, exposure, supply, flow, …

Similarity: correlation, partial correlation, granger causality, transfer entropy, …





Stavroglou et al (2016)
[Causality Networks of Financial Assets]

Typical view of cross asset correlations

Correlation Matrix Over the Last 15 Years (2001-2015)

		Equity					Fixed Income			Alternative Strategies					Alternative Assets		
		Large Cap	Mid Cap	Small Cap	Int'l	Emerging Mkts	Corp.	High Yield	Treas.	Long/ Short	Mkt Neutral	Event Driven	FI Arbitrage	Mgd Futures	Real Estate	Currency	Comm-odities
Equity	Large Cap	1.00															
	Mid Cap	0.93	1.00														
	Small Cap	0.88	0.96	1.00													
	Int'l	0.88	0.85	0.79	1.00												
	Emer. Mkts	0.78	0.80	0.75	0.87	1.00											
Fixed Income	Corp.	0.17	0.20	0.13	0.30	0.31	1.00										
	High Yield	0.66	0.71	0.66	0.69	0.71	0.52	1.00									
	Treas.	-0.36	-0.35	-0.38	-0.27	-0.25	0.63	-0.19	1.00								
Alt. Strategies	Long/Short	0.75	0.79	0.72	0.84	0.80	0.27	0.61	-0.28	1.00							
	Mkt Neutral	0.27	0.29	0.29	0.28	0.24	-0.09	0.37	-0.29	0.25	1.00						
	Event Driven	0.64	0.70	0.64	0.71	0.70	0.23	0.67	-0.34	0.83	0.32	1.00					
	FI Arbitrage	0.42	0.46	0.37	0.48	0.48	0.42	0.63	-0.10	0.51	0.36	0.55	1.00				
	Mgd Futures	-0.13	-0.10	-0.12	0.00	0.01	0.19	-0.12	0.29	0.19	-0.01	0.09	0.00	1.00			
Alt. Assets	Real Estate	0.08	0.12	0.14	0.08	0.05	-0.03	0.06	-0.08	0.05	0.14	0.04	0.03	0.00	1.00		
	Currency	-0.03	-0.02	0.01	0.02	0.01	0.11	-0.07	0.13	0.13	0.02	0.03	0.00	0.61	0.07	1.00	
	Commodities	0.32	0.38	0.33	0.45	0.47	0.11	0.35	-0.17	0.49	0.28	0.49	0.45	0.18	0.10	-0.08	1.00

High (0.9-1.0) | Moderate High (0.7-0.9) | Moderate (0.3-0.7) | Low (0.0-0.3) | Negative (<0.0)

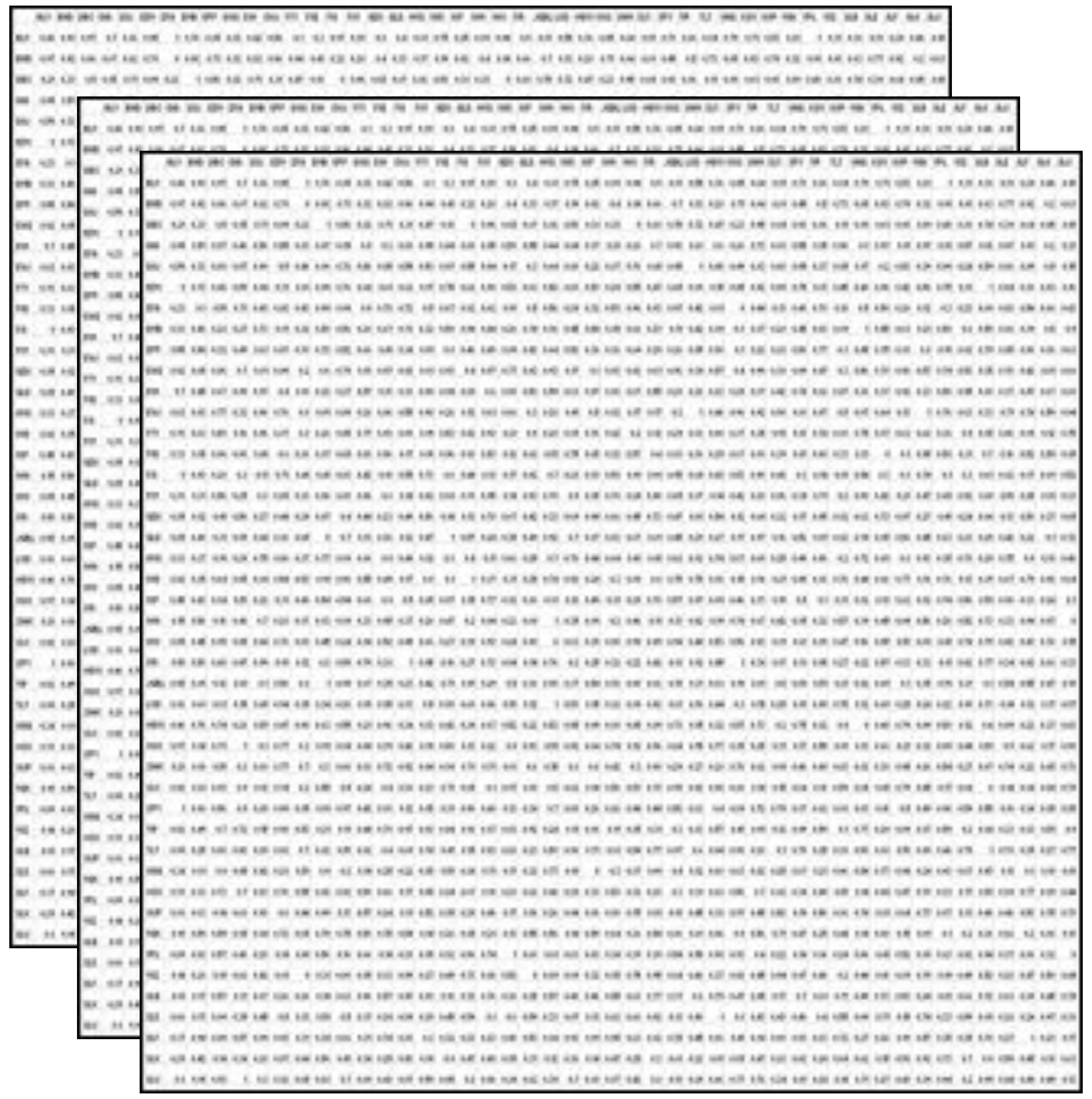
Low Diversification ⟷ High Diversification

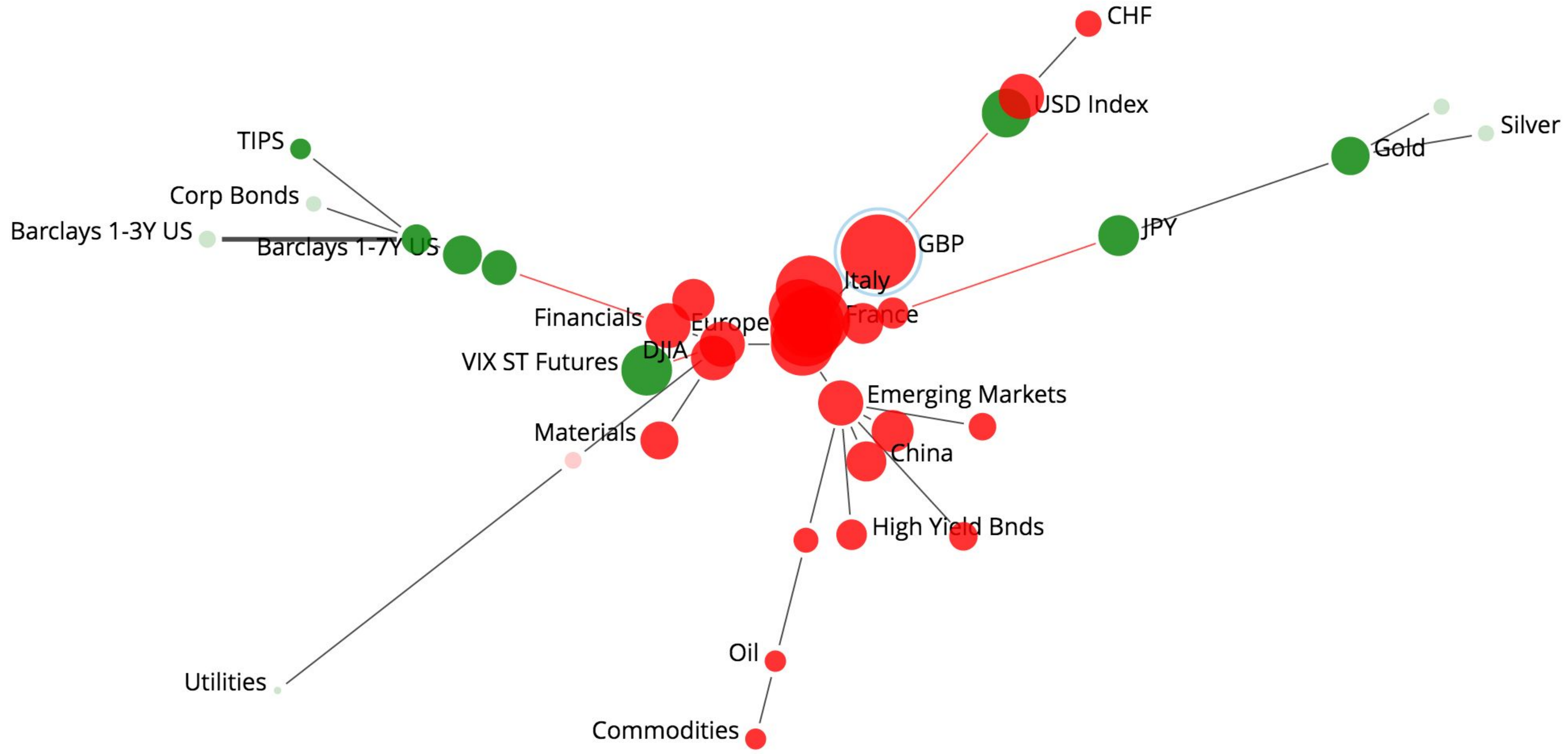
Correlation Networks

Interconnectivity of markets has increased

We need to be able to understand correlations structures of much larger scale.

Networks help develop intuition, and understand stress tests.





Universe of Global Assets (ETFs)

BND	Total Bond Index
DBC	Commodities
DIA	DJIA
DXJ	Japan Stocks (in JPY)
EEM	Emerging Markets
EFA	EAFE
EMB	EMBI
EPP	Asia ex Japan
EWG	Germany
EWI	Italy
EWJ	Japan
EWQ	France
EWU	UK
FXB	GBP
FXC	CAD
FXE	EUR
FXI	China
FXY	JPY
GDX	Gold Miners
GLD	Gold
IEF	Barclays 1-7Y US
IYR	Real Estate
JNK	High Yield Bonds
LQD	Corp Bonds
SLV	Silver
SPY	S&P 500
TIP	TIPS
TLT	20Y+ Gov't
USO	Oil
UUP	USD Index
VGK	Europe
VPL	Asia
VXX	VIX ST Futures
XIU	TSX 60
XLB	Materials
XLE	Energy
XLF	Financials
XLK	Tech
XLU	Utilities
CSJ	Barclays 1-3Y US
FXF	CHF

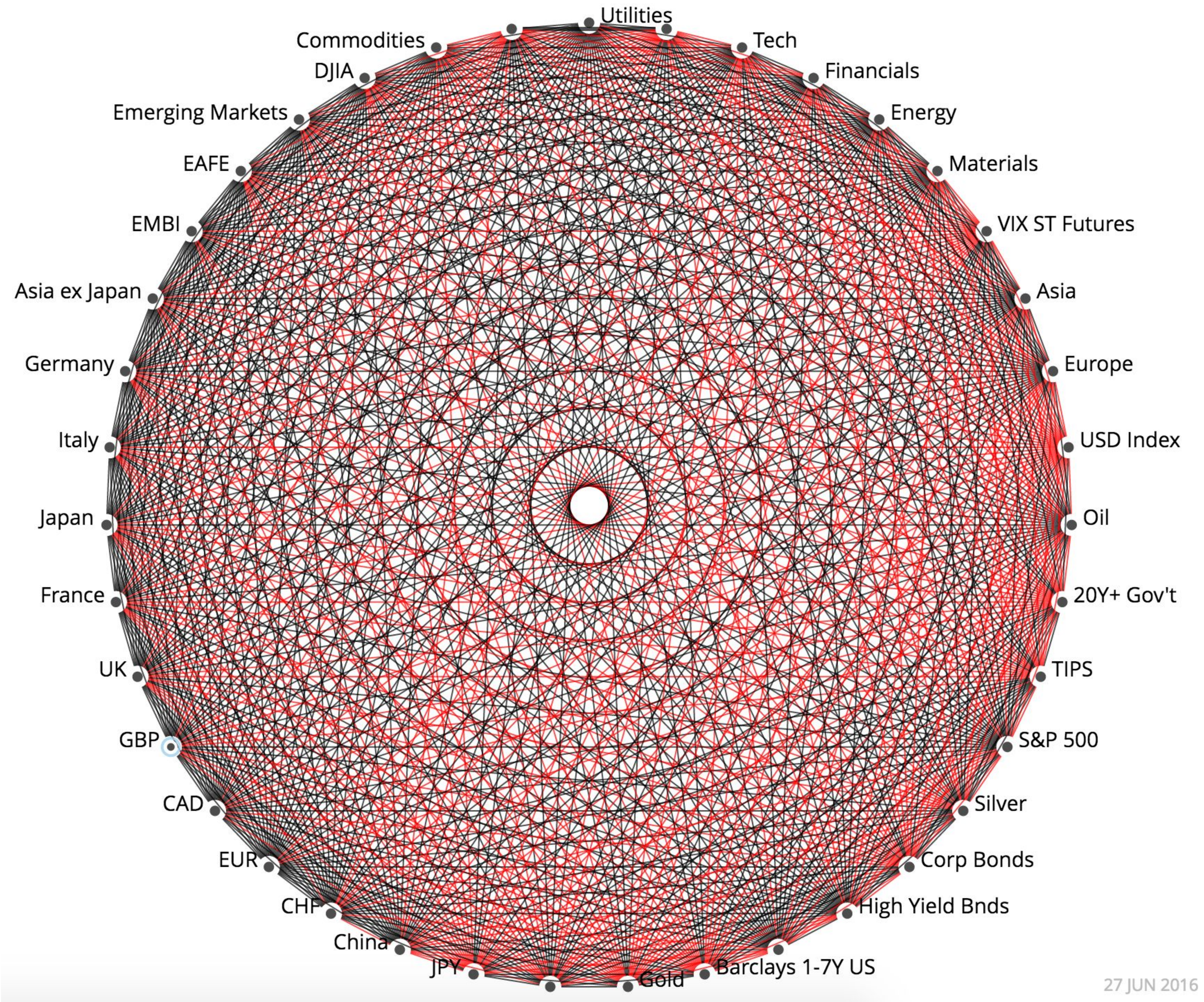
Correlation Network of the Assets

We can view any matrix as a network.

We encode correlations as links between the correlated nodes/assets.

Red link = negative correlation
Black link = positive correlation

However, this simple encoding does not give us much.



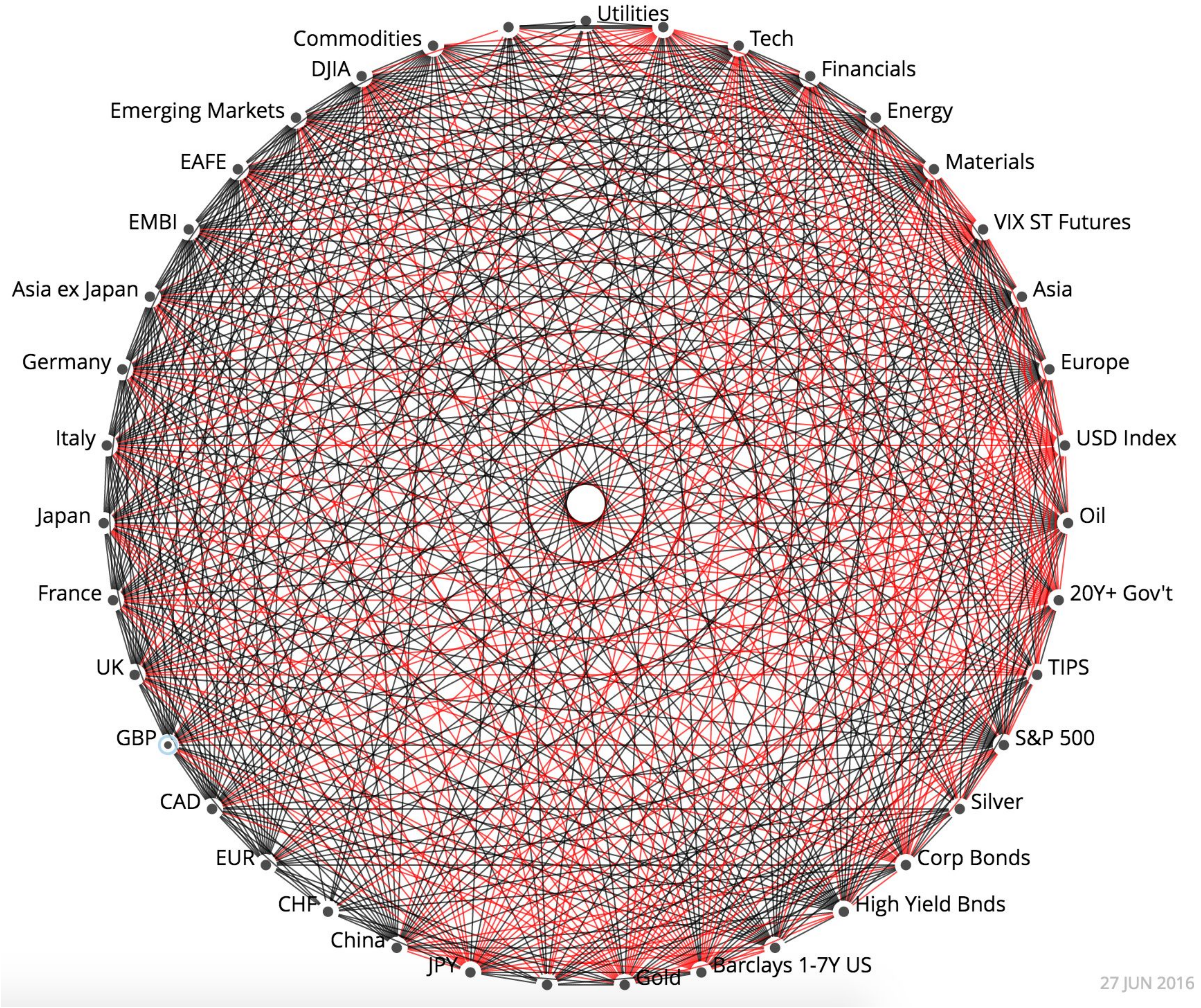
27 JUN 2016

Transactions & Similarity Based Networks

Not all correlations are statistically significantly different from 0.

Absence of link marks that asset is not significantly correlated (here at 95% level).

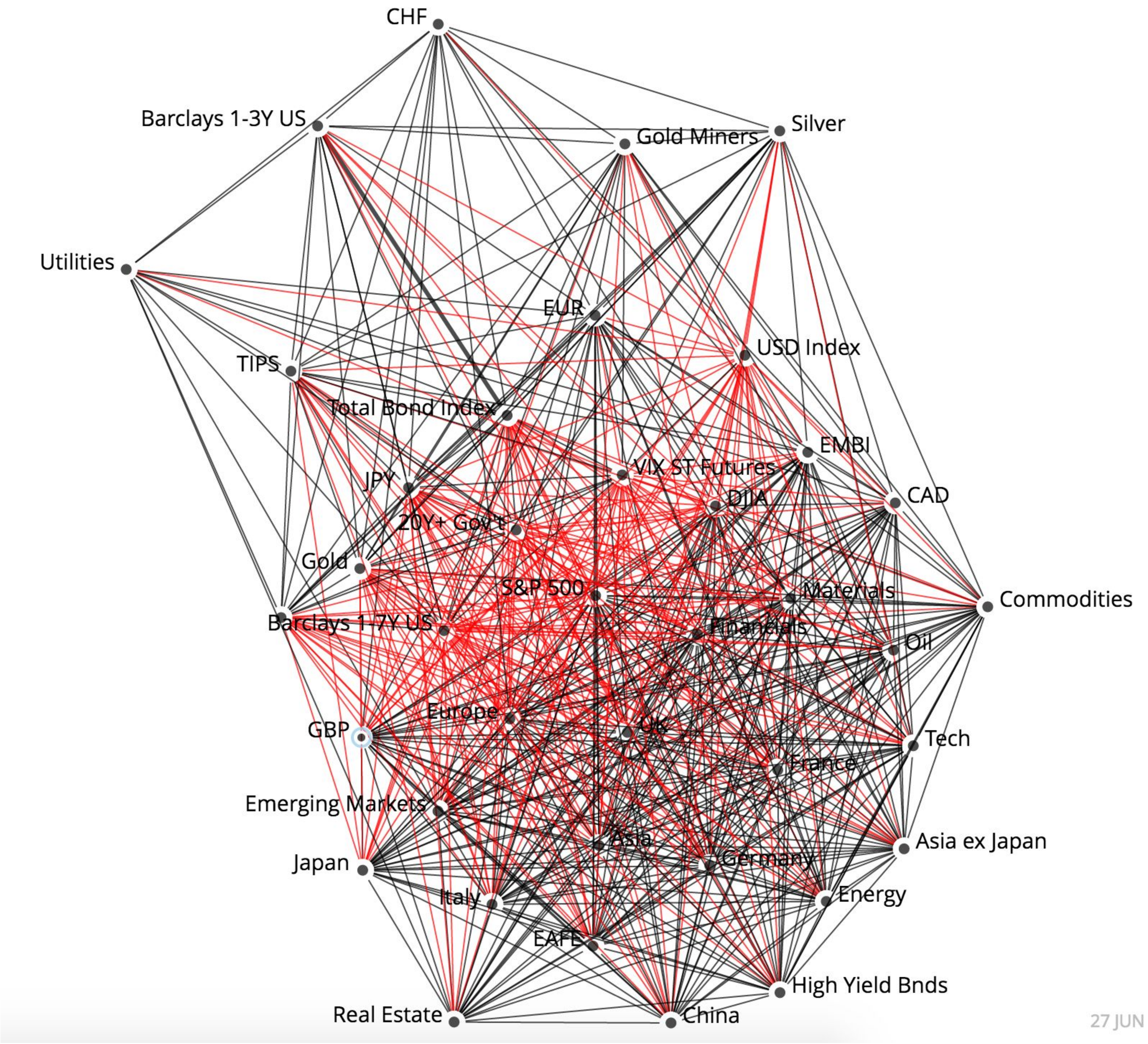
Due to the large number of estimates, we also need for multiple comparisons correction. Eg. Bonferroni or FDR.



Network Layout

We can use network layouts to better detect patterns from noise.

E.g. we can try a Force-Directed network layout to identify clusters.

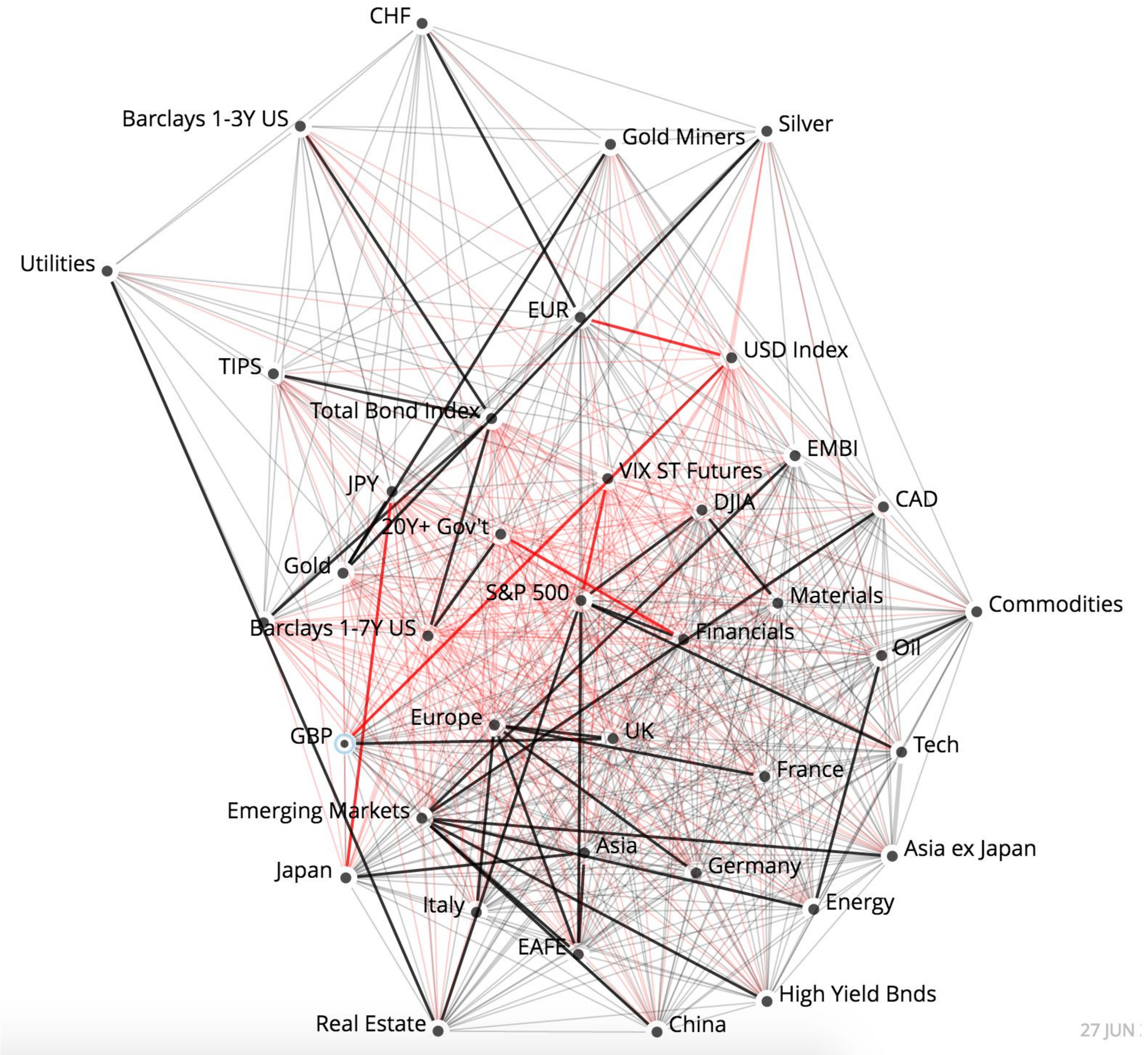


Filtering

Next, we identify the Minimum Spanning Tree and filter out other correlations (Mantegna, '99).

We need a distance function, here we look at maximum spanning tree with distance function: abs(cor)

This shows us the backbone correlation structure.

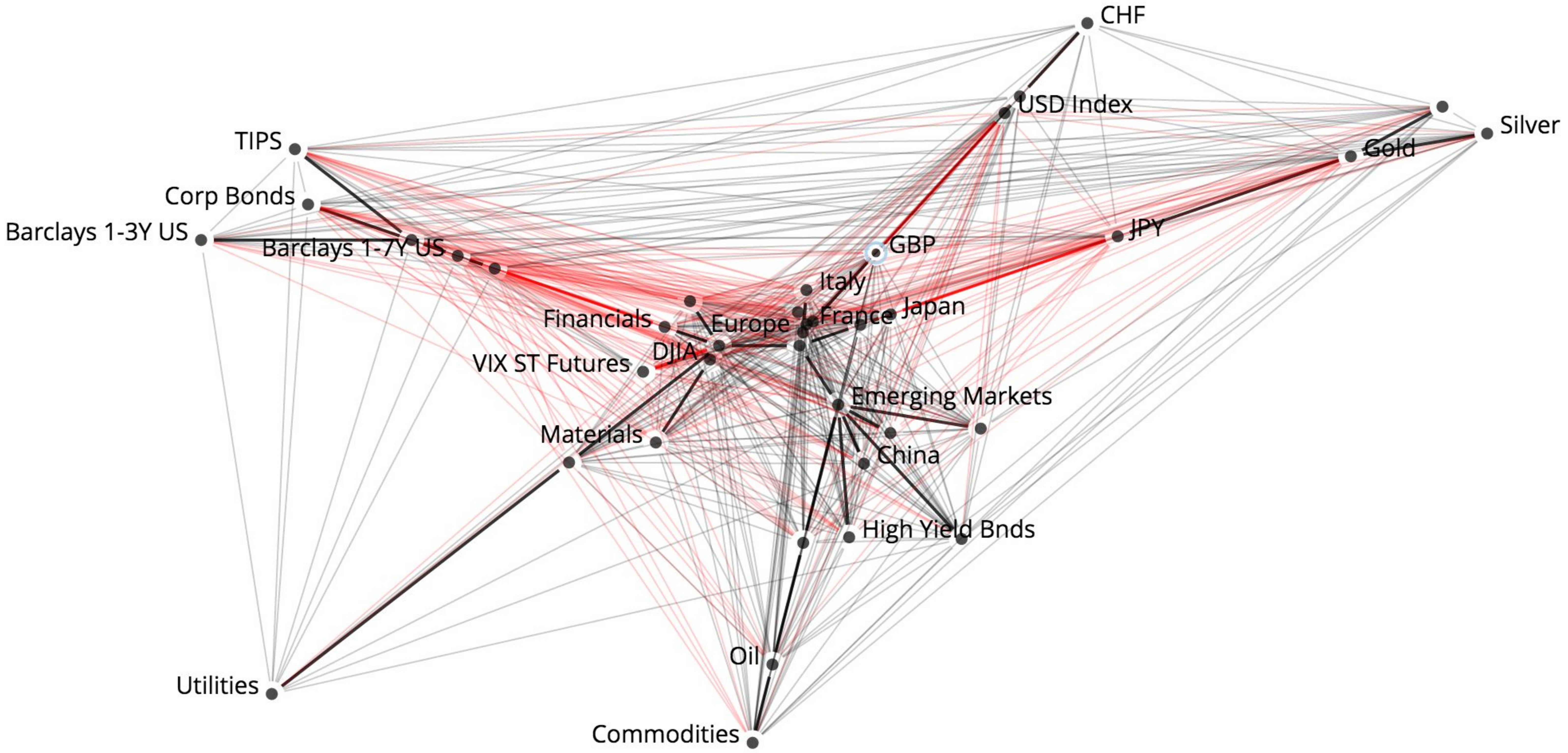


Radial Tree Layout

We use a radial tree layout algorithm (Bachmeier et al. ‘05) that places the assets so that:

- Shorter links in the tree indicate higher correlations
- Longer links indicate lower correlations

As a result, we also see how the assets cluster by asset class.



Radial Tree Layout

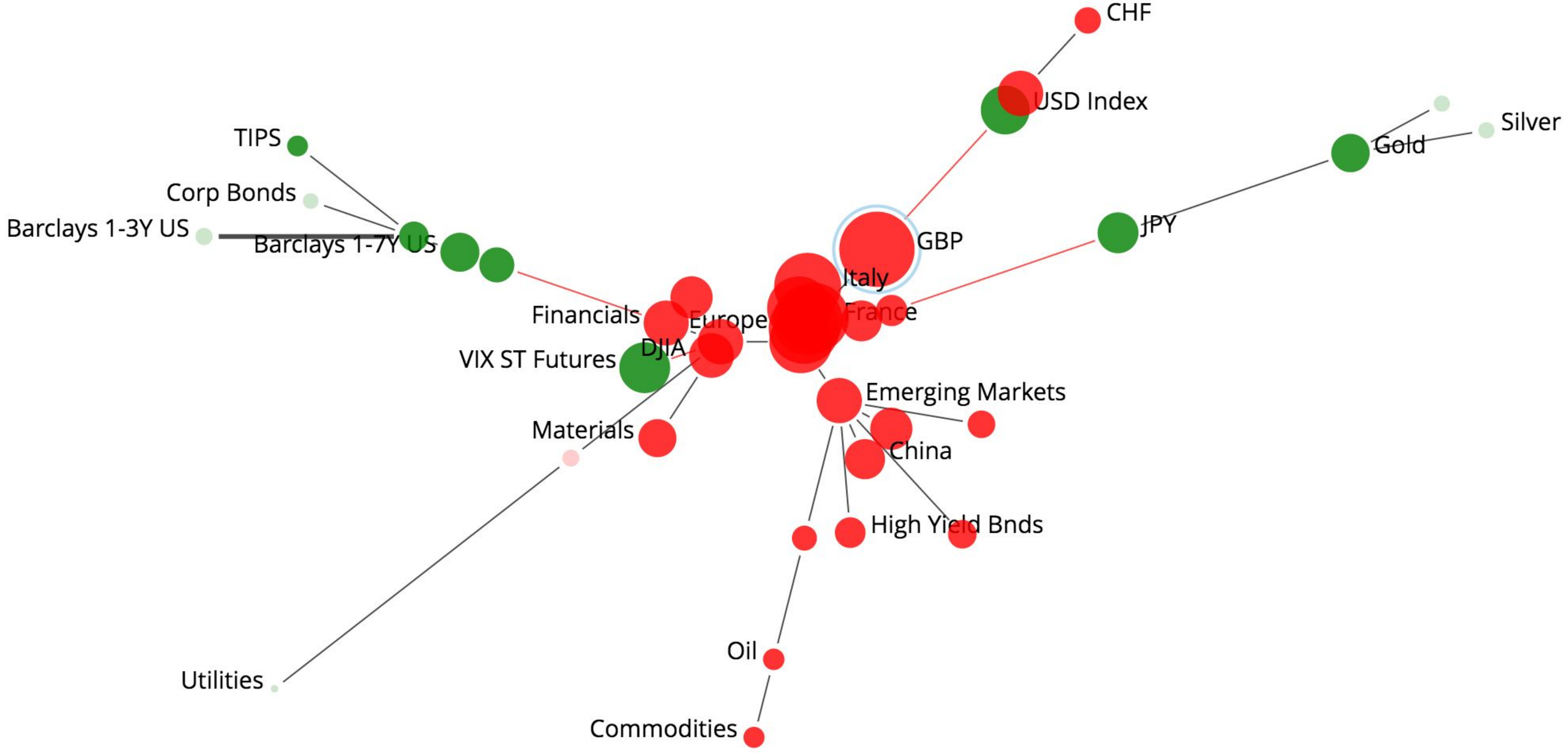
Focus on the links in the Spanning Tree to highlight clustering structure.

Node color indicates last daily return

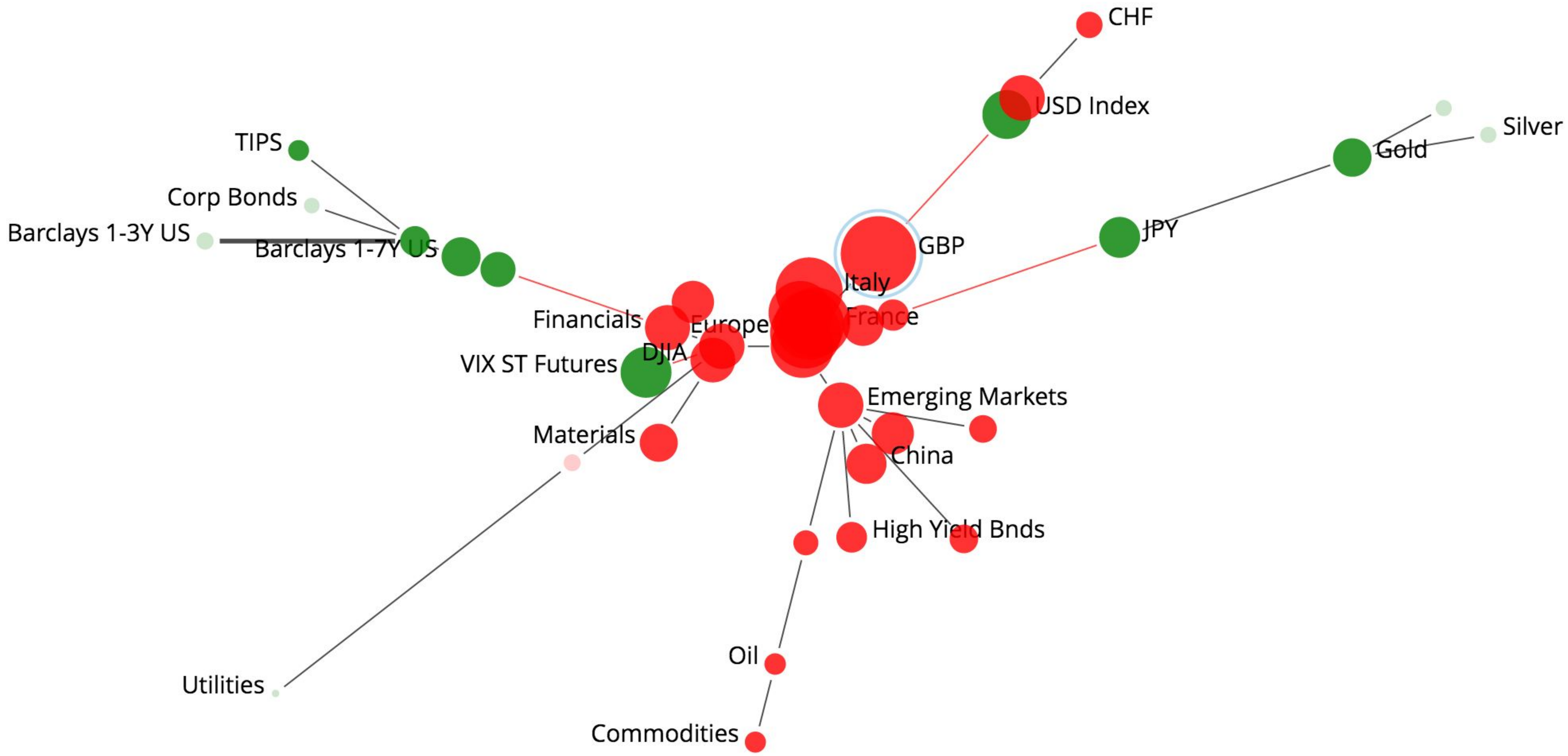
- Green = positive
- Red = negative

Node size indicates magnitude of return

Bright colors are VaR exceptions



Brexit, Friday 24 June 2016



Financial Cartography

Coordinate system

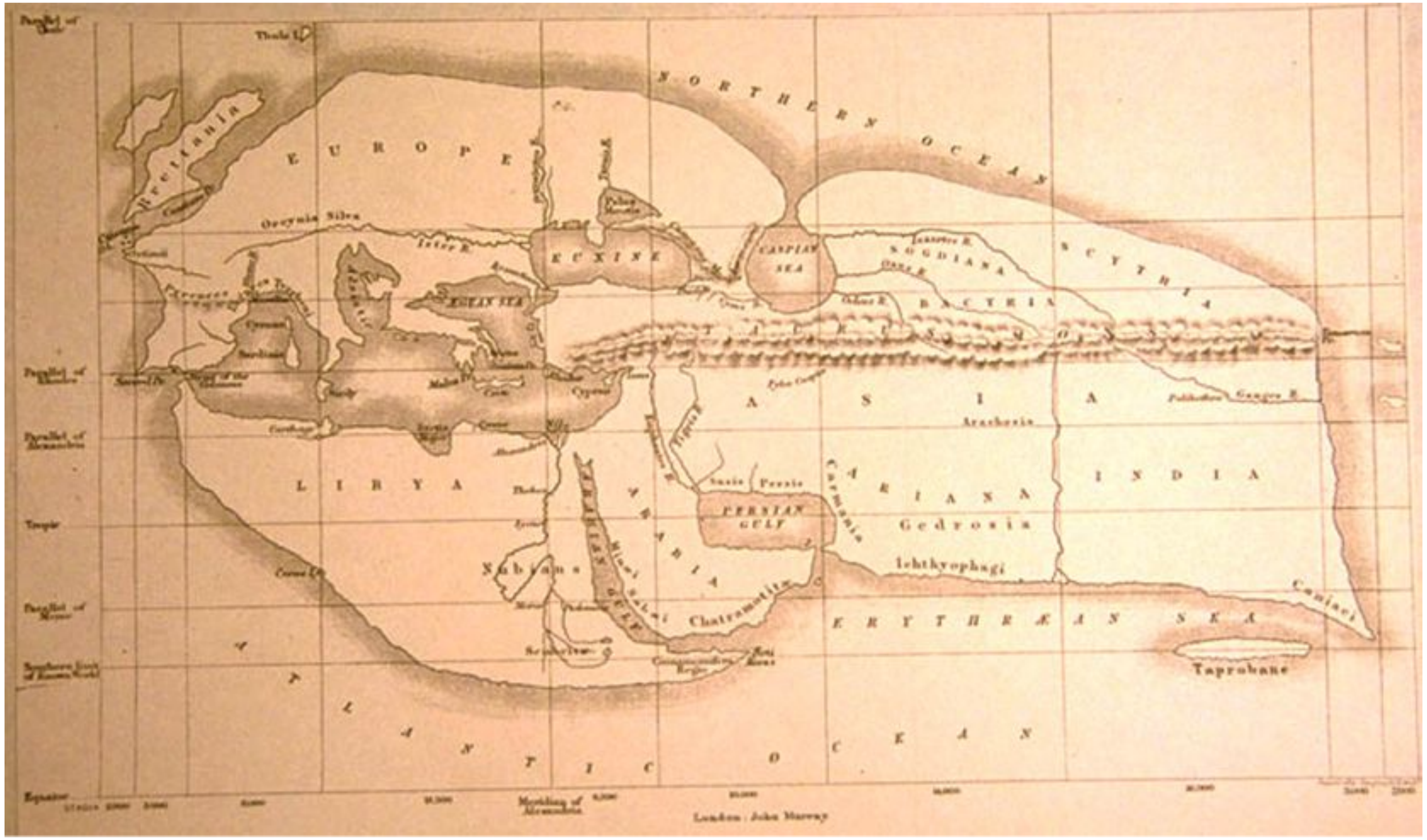
-> layout algorithm

System for visual encoding of map data

-> node sizes & colors

Dimensionality reduction & filtering

-> minimum spanning tree



Use Case: Monitoring Housing Markets

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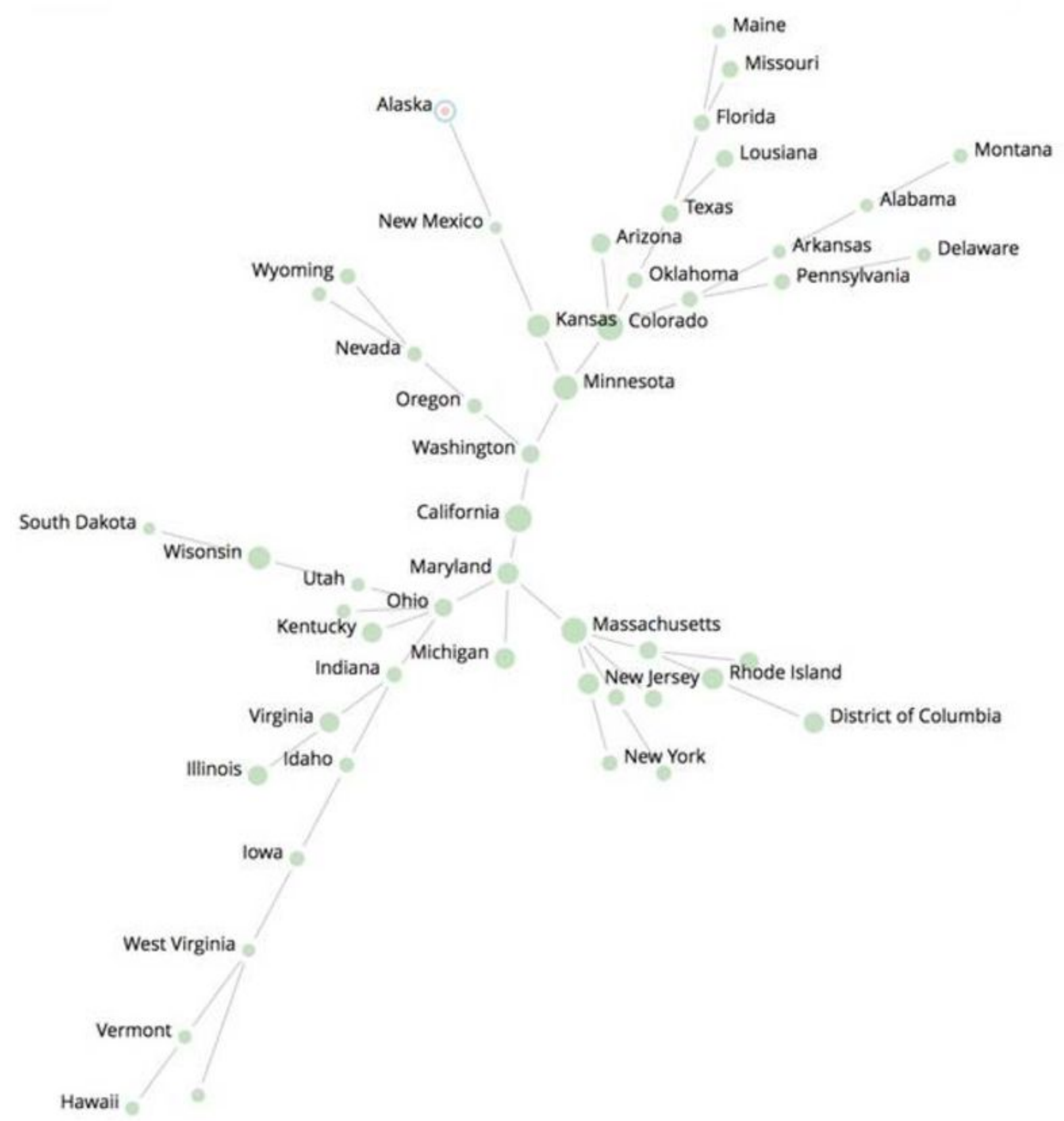
New Tools Give Better Picture, Literally, of Financial-System Risk

Researchers are using network analytics and advanced data modeling to identify weak spots in the system that otherwise might go unnoticed



This sprawling tree shows housing prices in U.S. markets moving with little correlation in 2000. The tree has gotten shorter and shorter since, indicating higher correlation between markets.
PHOTO: FINANCIAL NETWORK ANALYTICS

Soramaki et al (2016). 'A Network-Based Method for Visual Identification of Systemic Risks': Journal of Network Theory in Finance

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House Price Index Correlations

Correlations in changes of House Price Index by state. Data source: Quandl / Federal Reserve Economic Data.

The data displays a clear cascade of negative house price shocks starting in Q1 2007. Also notable is the increase in the overall level of correlations (and connectedness) from 2000 to 2014.

How to read it

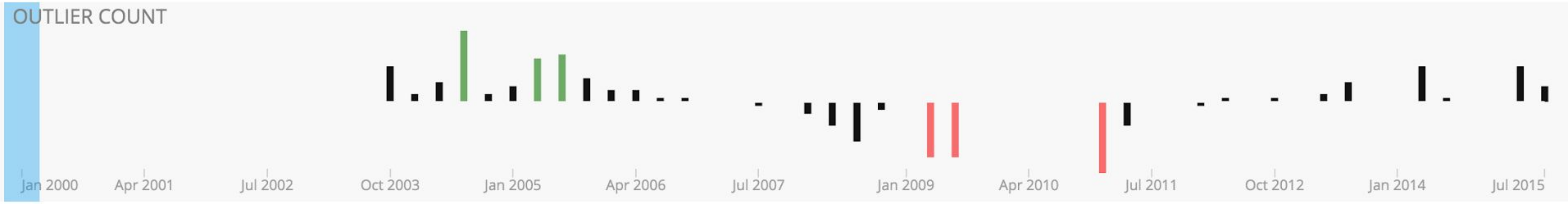
Nodes represent US States. Node color reflects change in price: green is positive, and red is negative. Node size scales with the magnitude of change, bigger nodes have larger price change. Outlier movements are marked with bright colors.

Links show strongest correlations. Among these correlations, shorter link means a stronger correlation.

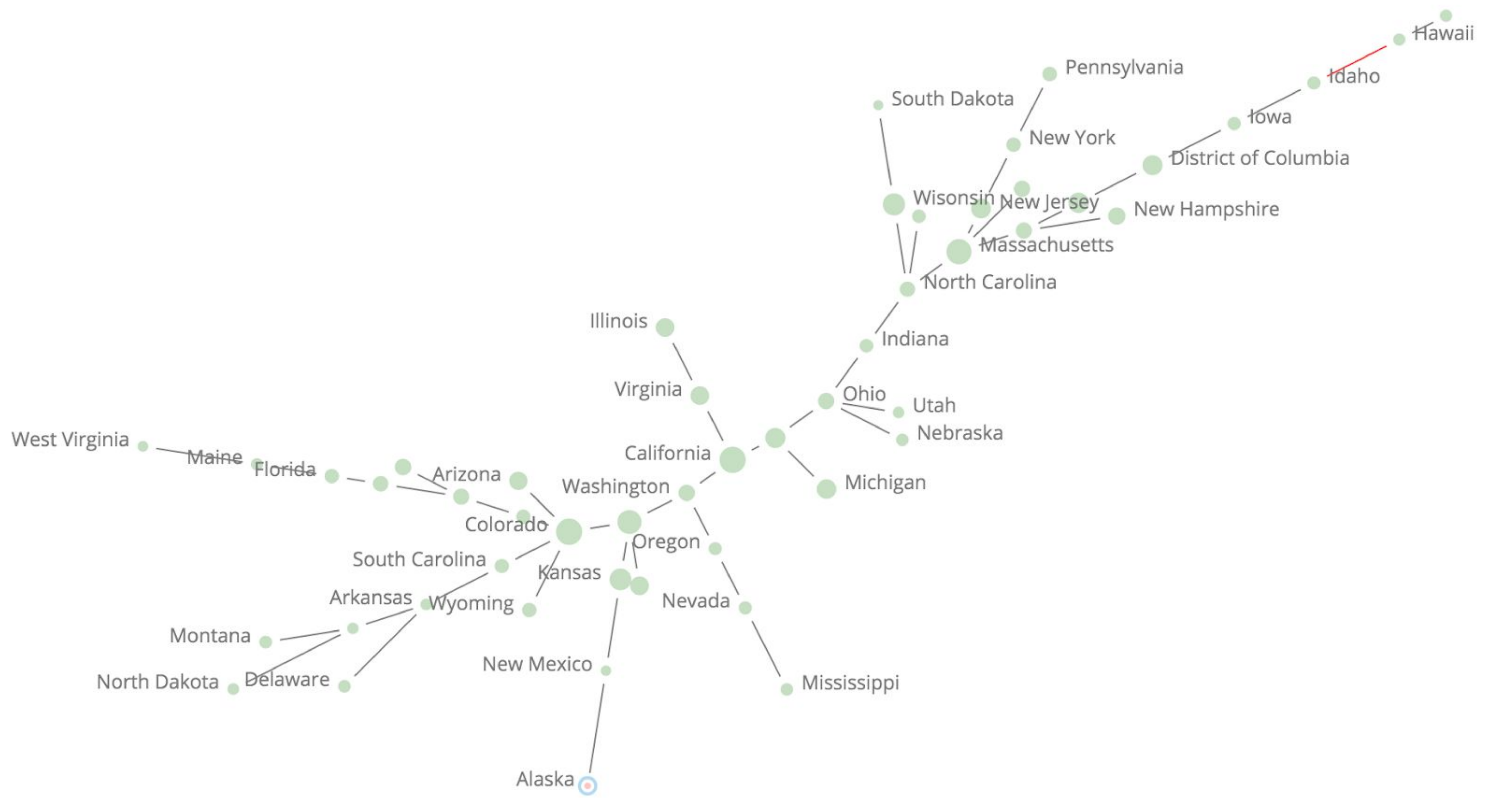
FNA

Sat, 1 Jan 2000 PLAY 1 Jul 1990 - 1 Jul 2015

OUTLIER COUNT



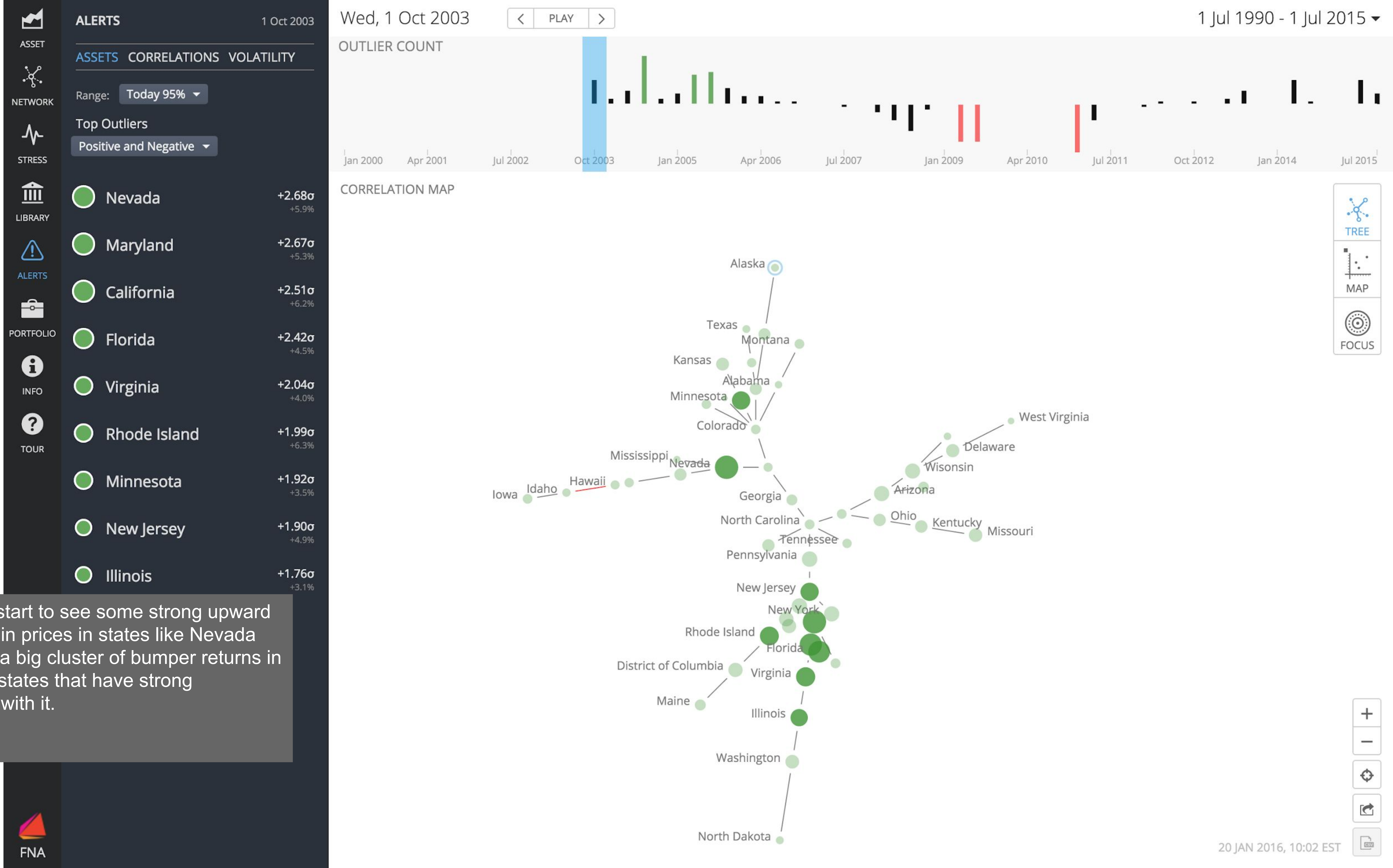
CORRELATION MAP



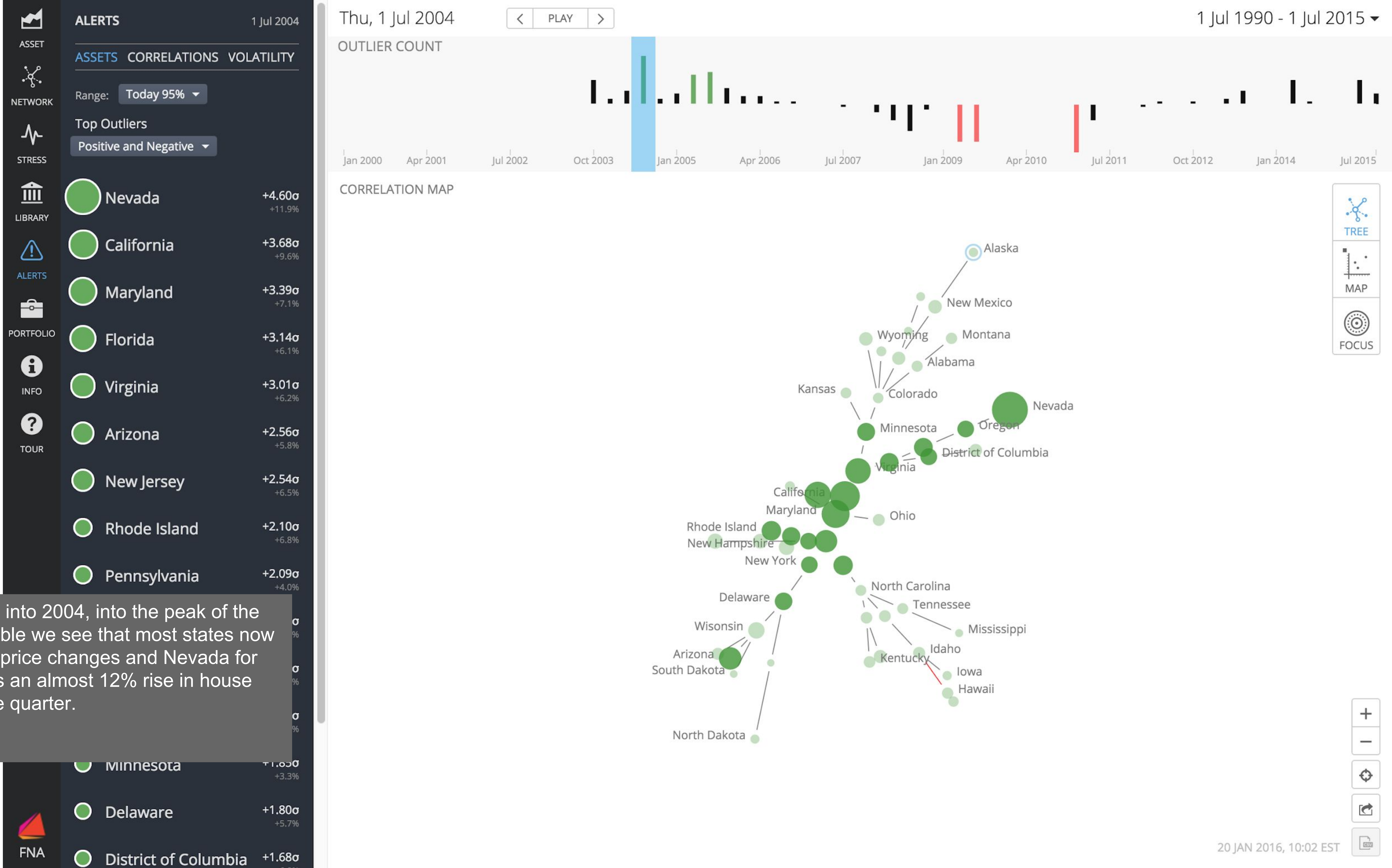
TREE
MAP
FOCUS

20 JAN 2016, 10:02 EST

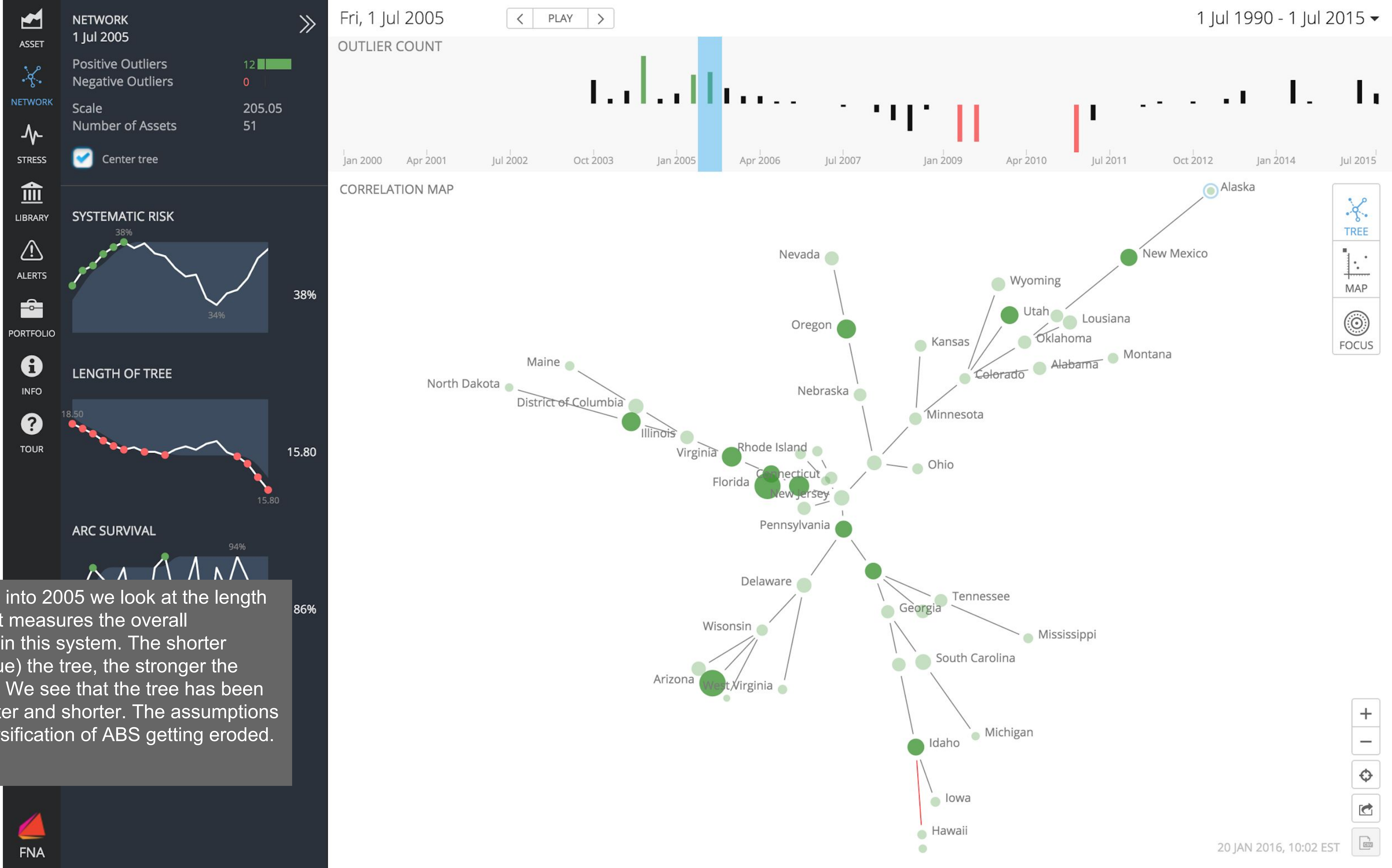
In this example we look at US house prices across states. We see the US states as nodes and strong correlation between house prices as link. In 2000 the tree is very spread out and prices are going slightly up. This is a time when ABS are developed with the assumption that real-estate risk can be diversified across US states.



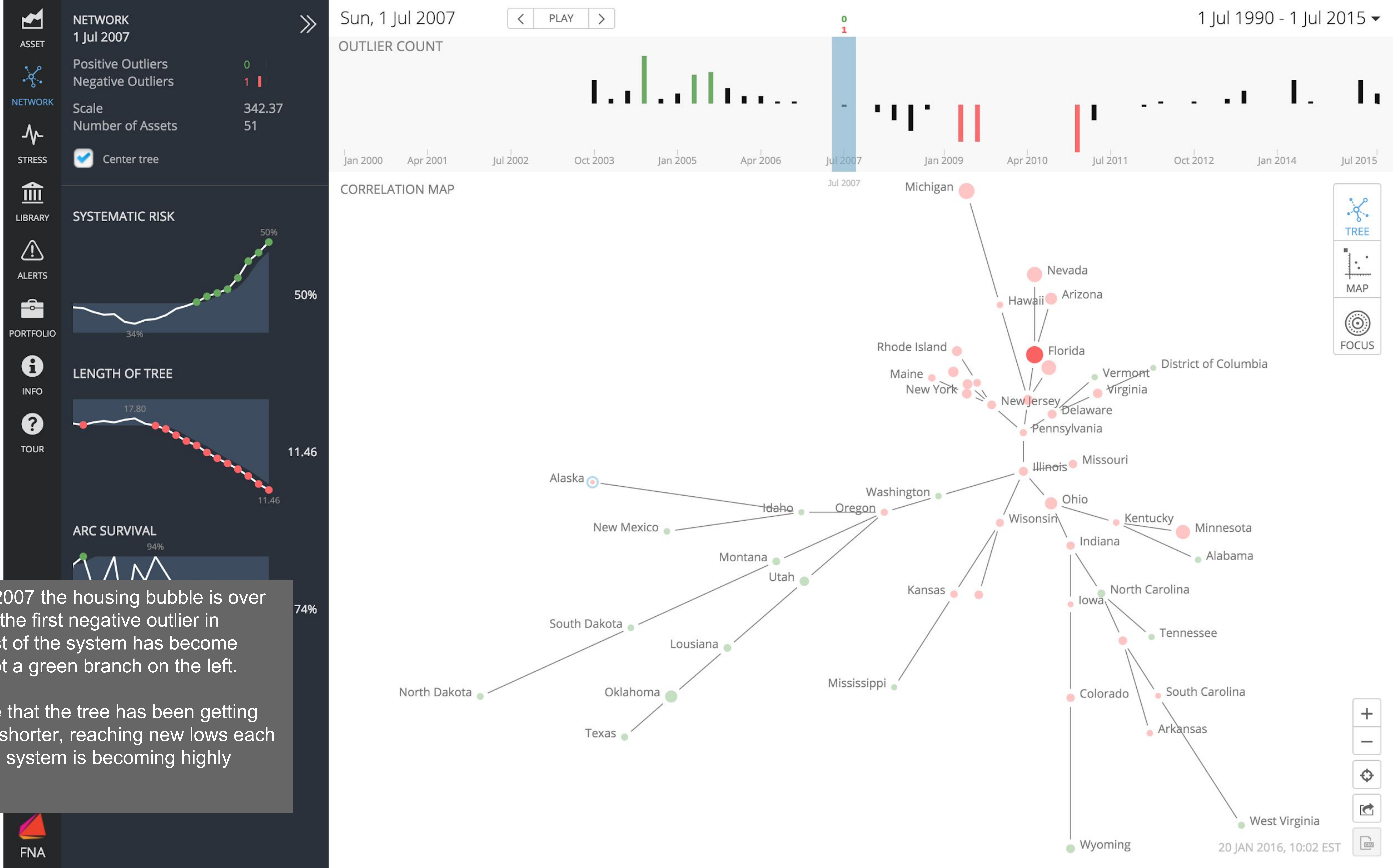
In 2003 we start to see some strong upward movements in prices in states like Nevada and we see a big cluster of bumper returns in Florida and states that have strong correlations with it.



As we move into 2004, into the peak of the housing bubble we see that most states now have outlier price changes and Nevada for example has an almost 12% rise in house prices in one quarter.

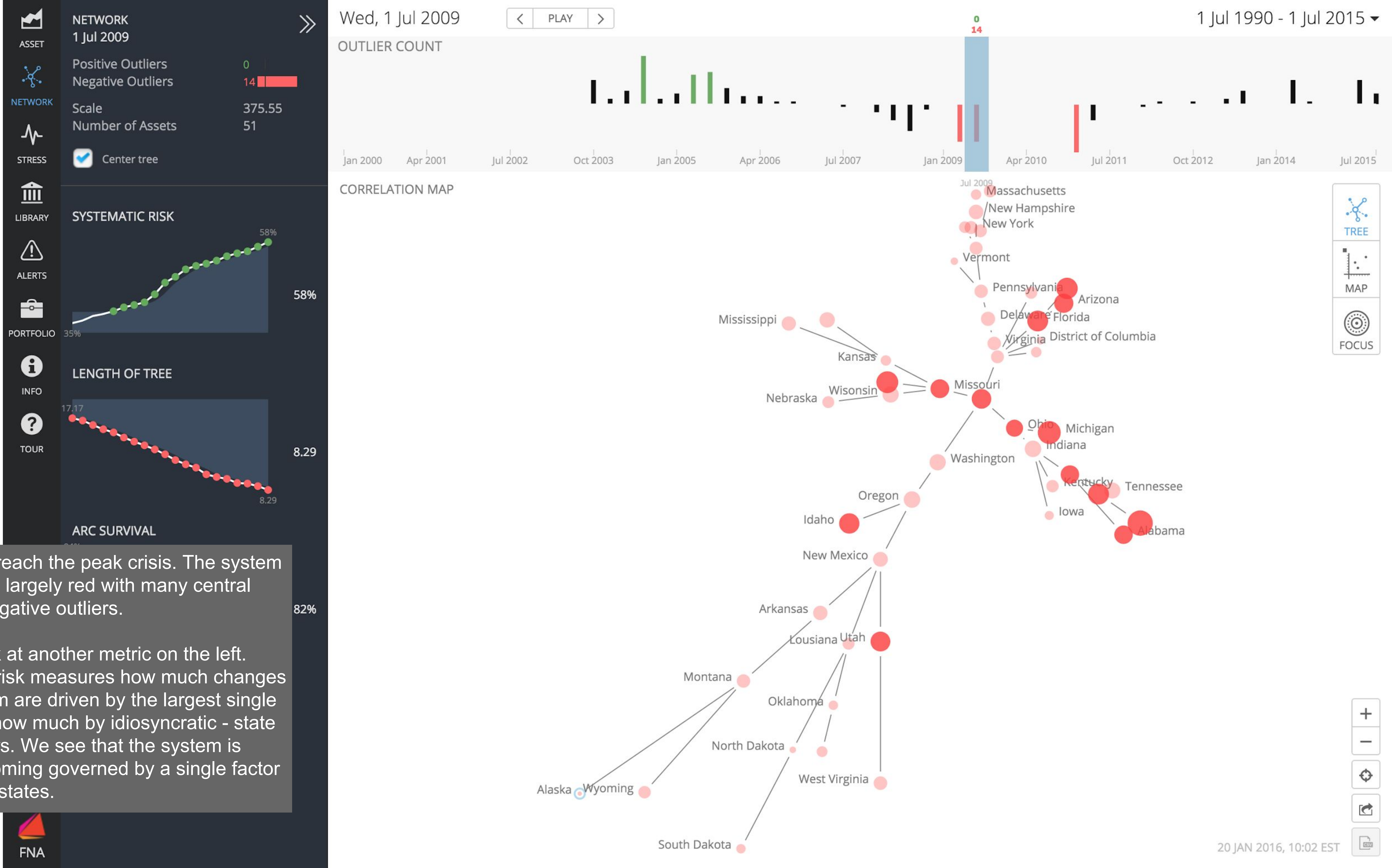


As we move into 2005 we look at the length of the tree. It measures the overall correlations in this system. The shorter (smaller value) the tree, the stronger the correlations. We see that the tree has been getting shorter and shorter. The assumptions behind diversification of ABS getting eroded.



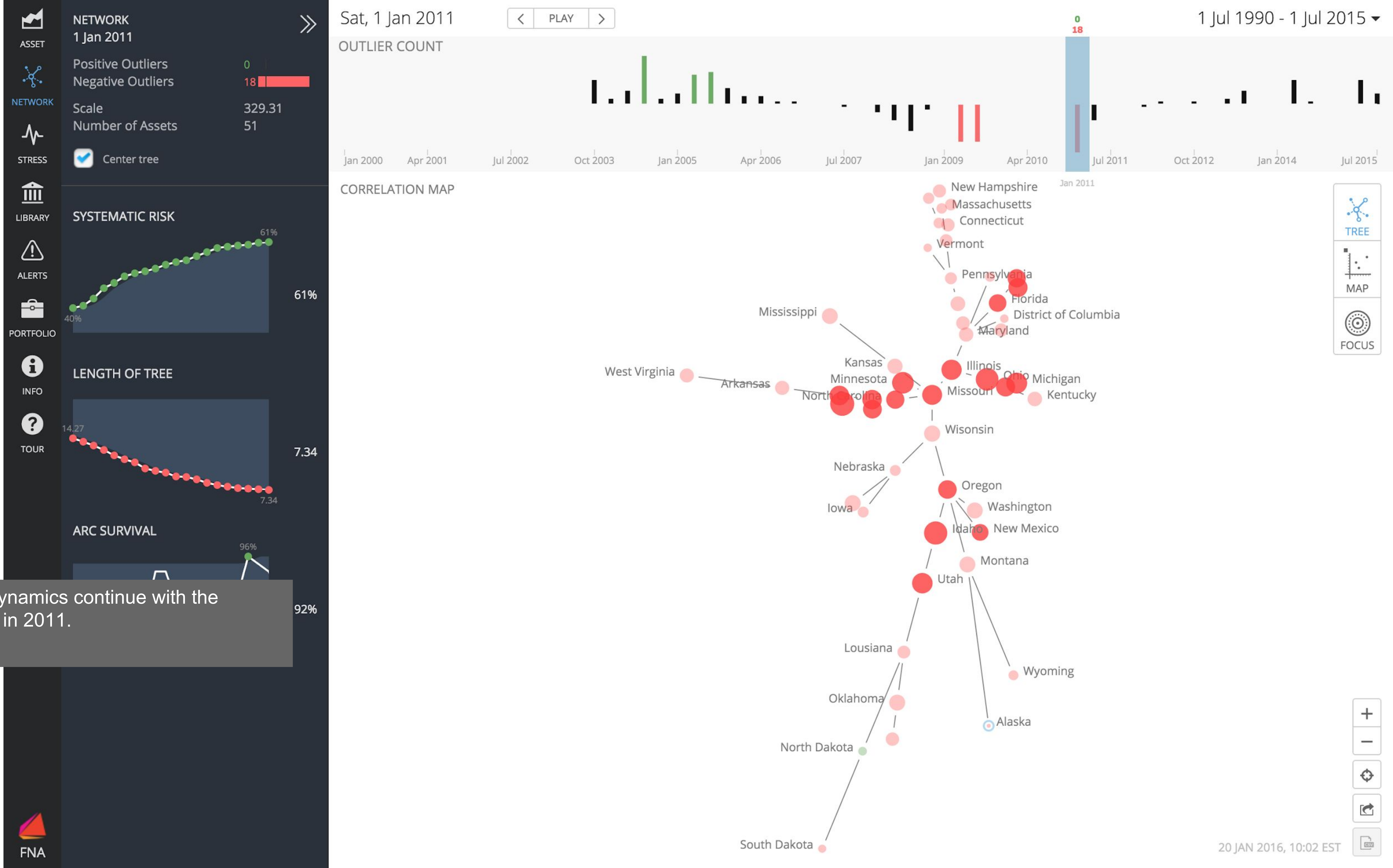
In summer 2007 the housing bubble is over and we see the first negative outlier in Florida. Most of the system has become redm, except a green branch on the left.

We also see that the tree has been getting shorter and shorter, reaching new lows each quarter. The system is becoming highly coupled.

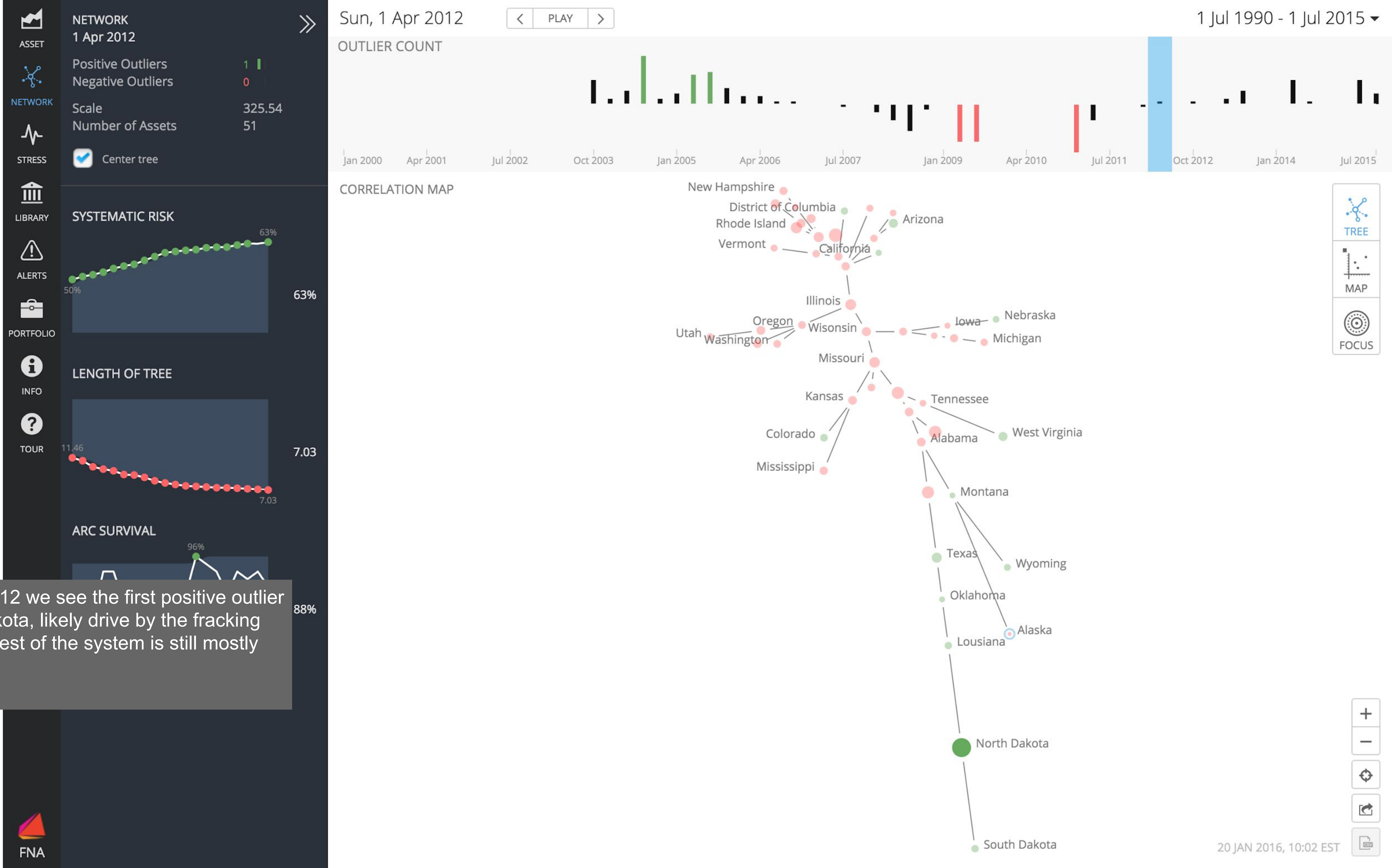


In 2009 we reach the peak crisis. The system has become largely red with many central states as negative outliers.

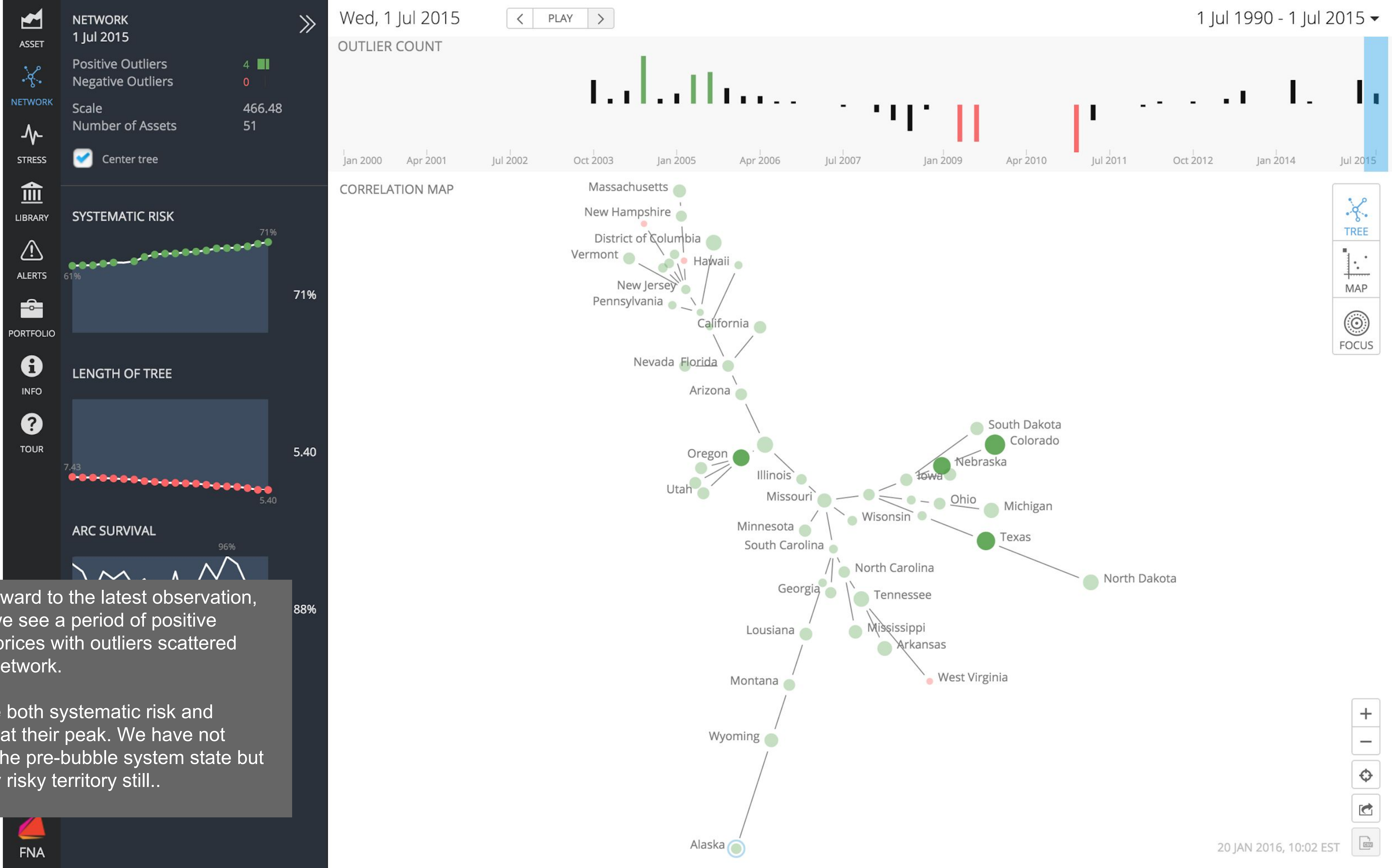
We can look at another metric on the left. Systematic risk measures how much changes in the system are driven by the largest single factor, and how much by idiosyncratic - state level - factors. We see that the system is quickly becoming governed by a single factor affecting all states.



The same dynamics continue with the “double dip” in 2011.



In Spring 2012 we see the first positive outlier in North Dakota, likely drive by the fracking boom. The rest of the system is still mostly negative.

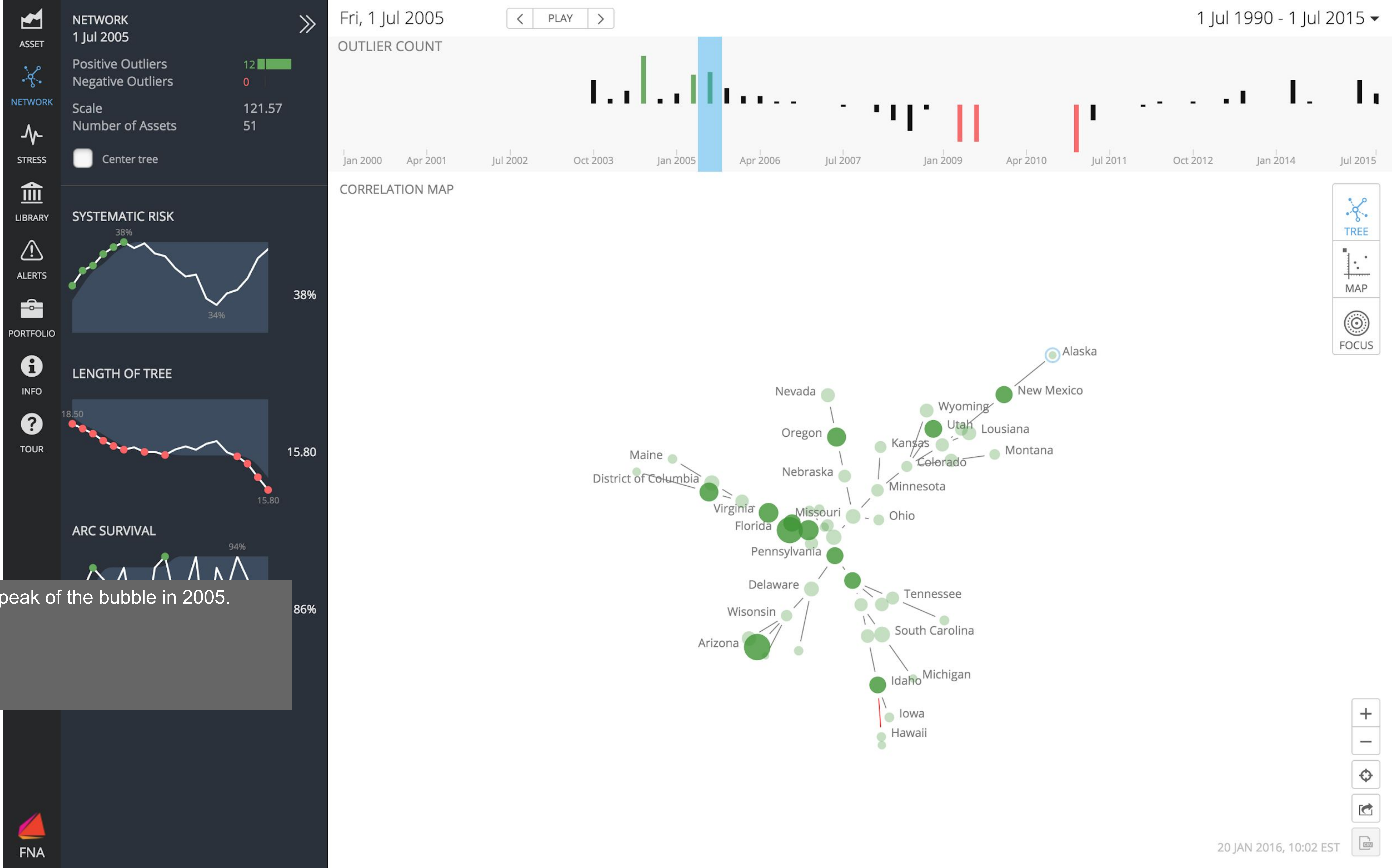


If we fast forward to the latest observation, July 2015, we see a period of positive changes in prices with outliers scattered across the network.

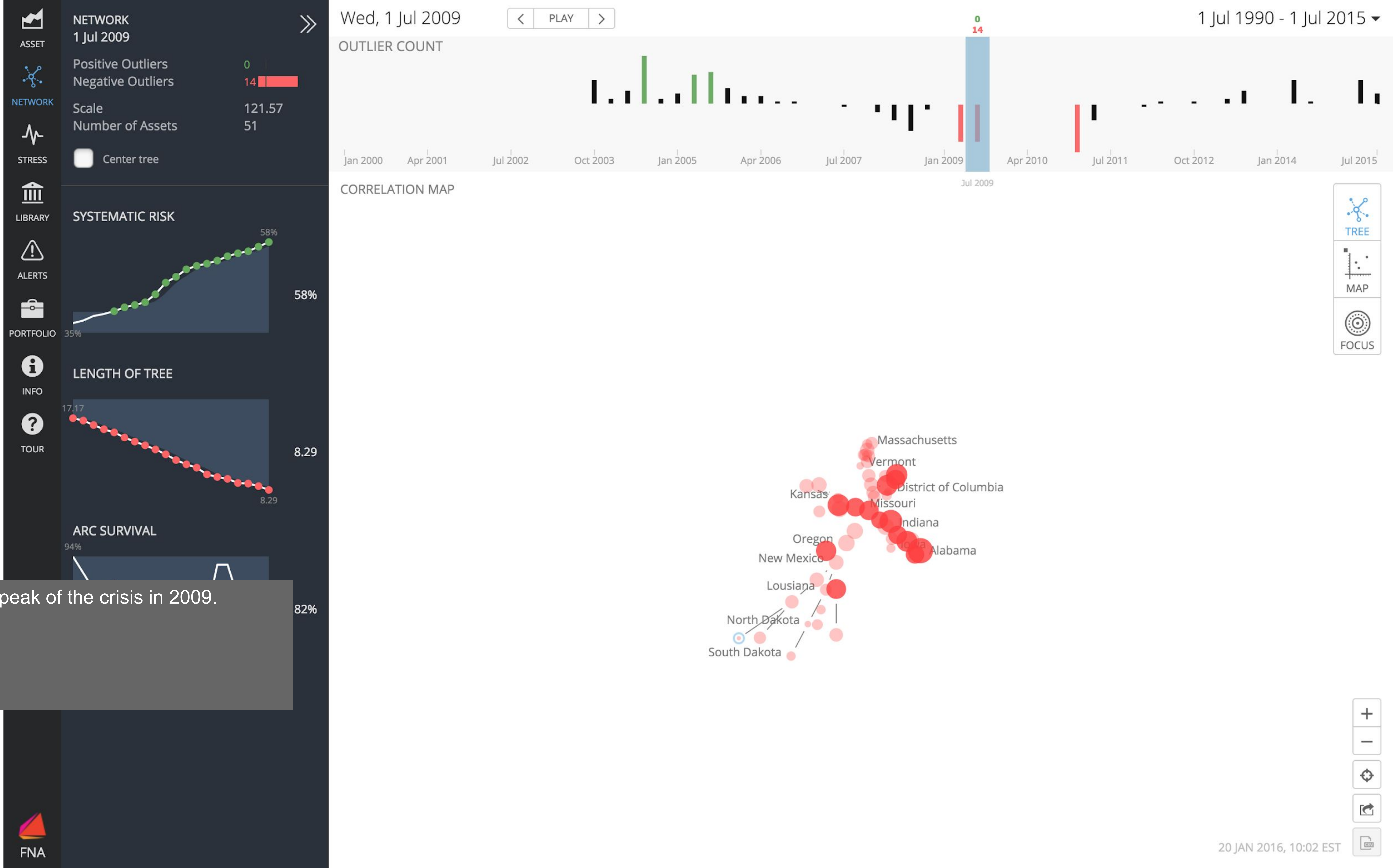
We also see both systematic risk and correlations at their peak. We have not returned to the pre-bubble system state but are in a very risky territory still..

We can see this clearly by looking at the size of the tree.

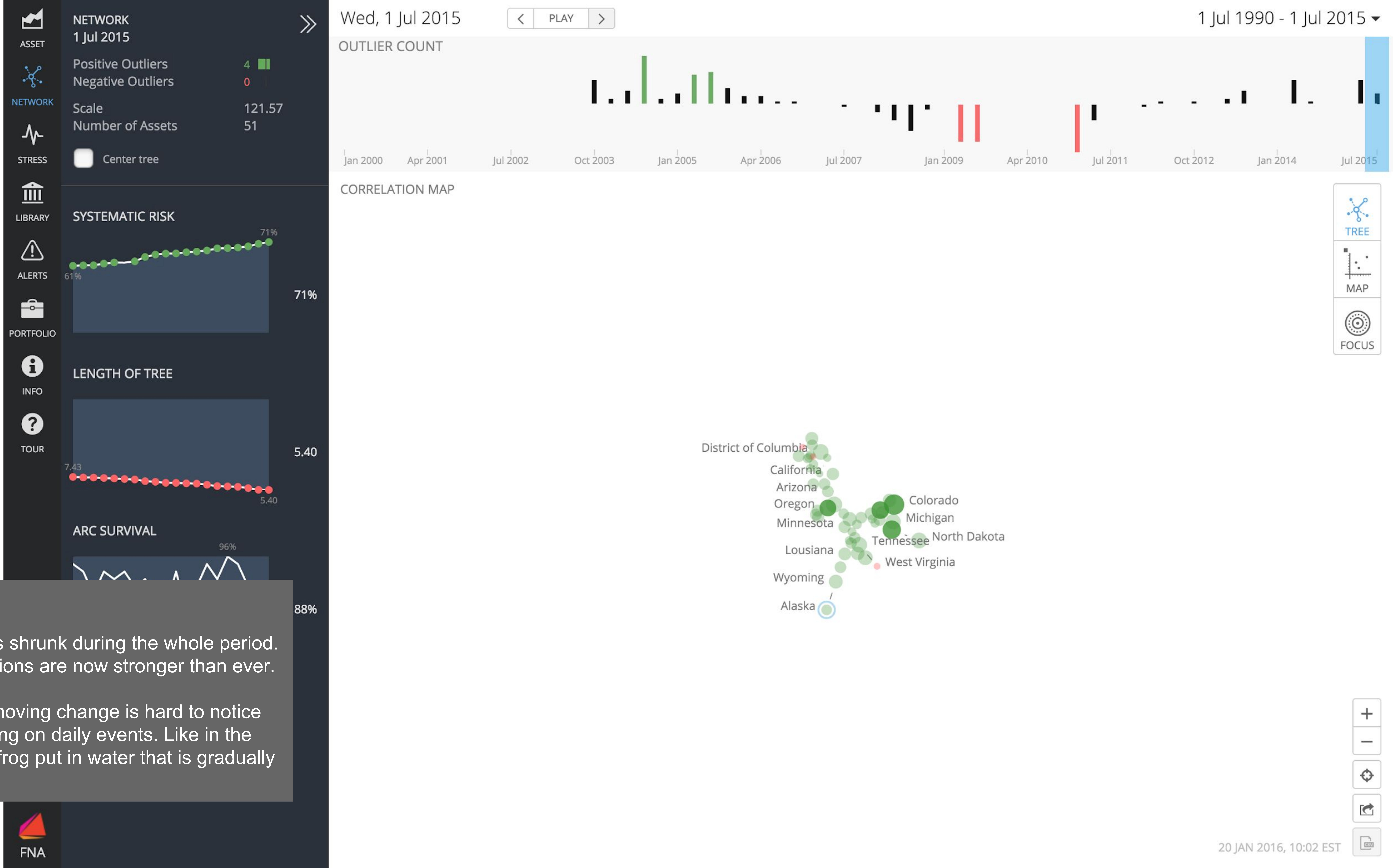
First in 2010.



Then at the peak of the bubble in 2005.



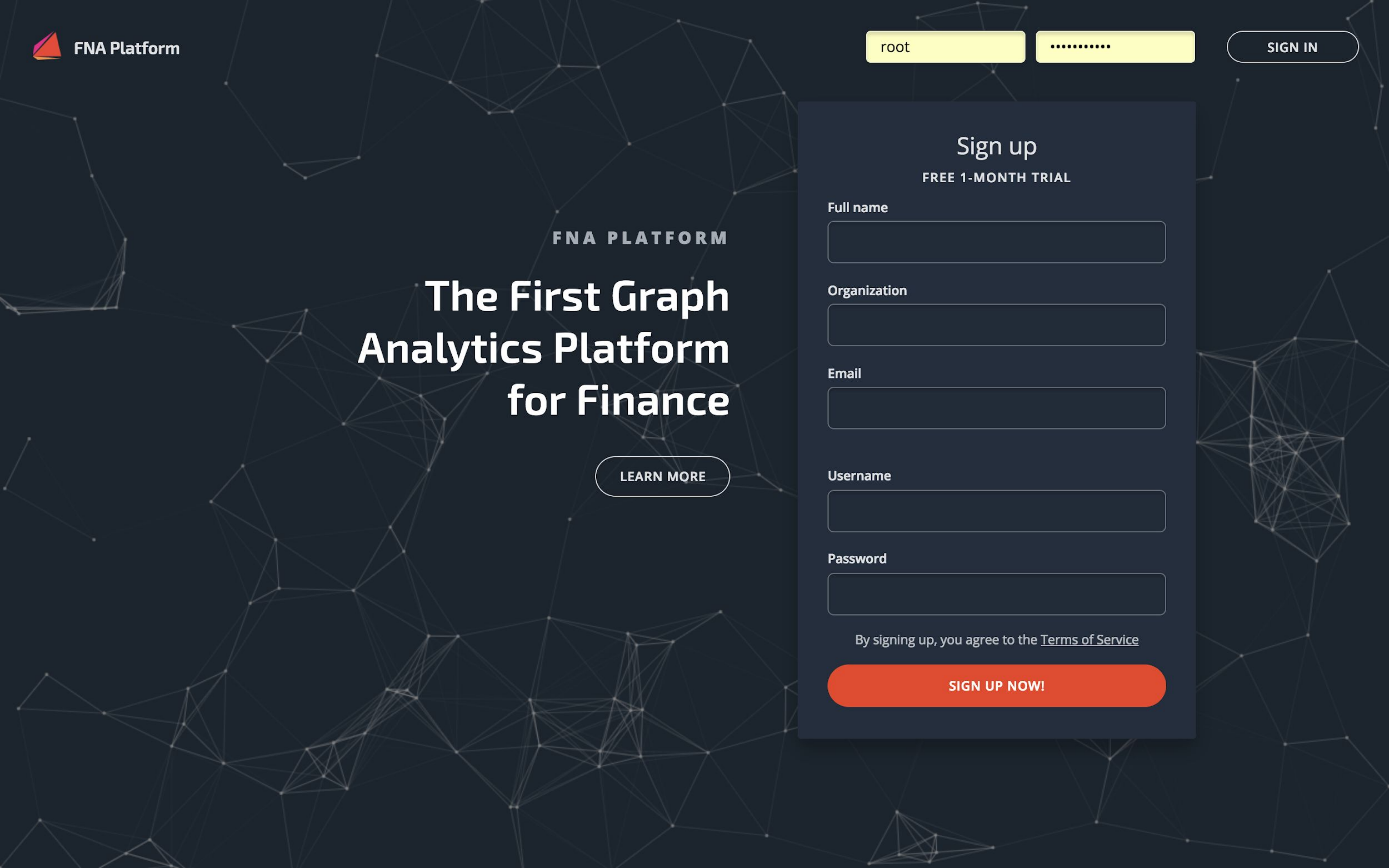
Then at the peak of the crisis in 2009.



And now.

The tree has shrunk during the whole period. The correlations are now stronger than ever.

Such slow moving change is hard to notice when focusing on daily events. Like in the story of the frog put in water that is gradually heated.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FNA

Introduction to Network Science & Visualization II

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Agenda

Financial Crime & Cyber Risks

- Fraud, AML & KYCC
- DDoS Attacks
- Related Parties Analysis

Financial Market Infrastructures

- Monitoring Members
- Designing liquidity efficient FMIs
- Predicting Liquidity
- Detecting Anomalous transactions

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Fraud

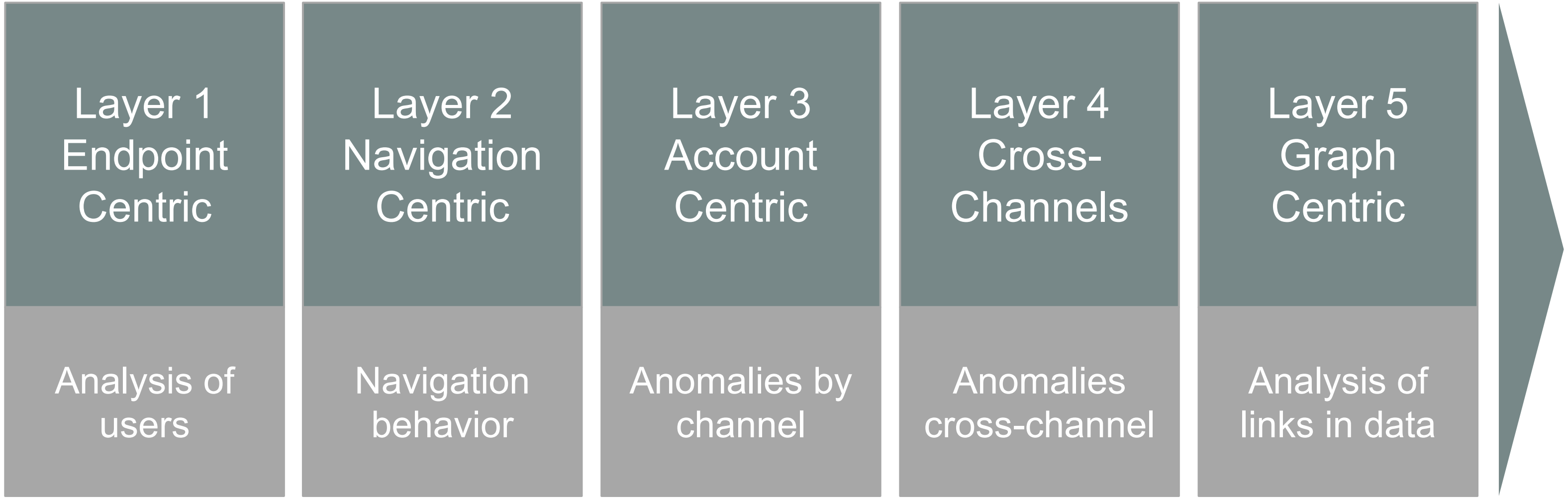
The Challenge

Intensified regulatory pressures has increased the number of false positives generated by existing software solutions

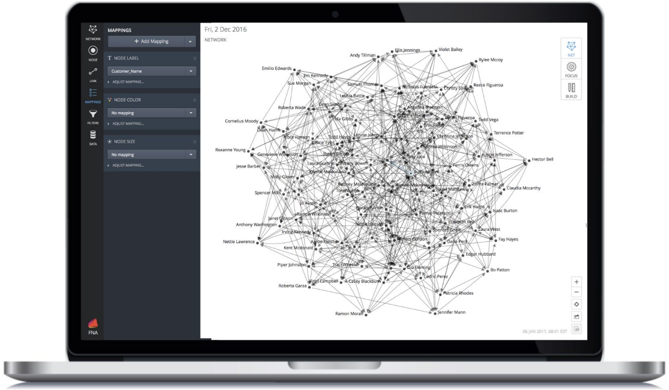
It is increasingly difficult for banks and financial institutions to quickly identify fraudsters.

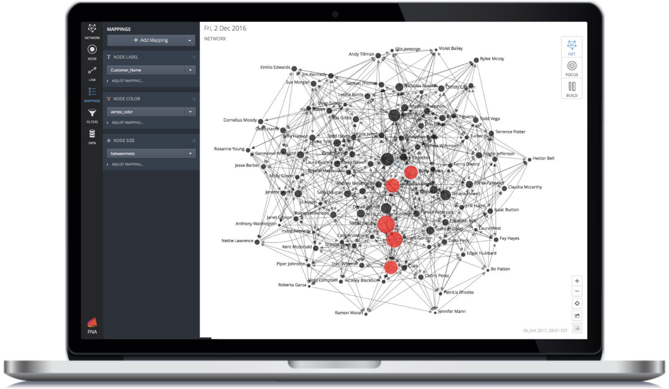
The cost is $50 billion in fraudulent transactions happening each year.

Gartner's Layered Model of Fraud Prevention



Use Case: Improving Fraud Detection





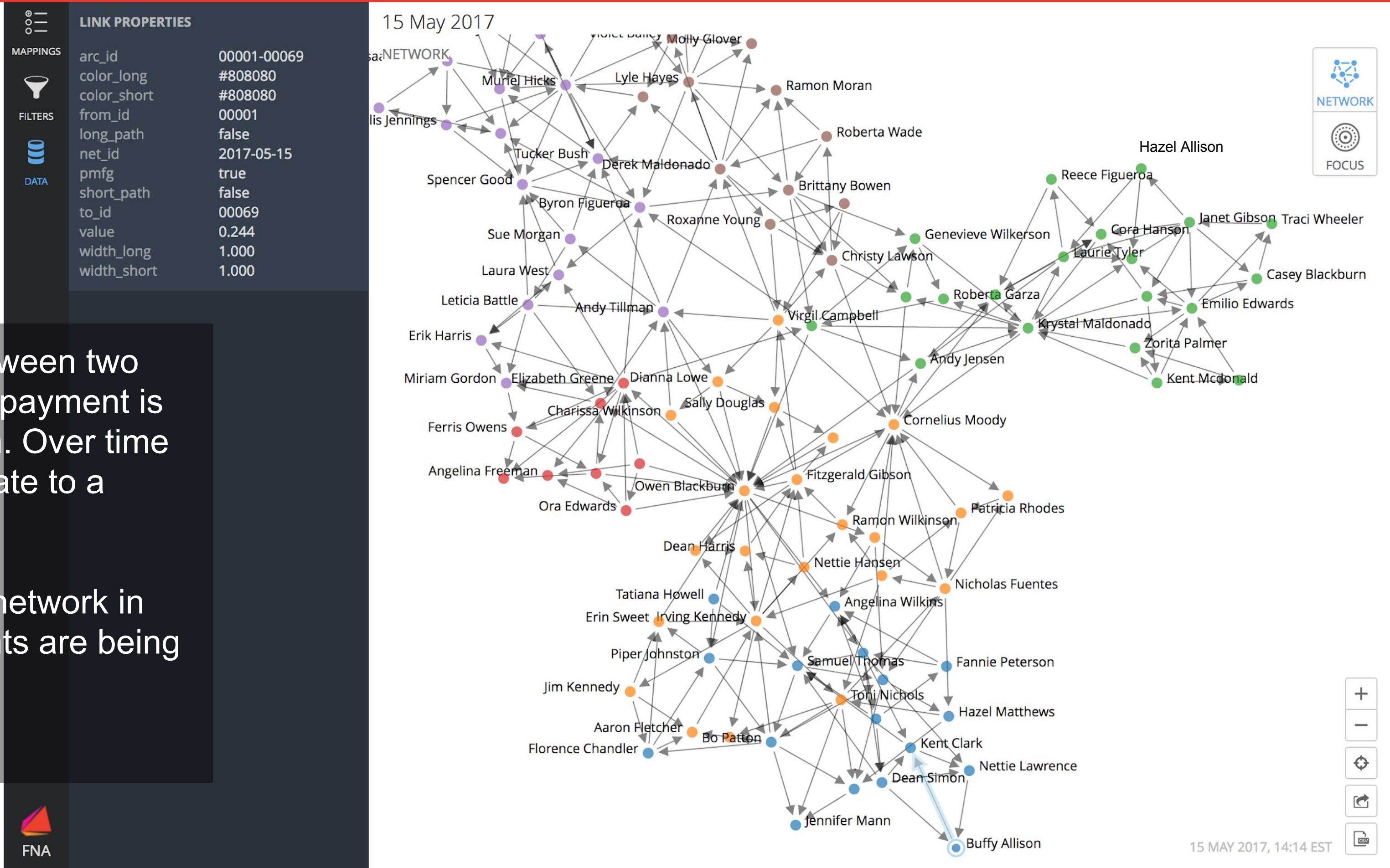
Background
In 2017 global banks were fined £5B for failures to detect and address money laundering. Current methods are insufficient in identifying money laundering, and costly in terms of large amounts of manual labour needed.

Method
Payments form networks which can be automatically analyzed by network science algorithms. Existing research on large datasets proved that particular graph properties are good predictors of fraudulent transactions.

Benefits
Graphs improve fraud detection by eliminating false positives and identifying true positives more accurately - saving time and money.

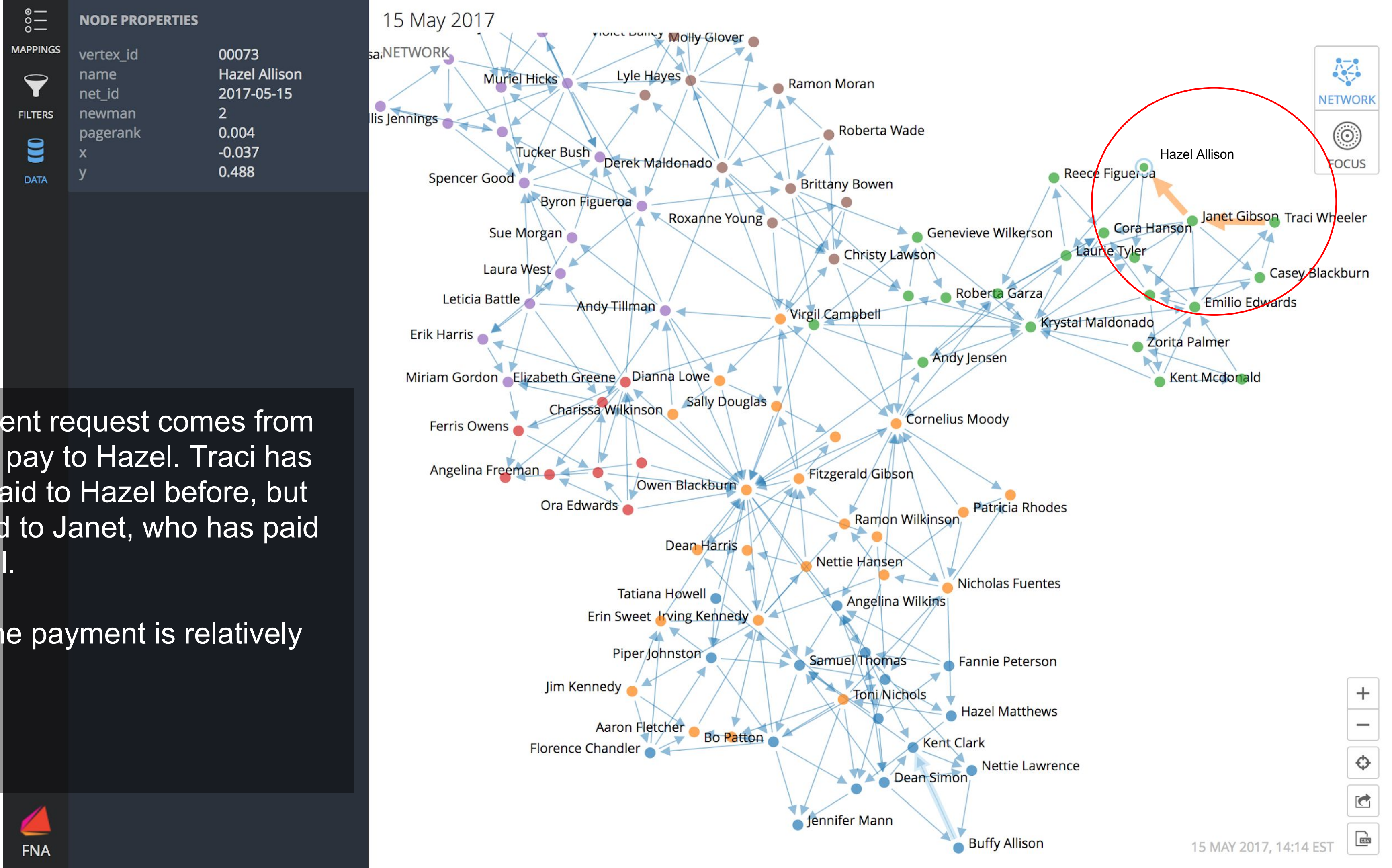
Molloy et al (2017), Graph Analytics for Real-time Scoring of Cross-channel Transactional Fraud

Basic Idea: Using Graphs in Automated Fraud Detection



We create a link between two account holders if a payment is made between them. Over time these links accumulate to a network.

We can update the network in real-time as payments are being processed.



A payment request comes from Traci to pay to Hazel. Traci has never paid to Hazel before, but has paid to Janet, who has paid to Hazel.

Thus, the payment is relatively normal.

MAPPINGS

FILTERS

DATA

NODE PROPERTIES

vertex_id	00001
name	Buffy Allison
net_id	2017-05-15
newman	3
pagerank	0.010
x	1.482
y	0.345

Another payment request comes from Traci to pay to Buffy. Traci and Buffy are very far apart in the network making the payment unusual.

We can operationalise how 'normal' the payment is with a network measure of distance, which in this case is 7 (and in previous case it was 2)

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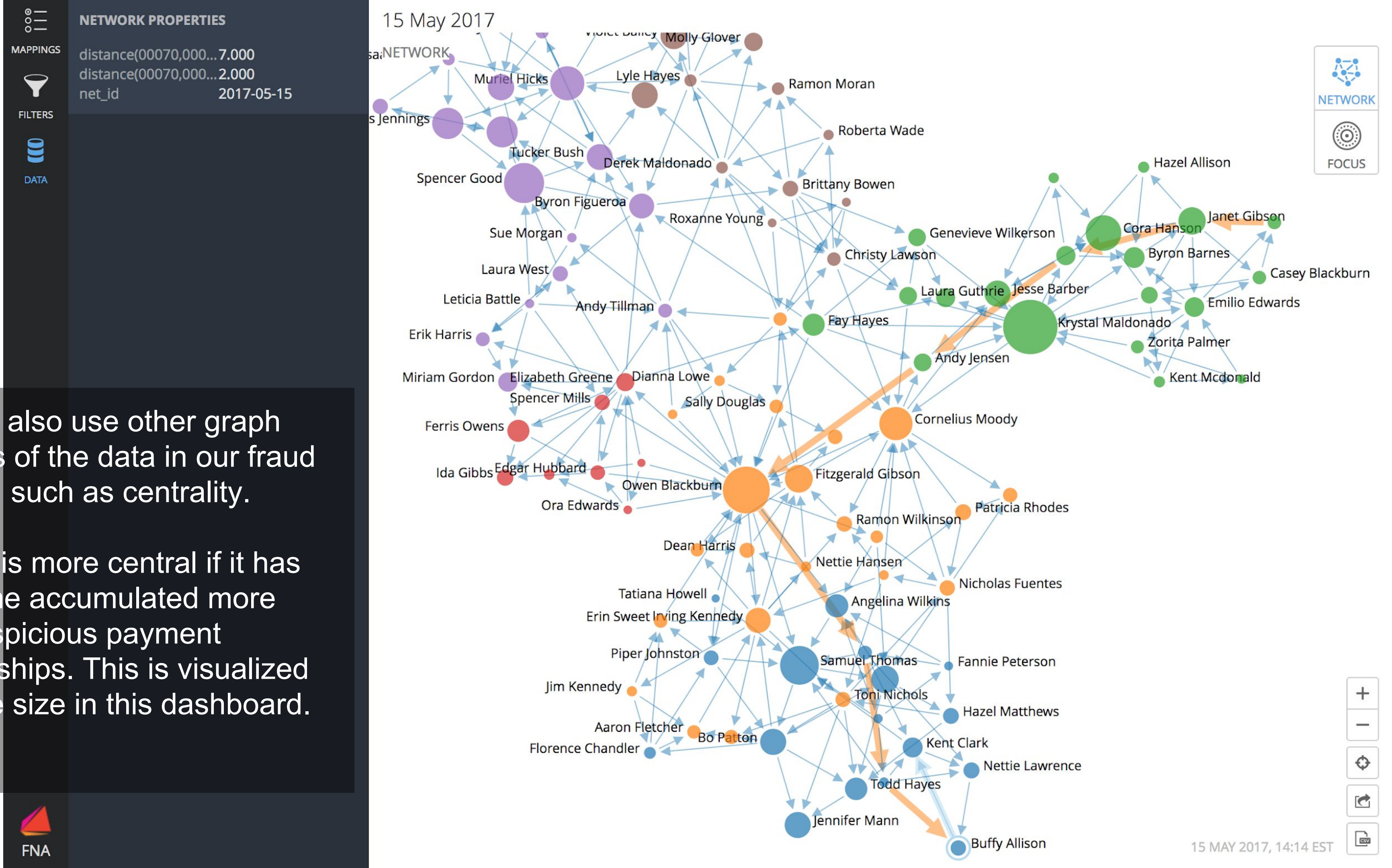

We can also use other graph features of the data in our fraud models, such as centrality.

A node is more central if it has over time accumulated more non-suspicious payment relationships. This is visualized as node size in this dashboard.

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AML and Suspicious Activity

Company Interconnectedness

Challenge

Understand corporate interconnections for due diligence, fraud/criminal investigation, KYC, KYCC.

Current Situation

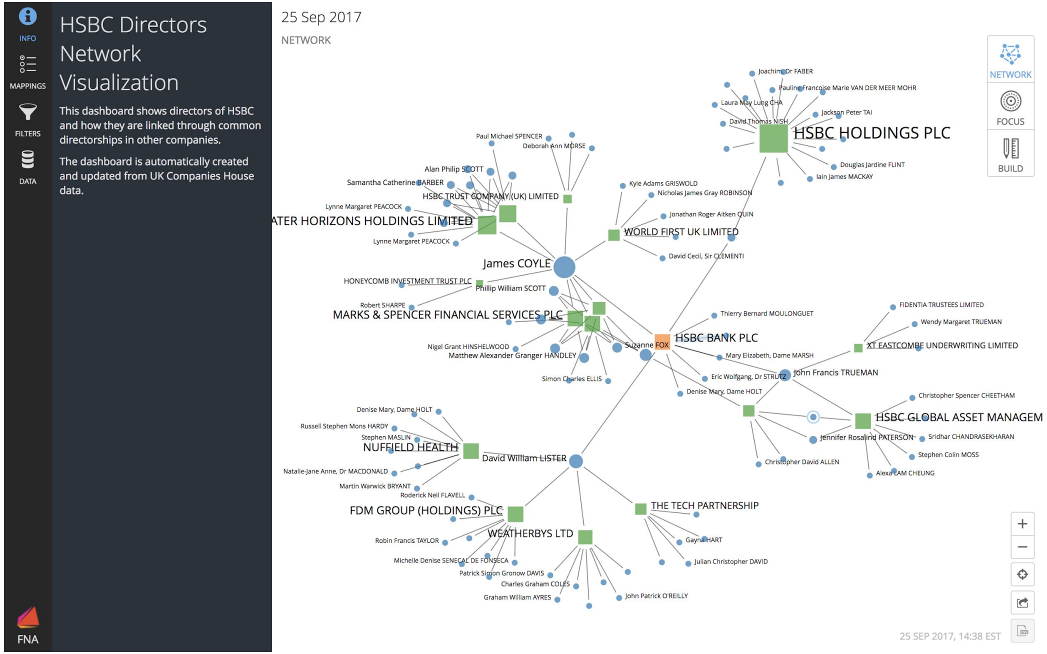
Manual investigation.

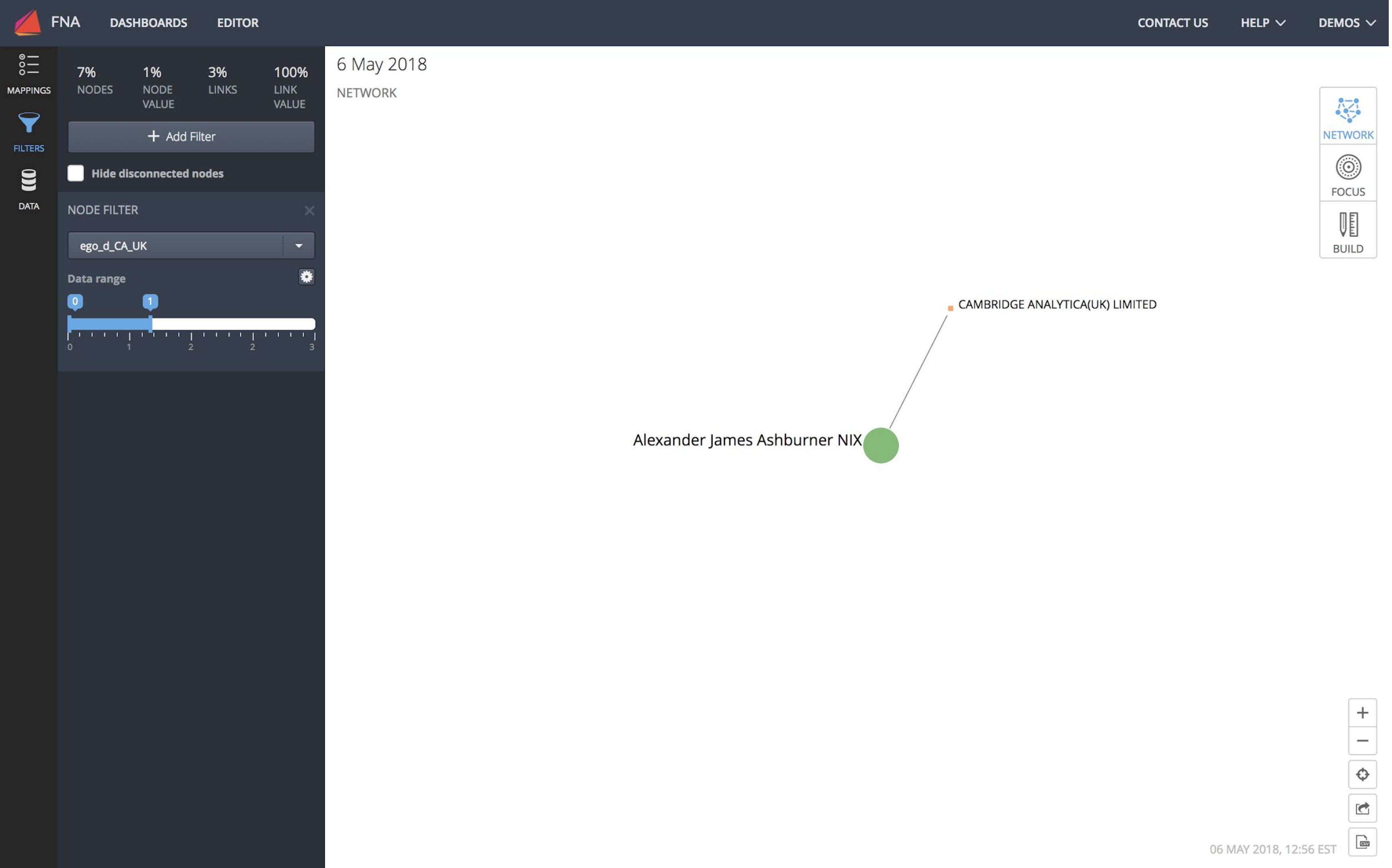
Solution

FNA has built a connection to Companies House register to automatically build graphs for any UK company.

Benefits

Save time and achieve a systemic view of company interconnectedness.

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7% NODES
1% NODE VALUE
3% LINKS
100% LINK VALUE
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NODE FILTER
ego_d_CA_UK
Data range
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NETWORK
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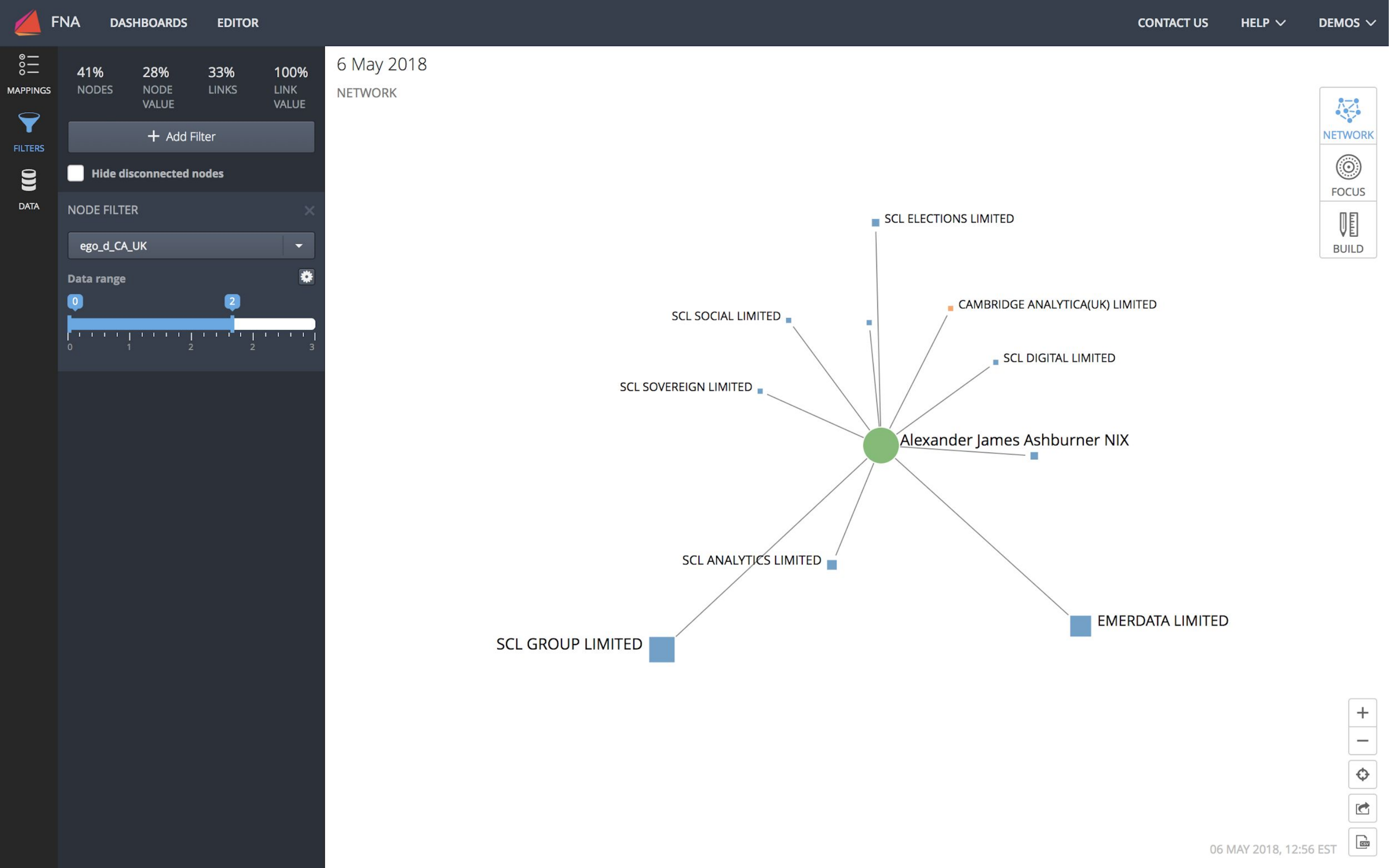
BUILD
CAMBRIDGE ANALYTICA(UK) LIMITED
Alexander James Ashburner NIX
06 MAY 2018, 12:56 EST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41% NODES
28% NODE VALUE
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100% LINK VALUE
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NODE FILTER
ego_d_CA_UK
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CAMBRIDGE ANALYTICA(UK) LIMITED
SCL SOCIAL LIMITED
SCL DIGITAL LIMITED
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SCL GROUP LIMITED
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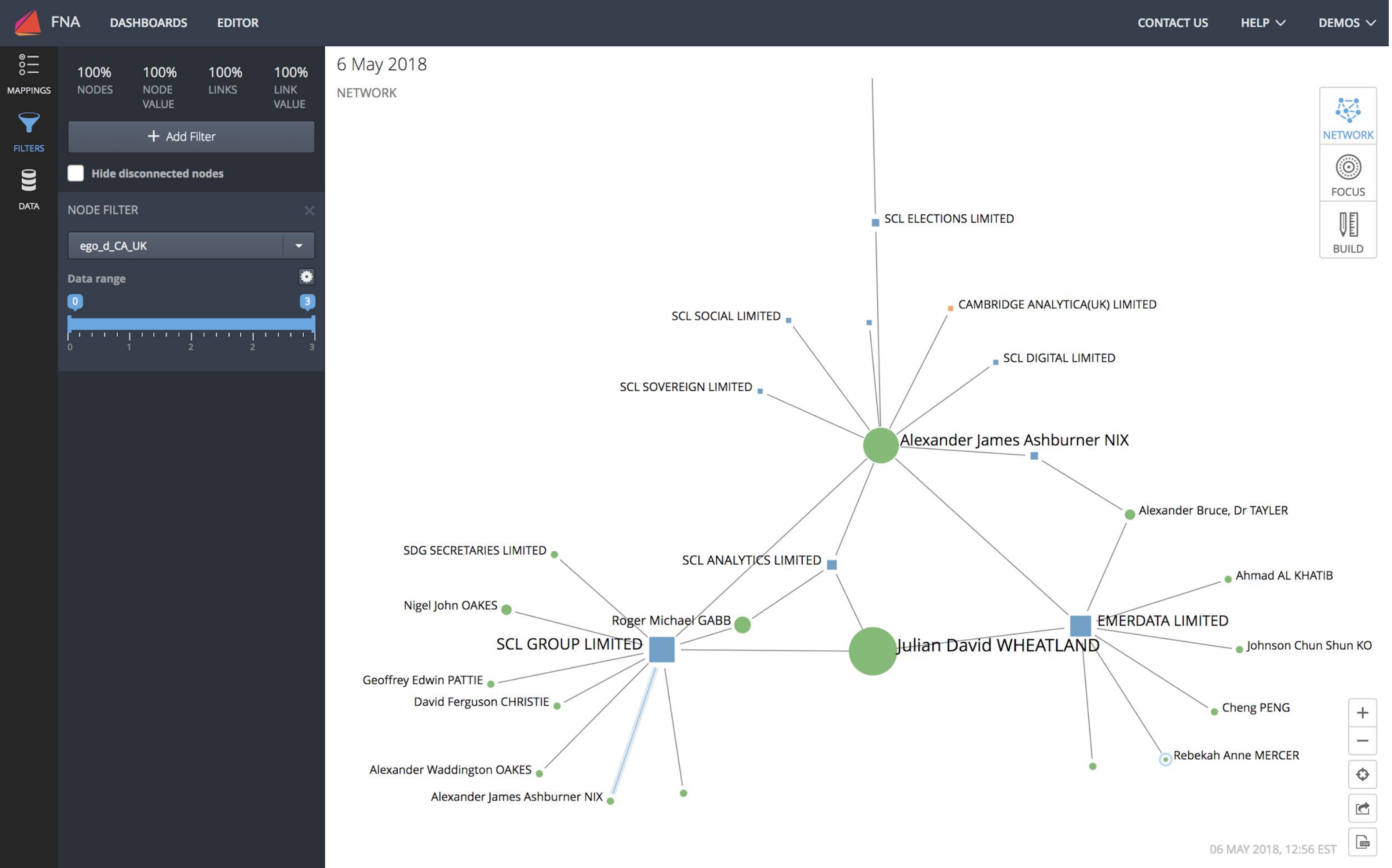
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Alexander Bruce, Dr TAYLER
SDG SECRETARIES LIMITED
SCL ANALYTICS LIMITED
Ahmad AL KHATIB
Nigel John OAKES
Roger Michael GABB
EMERDATA LIMITED
SCL GROUP LIMITED
Julian David WHEATLAND
Johnson Chun Shun KO
Geoffrey Edwin PATTIE
David Ferguson CHRISTIE
Cheng PENG
Rebekah Anne MERCER
Alexander Waddington OAKES
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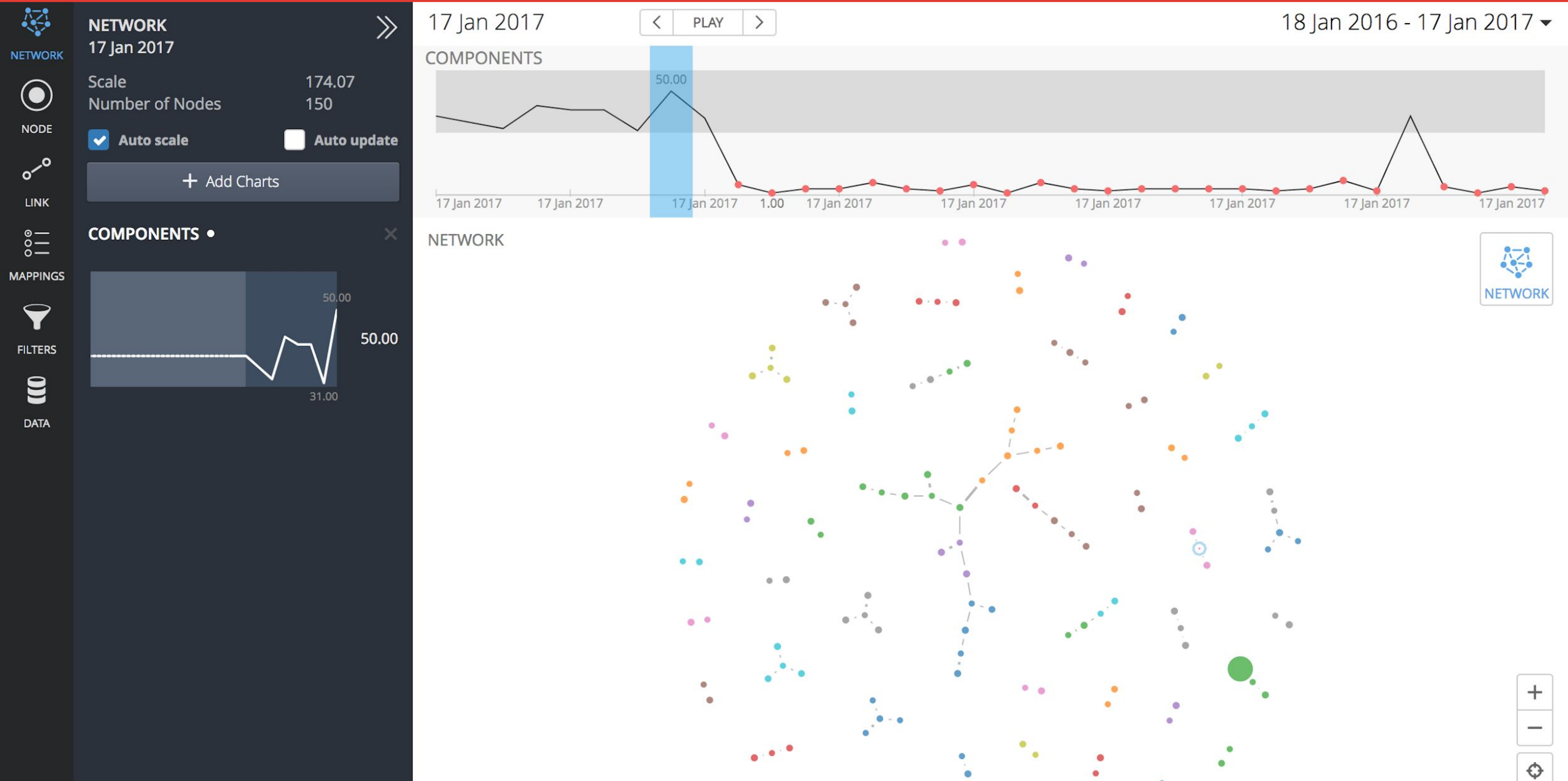
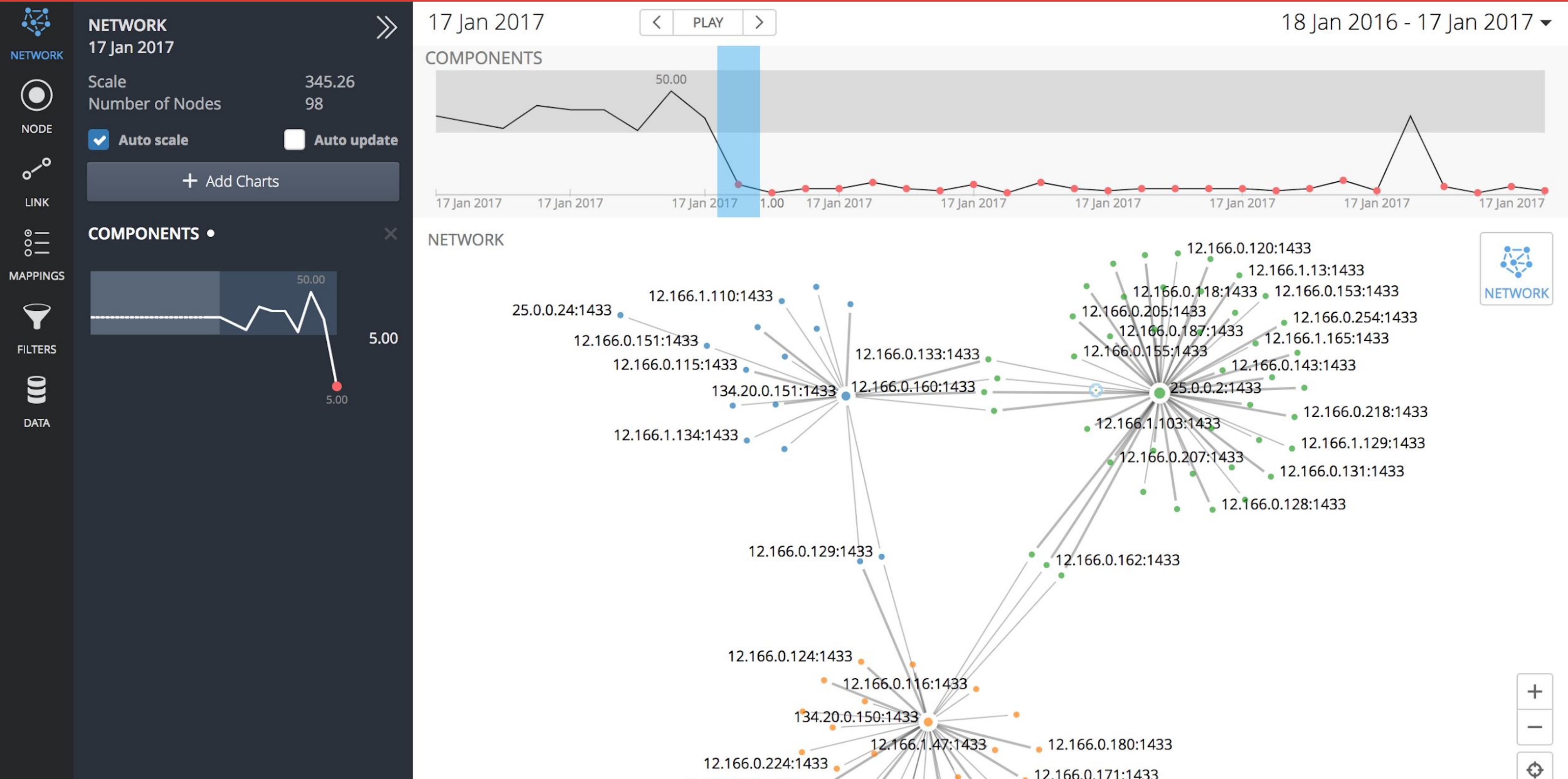
DDoS Attacks

Detect Anomalies in Cyber Networks in Real-time



Identify Patterns of DDoS attacks



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Supply Chains Networks

MAPPINGS

FILTERS

DATA

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LINK PROPERTIES

arc_id	3M CO-SAMSUNG ELECTRON
buyer-country	KR
from_id	3M CO
net_id	2012-01-01
share-of-buyer-cost	0.710
share-of-supplier-r...	2.370
supplier-country	US
to_id	SAMSUNG ELECTRON
value	706.490

1 Jan 2012

NETWORK

NETWORK

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15 MAY 2017, 15:27 EST

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Monitoring & Simulating FMIs & their Members

Use Case: Understanding Interconnectedness

Mapping SWIFTs global payment network

Background
SWIFT message services are used by over 11,000 financial institutions in more than 200 countries. SWIFT was interested what insights could be drawn from the "Big Data" that it collects when transmitting messages between financial institutions.

Objective
Analyse the payment networks created by flows of SWIFT MT103 messages to draw insights about macroeconomic, geo-political and compliance topics.

Insights
Analysis of the SWIFT payment networks revealed a number of insights, including the phenomena of de-risking, payment country blocks relevant for sanctions analysis and how geopolitics shape them, and estimated the cost of the financial crisis at $5 Trillion. The outcome of the research was presented at Sibos 2014 by SWIFT CEO Gottfried Leibbrandt.

SWIFT Institute Research Paper: The global network of payment flows
Research Paper: The Impact of Anti-Money Laundering Regulation on Payment Flows

SWIFT - Big Data Problem

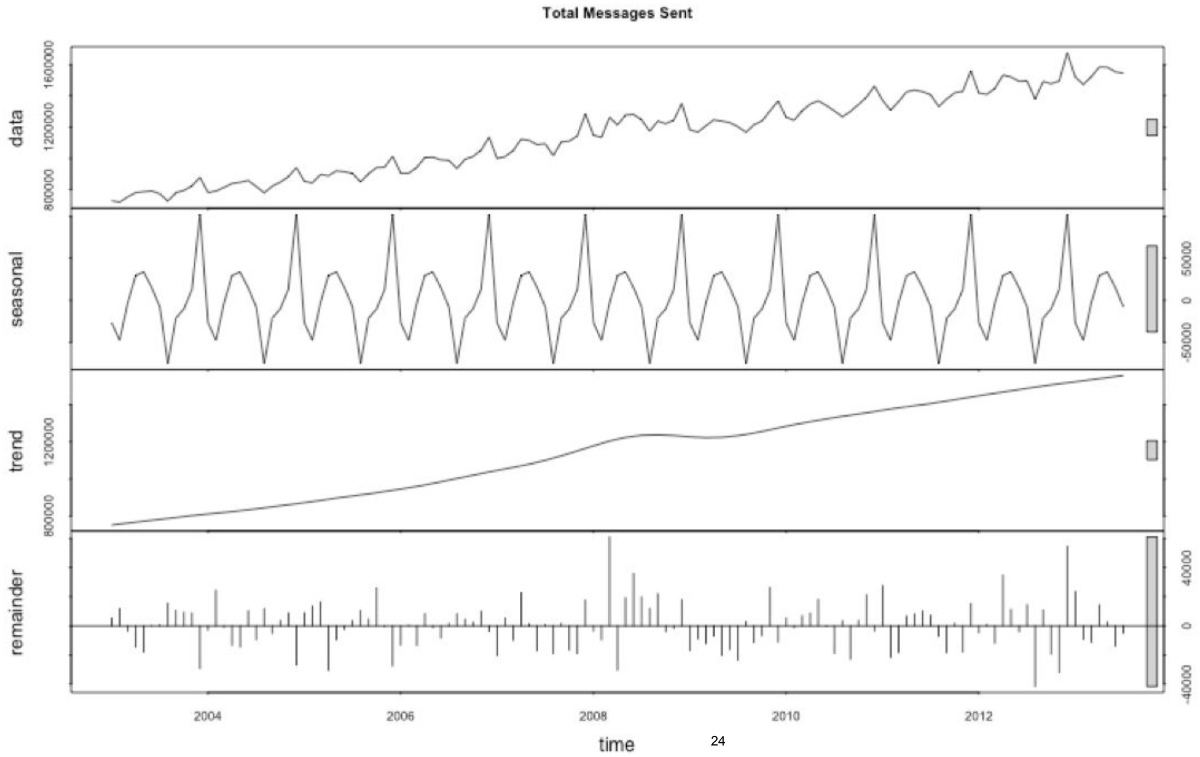
Big data problem: Three billion messages exchanged among banks in 231 countries.

We focus on aggregated links among countries.

Analysis and visualization a challenge. We don't want to show much information (as on this picture).

SWIFT - The Cost of Financial Crisis $5tr?

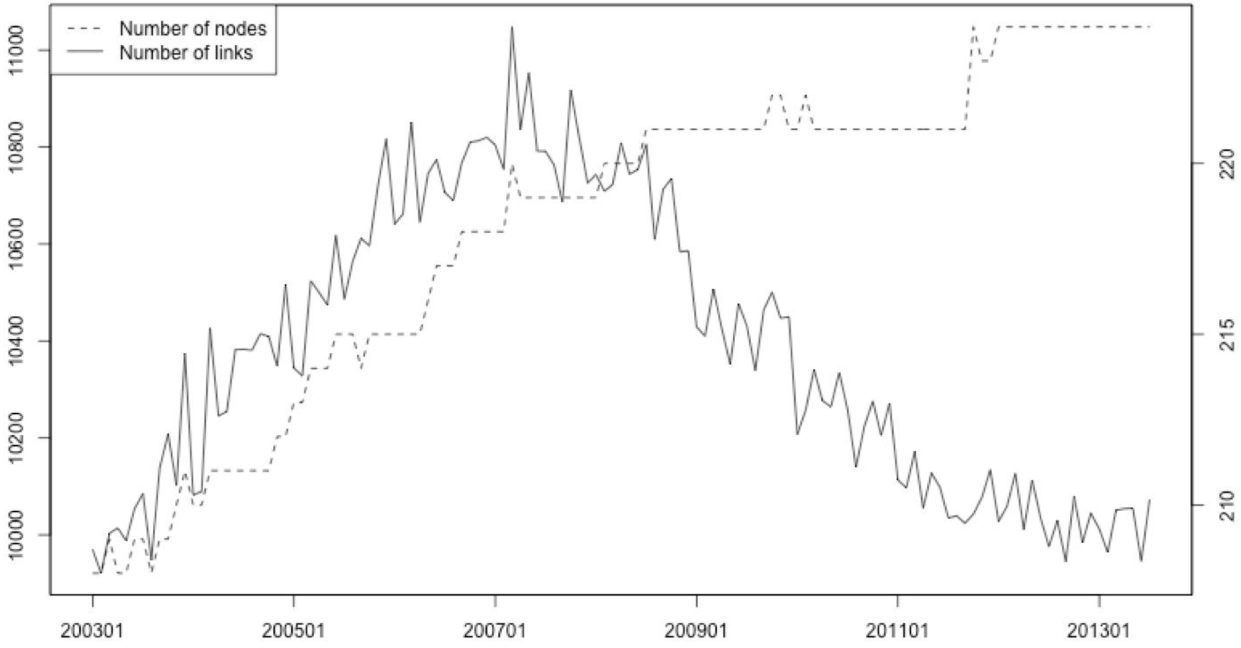
The number of messages is 5.5% lower (post-crisis than they would have been had the pre-crisis trend continued unabated throughout the entire period.



SWIFT - De-risking

Of the 1054 links gained until 2007, in 74% one (or both) were rated as medium or low on the United Nations Human Development Index.

Of the 990 links lost after 2007, 80% involved at least one country listed as an offshore financial center.



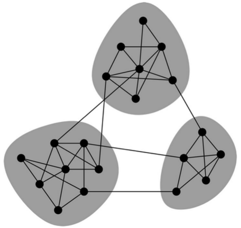
SWIFT - Communities

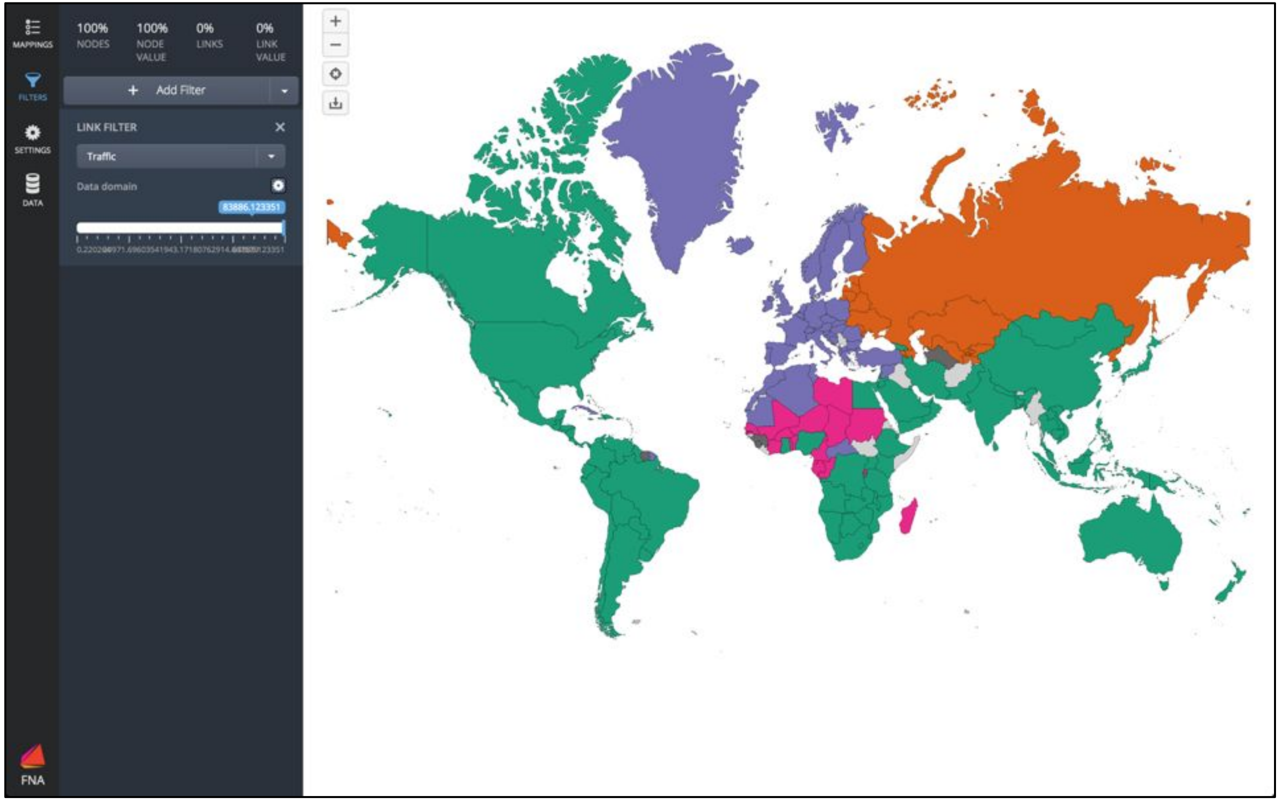
Are there meaningful subgroups among the countries?

Can we group the countries so that messages are sent mostly within groups?

Modularity - measure of concentration of links within communities vs. between communities.

Example Communities

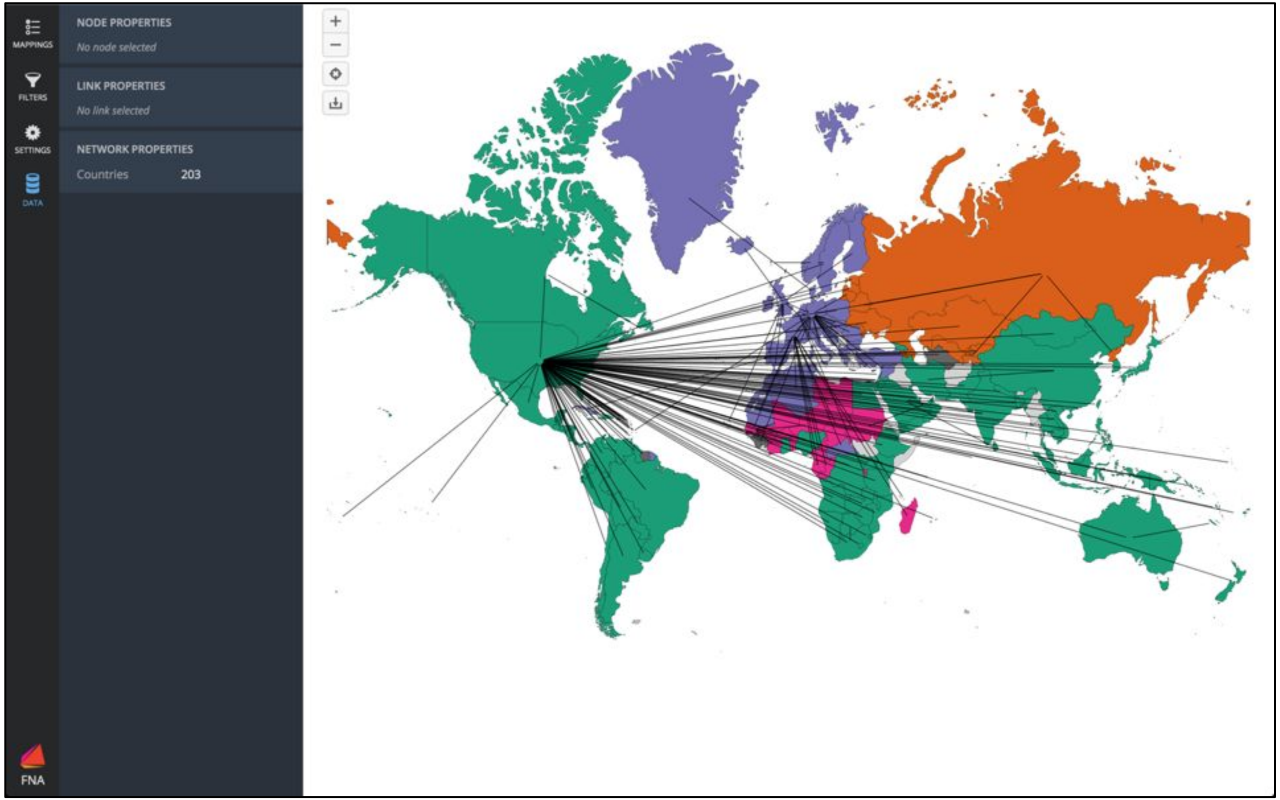




SWIFT - Communities

We overlay the Minimum Spanning Tree showing the strongest links for each country.

We see US, Germany and France as large hubs.



Soramaki and Cook (2014), '[The global network of payment flows]()', Journal of Financial Market Infrastructure

Use Case: Monitoring Liquidity and Solvency of FIs

Background

The Central Bank of Colombia has been using balance sheet and regulatory reporting data to understand the liquidity and solvency of participants in the Colombian financial system. However, the analysis is time consuming and the data comes months late.

Objective

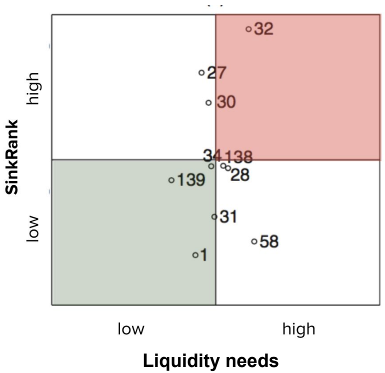
Using network analysis of data from the interbank payment system would allow the Bank to get early warning about risks substantially faster.

Outcomes

Using the FNA Platform, the Bank is now able to monitor its banking system in near real time. Automatic alerts notify the bank of any abnormal behavior in the network. Furthermore, automated stress tests where they fail the two largest participants in the network help to understand the riskiness of the system.

Carlos León et al (2015). [Assessing Systemic Importance With a Fuzzy Logic Inference System].

Use Case: Monitoring Liquidity and Solvency of FIs



Background

Bank of Korea, South Korea's central bank, was looking for ways to have early warning about intraday liquidity problems in its systemically important BoK-Wire+ interbank payment system.

Objective

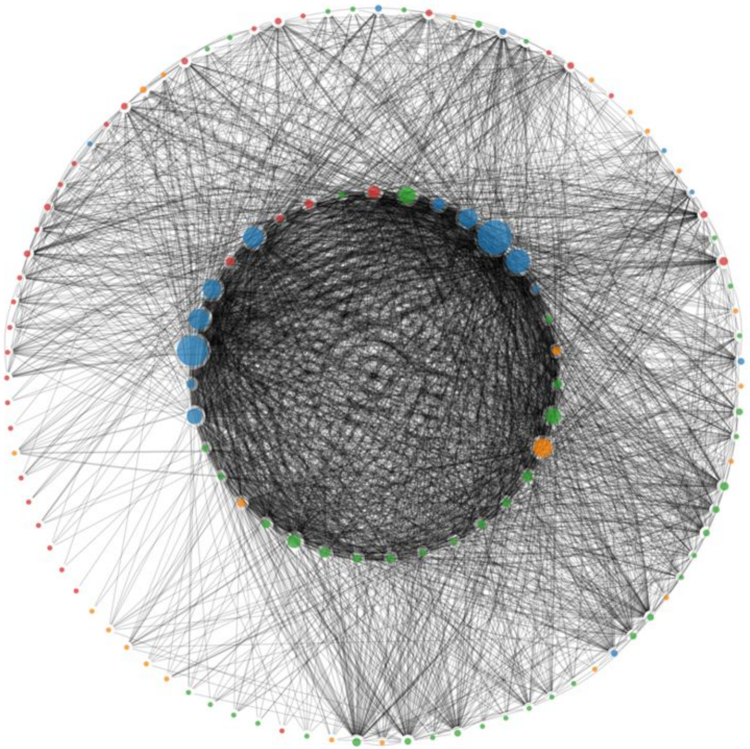
To develop methods to predict the liquidity position of each member in BoK-Wire+ in real-time, as well as measure the importance of member in terms of the liquidity and operational risk a liquidity shortage would cause.

Outcomes

Bank of Korea and FNA developed a framework for identifying bank's liquidity problems in real time and using FNA's SinkRank algorithm to identify most critical banks. The results were published as a research paper.

BoK Research paper: Network Indicators for Monitoring Intraday Liquidity in BOK-Wire+
Journal article: SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems

Predicting Liquidity: Problem

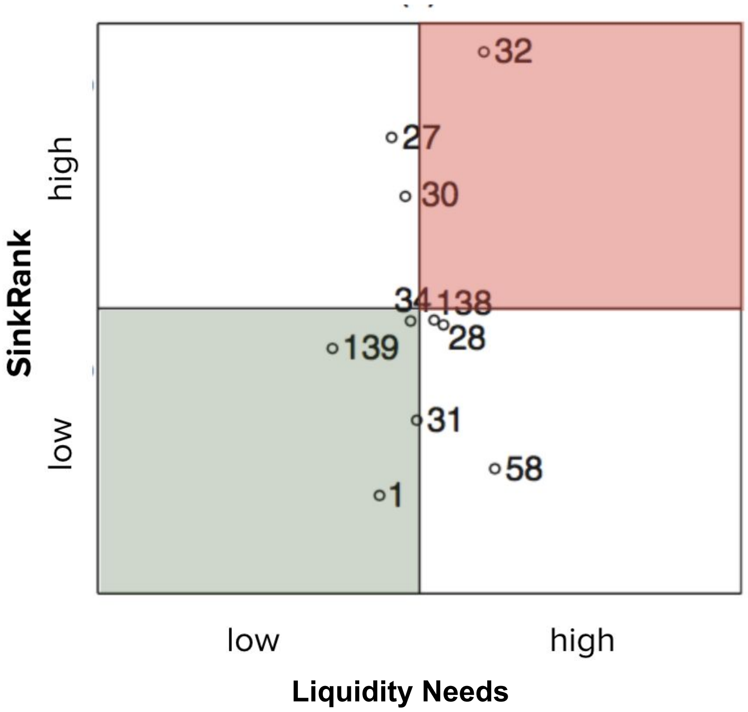


Key issue in payment system is that each bank is dependent on incoming funds to make their own payments.

Objective of this work was to develop measures for ongoing monitoring of systemic risk in payment systems

Baek, Soramäki and Yoon (2014). Network Indicators for Monitoring Intraday Liquidity in BOK-Wire+. Journal of Financial Market Infrastructures 2:3.

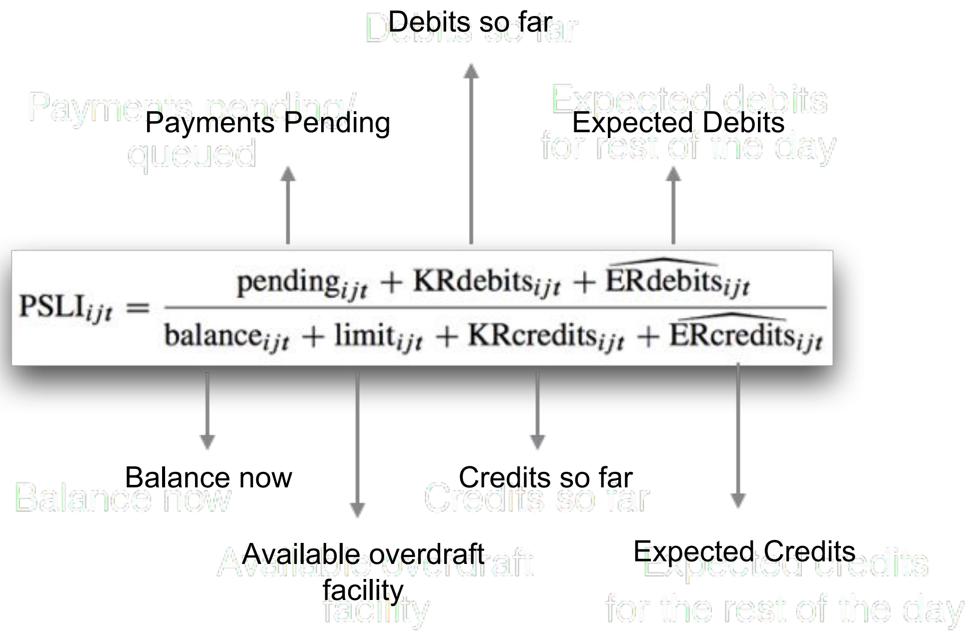
Predicting Liquidity: Framework



Analytics need to be operationalized into a robust and repeatable decision making framework

Predicting Liquidity: PSLI

PSLI (Payment System Liquidity Indicator) is the ratio of <u>projected</u> liquidity demands and <u>projected</u> liquidity supply:



$$\mathrm{PSLI}_{ijt} = \frac{\mathrm{pending}_{ijt} + \mathrm{KRdebits}_{ijt} + \widehat{\mathrm{ERdebits}}_{ijt}}{\mathrm{balance}_{ijt} + \mathrm{limit}_{ijt} + \mathrm{KRcredits}_{ijt} + \widehat{\mathrm{ERcredits}}_{ijt}}$$

Predicting Liquidity: PSLI

Expected credits and debits are estimated on the basis of a regression model.

The model takes into account the value already settled on the given day, effects related to reserve maintenance and to US holidays and the trade values of bonds and spot exchange.

The model has a good fit.

	Model 1			Model 2	
	Coefficient	t		Coefficient	t
tue	−0.2939**	−3.09	tue	−0.2692**	−3.49
wed	−0.5075***	−5.05	wed	−0.4879***	−5.67
thu	0.6049***	6.63	thu	0.6054***	7.93
fri	−0.0128	−0.14	—	—	—
reserve_check	−5.2343***	−35.43	reserve_check	−5.2310***	−35.50
us_hol	−1.0795***	−6.53	us_hol	−1.0934***	−6.82
bond	0.0037	0.87	—	—	—
fx	0.0001	0.04	—	—	—
_Ireceiver_1	3.0615***	14.87	_Ireceiver_1	3.1743***	31.34
_Ireceiver_27	12.0550***	38.07	_Ireceiver_27	12.1676***	130.47
_Ireceiver_28	6.7873***	28.69	_Ireceiver_28	6.9051***	80.15
_Ireceiver_30	13.5095***	59.61	_Ireceiver_30	13.6257***	87.87
_Ireceiver_31	2.8790***	34.04	_Ireceiver_31	2.9899***	32.92
_Ireceiver_32	19.3134***	56.84	_Ireceiver_32	19.4082***	89.10
_Ireceiver_34	8.2016***	14.30	_Ireceiver_34	8.3231***	118.77
_Ireceiver_58	2.3454***	68.63	_Ireceiver_58	2.4588***	26.63
_Ireceiver_138	7.6201***	42.56	_Ireceiver_138	7.7360***	87.08
_Ireceiver_139	6.0048***	11.62	_Ireceiver_139	6.1261***	56.87
	Number of obs = 2 480			Number of obs = 2 490	
	$F(18,2462) = 4\,159.70$			$F(15,2475) = 5\,031.22$	
	Prob > F = 0.0000			Prob > F = 0.0000	
	R-squared = 0.9682			R-squared = 0.9682	
	Adj R-squared = 0.9679			Adj R-squared = 0.9681	

*, ** and *** represent statistical significance at the 5%, 1% and 0.1% levels, respectively.

Measuring Importance: SinkRank

Payments move liquidity in the network.

Payments take place on links at some given frequency that can be measured (eg based on historical or projected flows).

We are concerned on operational failures.The sink can receive payments but cannot send any.

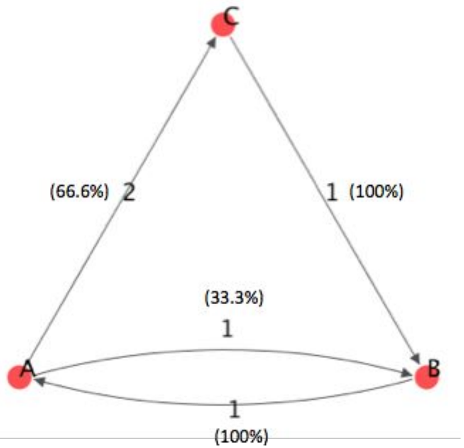
Example:

Let’s start by considering one unit of liquidity that is moved by payments in a simple system of three banks.

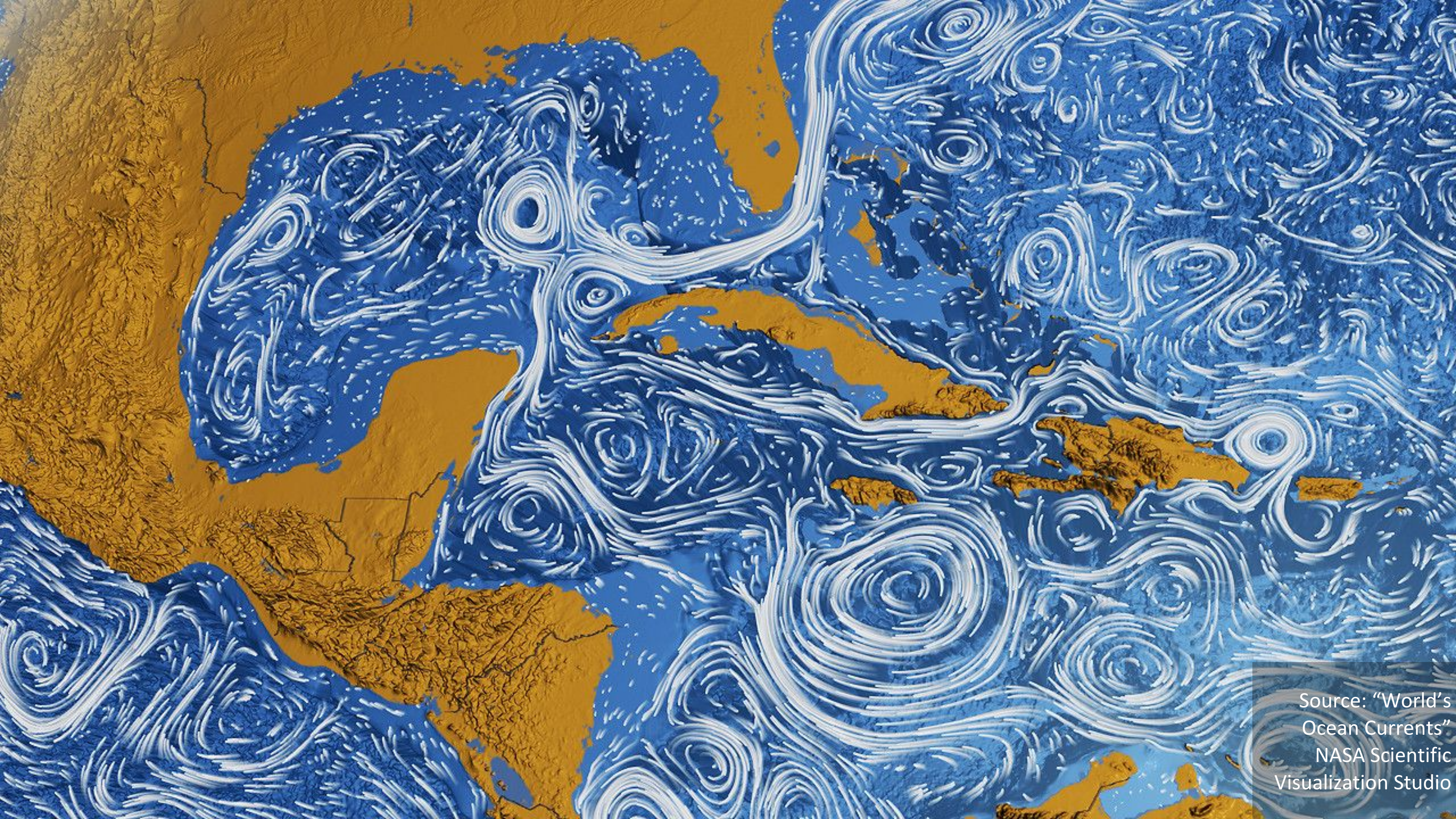
At the time of analysis, the unit of liquidity can be at either A, B or C.

What is the distance of the unit to the different ’sink nodes’?

Soramaki and Cook (2013) [SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems]()



To A	From B	1
	From C	2
To B	From A	$\frac{2}{3}\cdot 2+\frac{1}{3}\cdot 1=\frac{5}{3}$
	From C	1
To C	From A	$\sum_{i=1}^{\infty}(2i-i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=2$
	From B	$\sum_{i=1}^{\infty}(2i)\left(\frac{2}{3}\right)\left(\frac{1}{3}\right)^{i-1}=3$



Source: “World’s Ocean Currents” NASA Scientific Visualization Studio

Measuring Importance: SinkRank

SinkRank is suited for Predictive Modeling

Given an observed distribution of liquidity, and a historical pattern of payment flows

- What is the distribution if bank A has an operational disruption at noon?
- Who is affected first?
- Who is affected most?
- How is Bank C affected in an hour?

Valuable information for decision making

- Crisis management
- Participant behavior

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Using Network Simulations to Design FMIs

What are Simulations

Methodology to understand complex systems – systems that are large with many interacting elements and or non-linearities (such as payment systems)

In contrast to traditional statistical models, which attempt to find analytical solutions

Usually a special purpose computer program is used that takes granular inputs, applies the simulation rules and generates outputs

Take into account second rounds effects, third round, …

Inputs can be stochastic or deterministic. Behavior can be static, pre-programmed, evolving or co-learning

Short History of FMI Simulations

1997 : Bank of Finland

Evaluate liquidity needs of banks when Finland's RTGS system was joined with TARGET

2000 : Bank of Japan and FRBNY

Test LSM features for BoJ-Net/Fedwire

2001 - : CLS approval process and ongoing oversight

Test CLS risk management

Evaluate settlement' members capacity for pay-ins

Understand how the system works

Since: Bank of Canada, Banque de France, Nederlandsche Bank, Norges Bank, TARGET2, and many others

2010 - : Bank of England, CHAPS

Evaluate alternative liquidity saving mechanisms

Use as platform for discussions with banks

Agent Based Modeling

Analytical models need to make many simplifying assumptions.

Problem with static simulations based on historical records is that behavior of banks is not taken into account.

This behavior may have material impact on results in most simulation questions, eg:

- When system features are changed
- In stress situations
- As a reaction to other behavioral changes

-> Agent Based Modeling

Agent Based Models

Each agent has a set of rules that define its behavior
-> system level emergent behavior

Choices

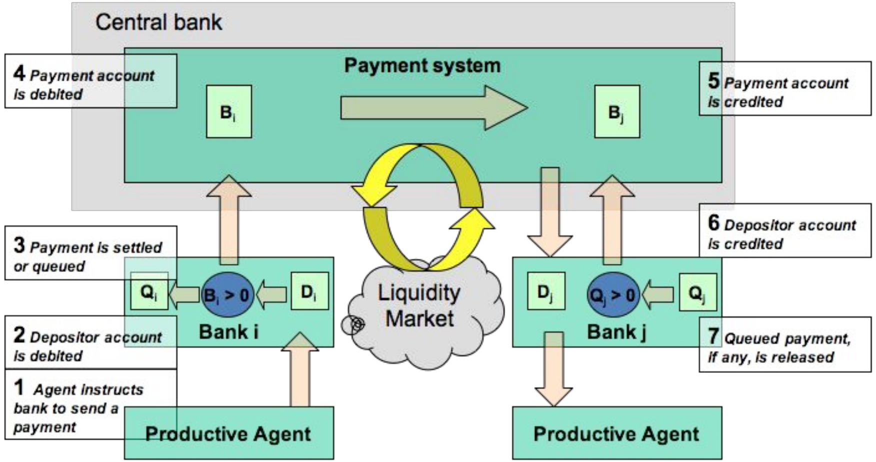
- design of rules
- homogeneous vs heterogeneous agents
- static vs learning agents

Pros

- ability to model complex behaviors
- flexible and realistic
- real systems are sensitive to details of implementation

Cons

- time consuming to set up
- need many input parameters
- results very sensitive to modeling assumptions



Beyeler, Glass, Bech and Soramäki (2007), Physica A, 384-2, pp 693-718.

Agent Based Models

Existing literature very short

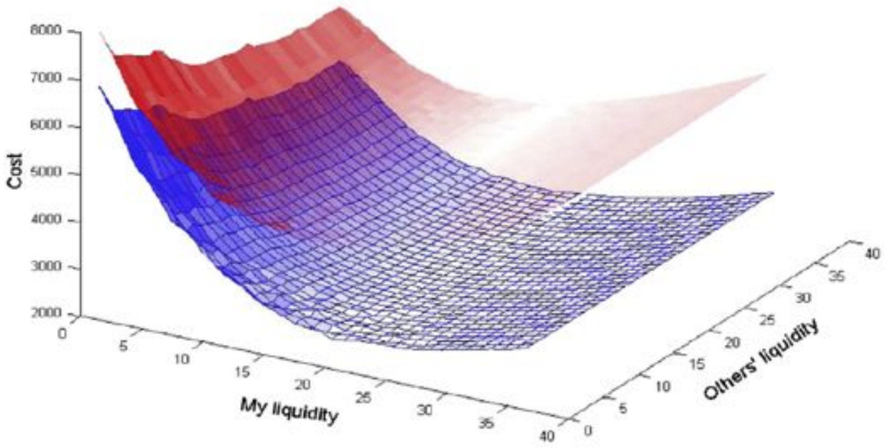
- Galbiati and Soramäki (2008, 2010)
- Arciero et al (2009)
- McLafferty-Denbee (2013)
- Soramäki and Cook (2015)

Results

- Behavior has material impact on results
- Behavior increases delays (or moves away from social liquidity/delay optimum)

Questions

- Money market model
- One vs multiperiod, learning vs fixed populations
- Which payments are discretionary / known
- What is the cost of liquidity/delay tradeoff
- Human vs machine behavior



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Data Needs

Data Needs

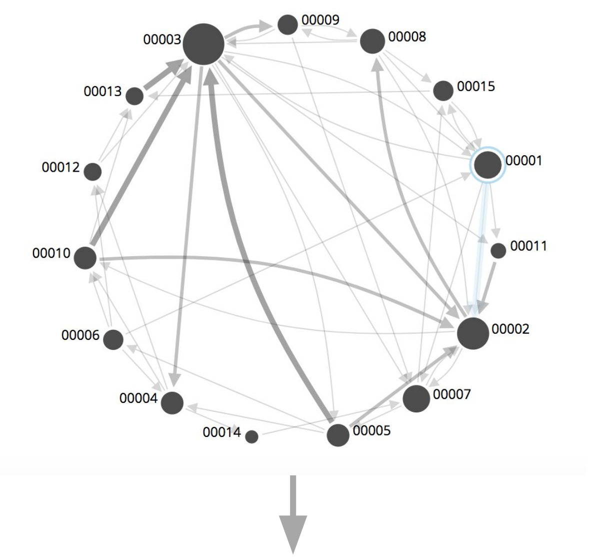
Historical transaction data

- From interbank payment systems
- At minimum: date, time, sender, receiver, value
- More data on type of payment, economic purpose, second tier (if any), type of institution, etc. useful

Representative transaction data

- Based on aggregates or sampling of real data
- Based on a network model (defining bilateral flows)
- Assumptions about:
  - Timing of payments
  - Value distribution
  - Correlations (eg do larger participant send larger payments)
- System stability (net flows over longer times)

FNA R&D: Generating Representative Transaction Data




```
date,time,value,sender,receiver
2017-06-03,08:03:36,5,A,B
2017-06-03,08:06:12,7,A,C
2017-06-03,09:13:35,11,D,A
2017-06-03,11:19:26,1,C,B
2017-06-03,13:25:11,4,B,D
```

Background
Real transaction data held by FMI's and Banks is highly confidential and hard to get access to. Also as historical records, it cannot be used as input data in simulations about future infrastructures that may process very different flows.

Method
FNA has developed and vetted in several client projects a method for generating representative transaction data that contains all known network and statistical properties of the real transaction data.

Outcome
The cost of simulations is lower and the speed at which projects can be completed is higher - lowering the entry barriers to start simulations. Often results with representative data prove the value of the simulations and real data can be used for sensitivity analysis.

Summary of Research (slides)

FMI Simulations: Application Areas

1. Evaluate Changes in Environment
2. Stress Testing & Scenarios
3. Payment System Design
4. Model Validation
5. Monitoring

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Framework for evaluating trade-off between liquidity and delay

Motivation

Baek, Soramäki and Yoon (2014).
J. of Financial Market Infrastructures

Settlement in RTGS consumes large amounts of cash

Cash/liquidity is not free

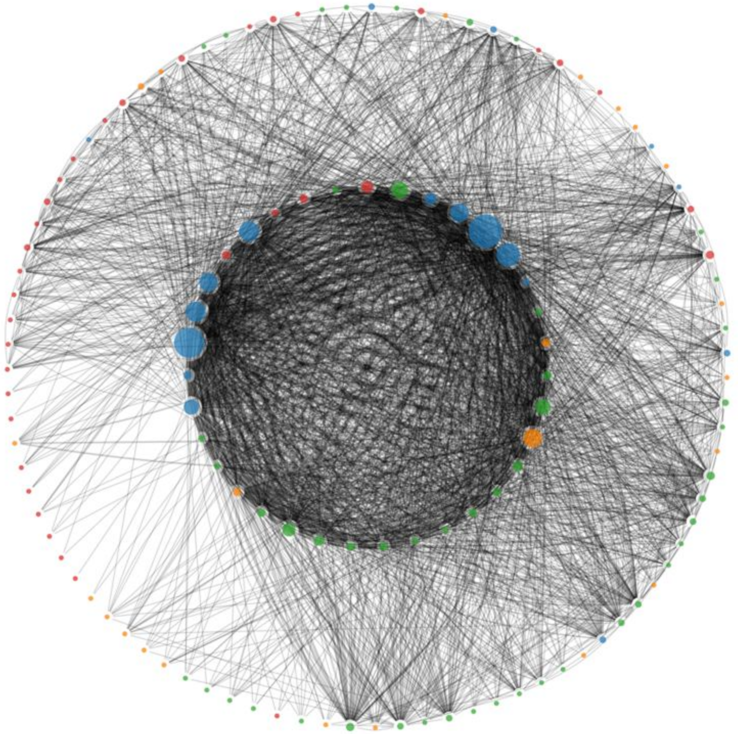
Customers' increasing demands for faster payments means delays cost too

The tradeoff is not going away even with Blockchain

There is no natural co-operative outcome

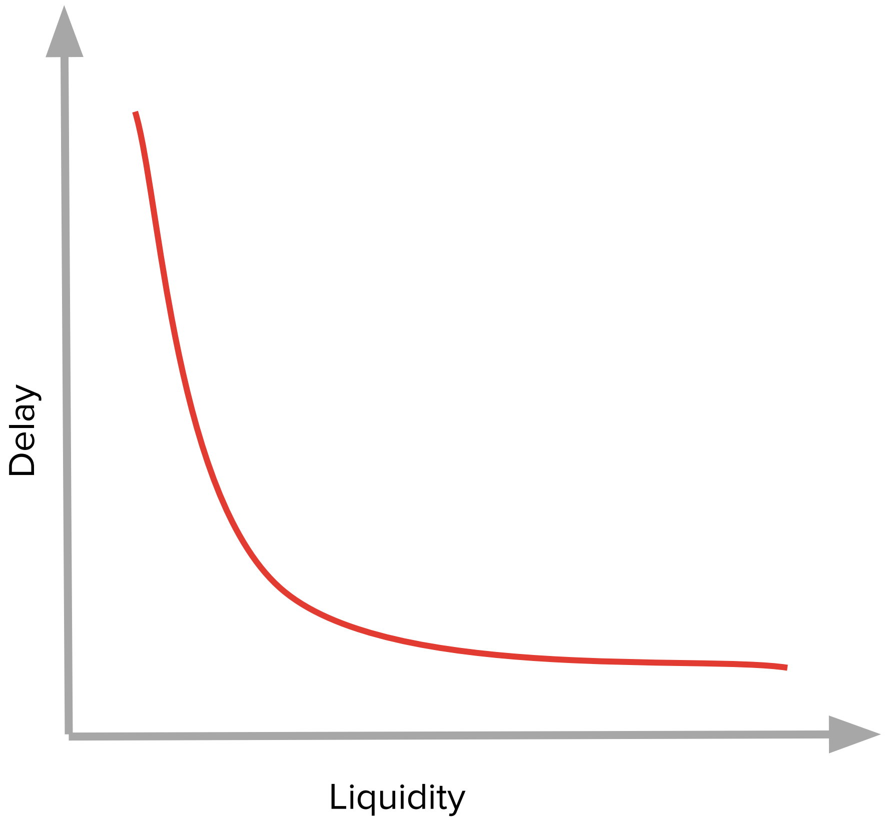
A complex system, hard to analyse

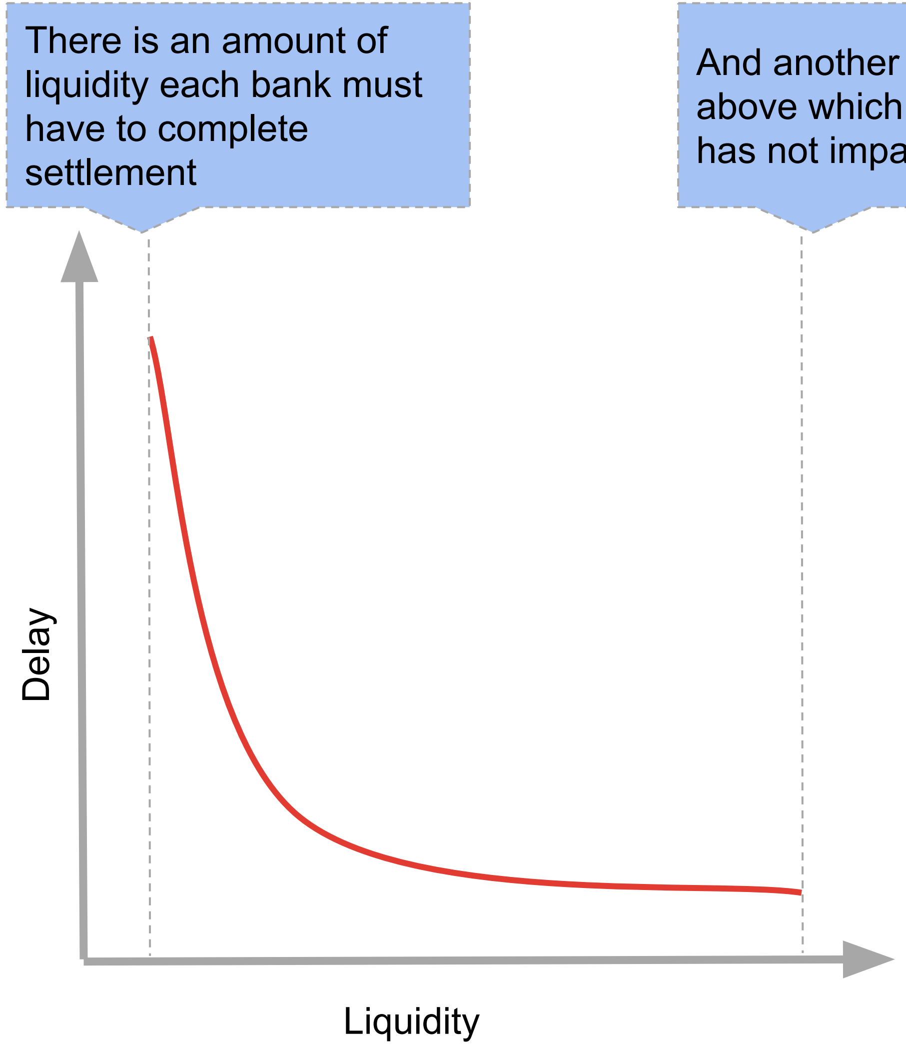
Bottom line impact

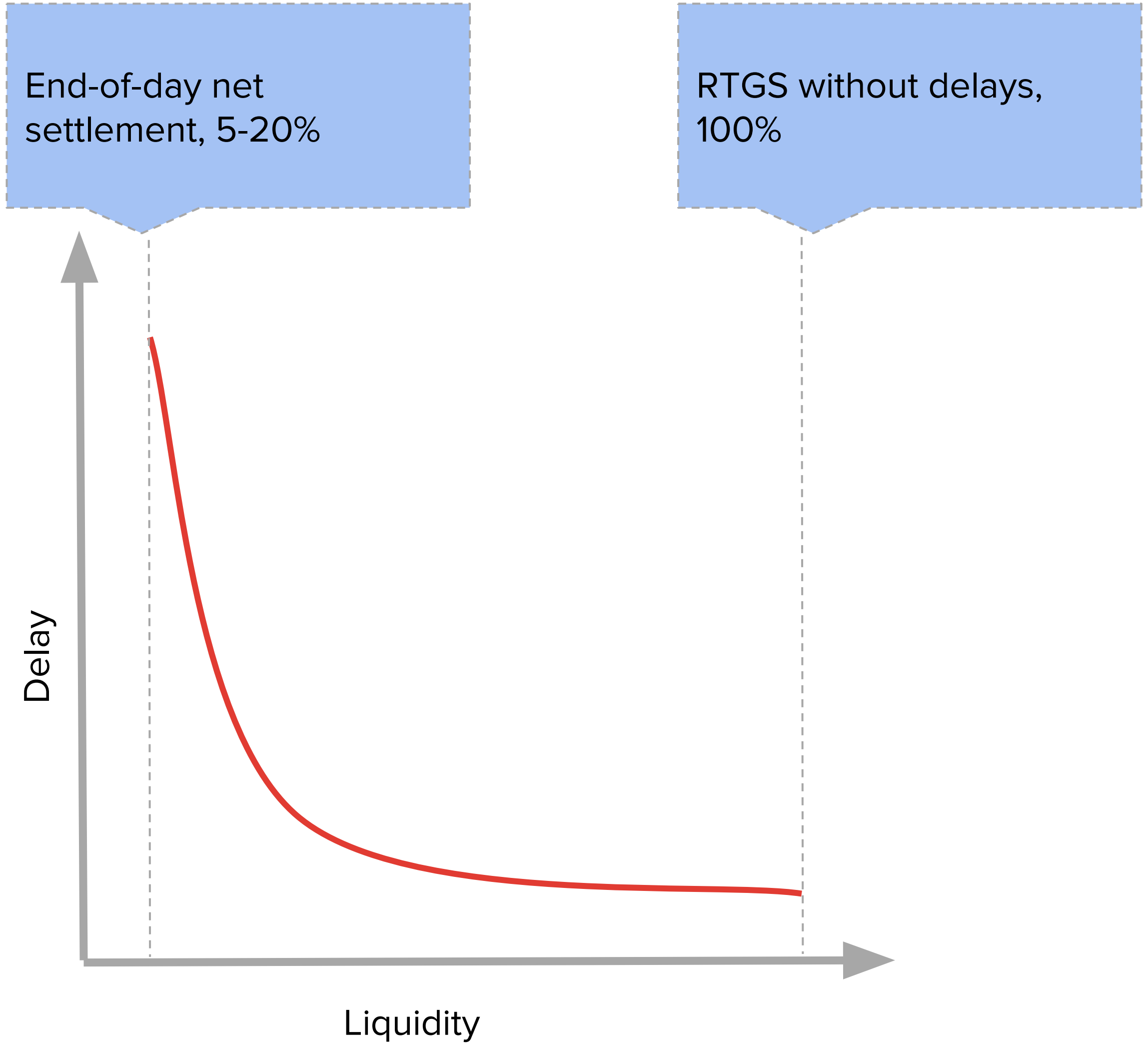


BoK-Wire+

Koponen and Soramäki (1998).
BoF monograph.



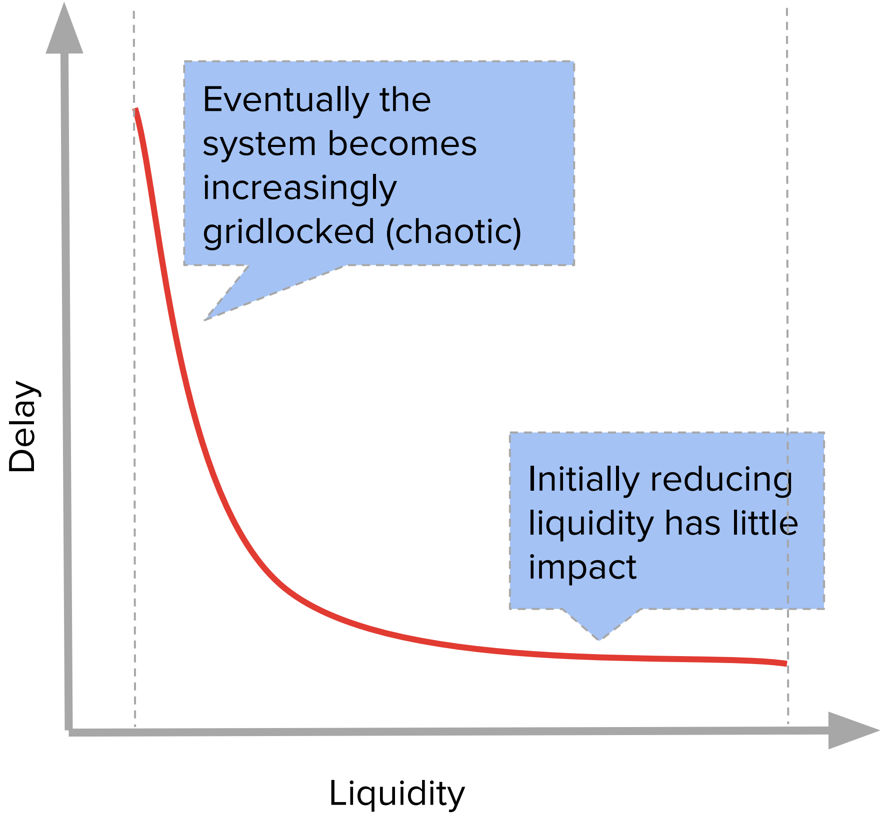

There is an amount of liquidity each bank must have to complete settlement
And another amount above which adding more has not impact
Delay
Liquidity



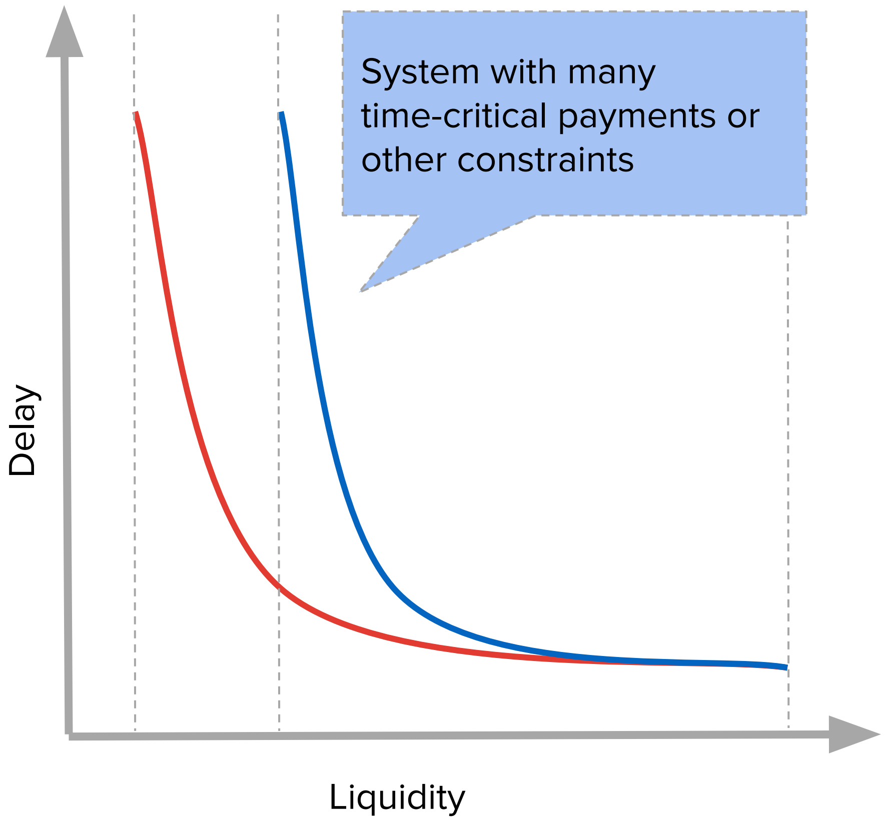
End-of-day net settlement, 5-20%
RTGS without delays, 100%
Delay
Liquidity

A convex shape for trade-off

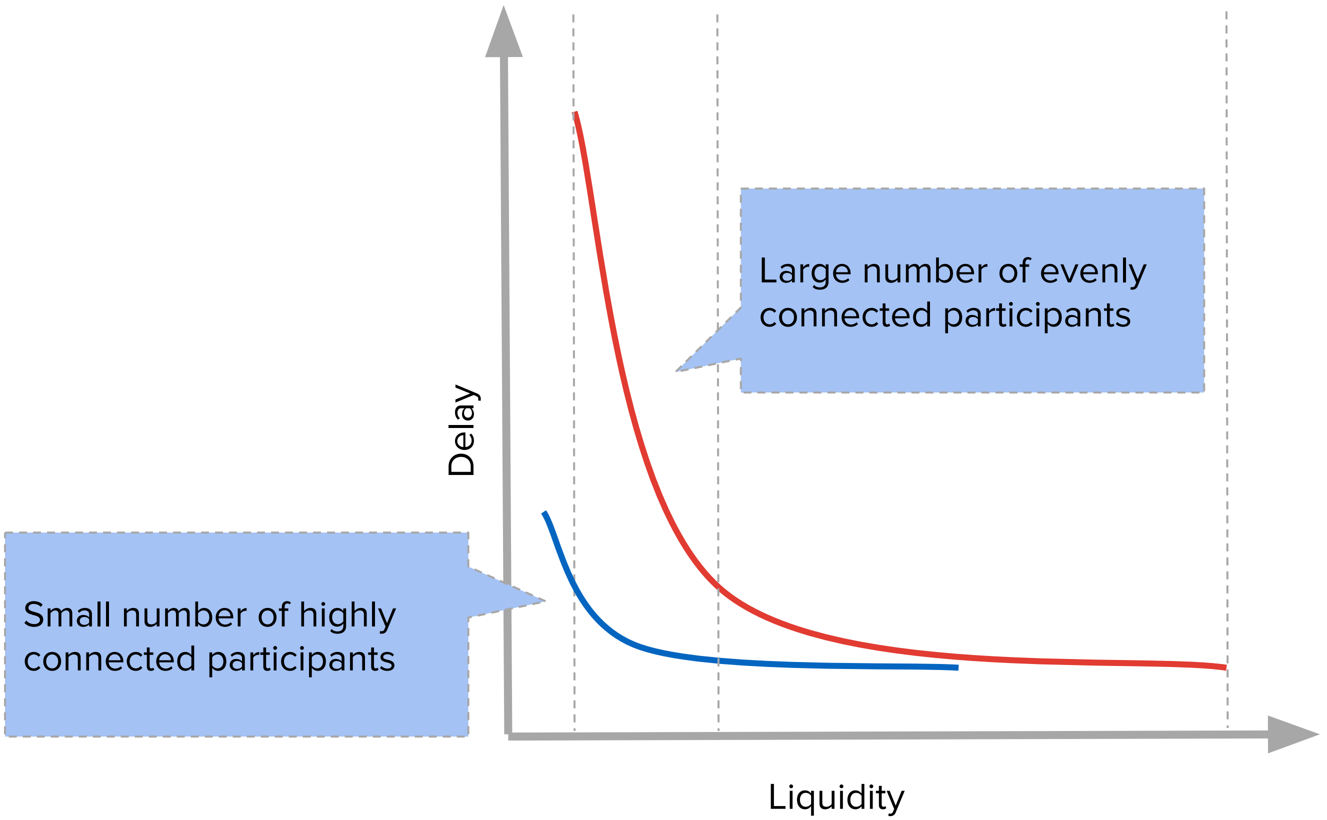
Bayeler, Glass, Bech, Soramäki (2007). Physica A.



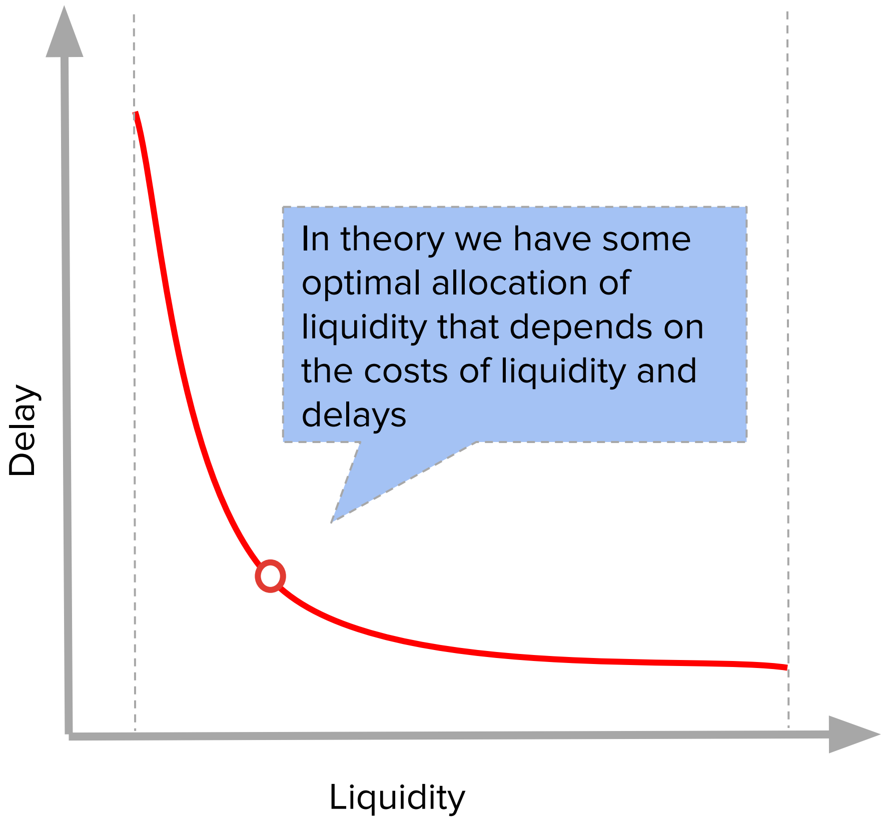
Institutional aspects matter



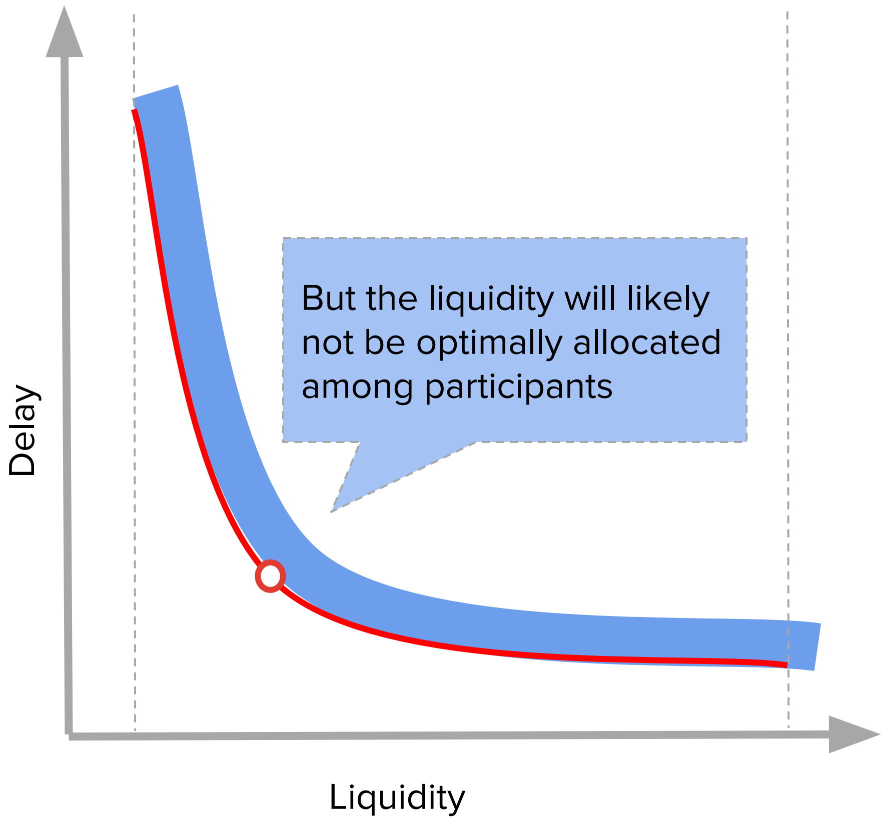
Network topology matters



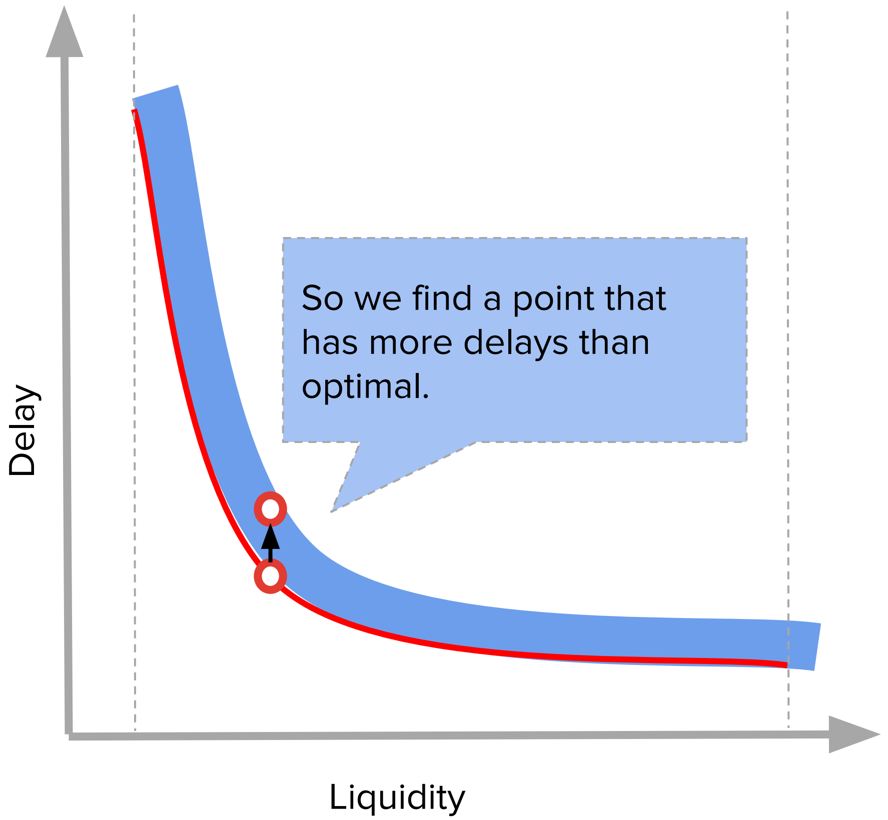
Where should we be on this curve?



Liquidity distribution matters

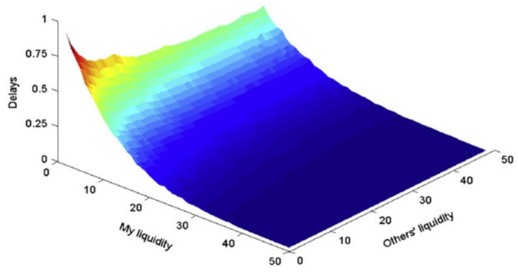


Liquidity distribution matters

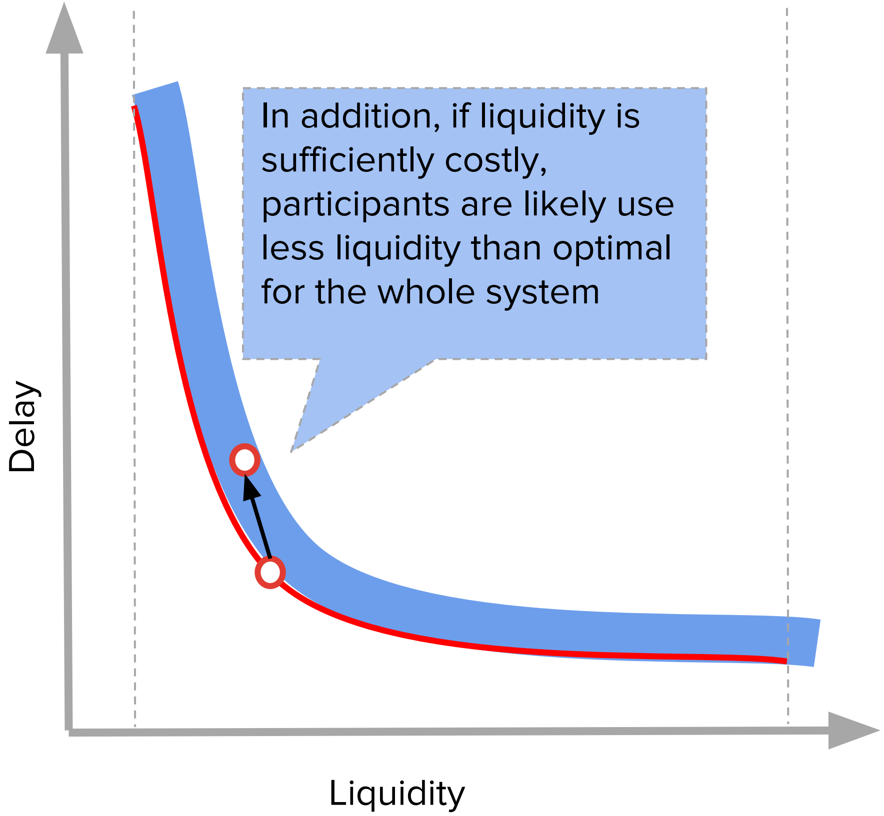


Incentives matter

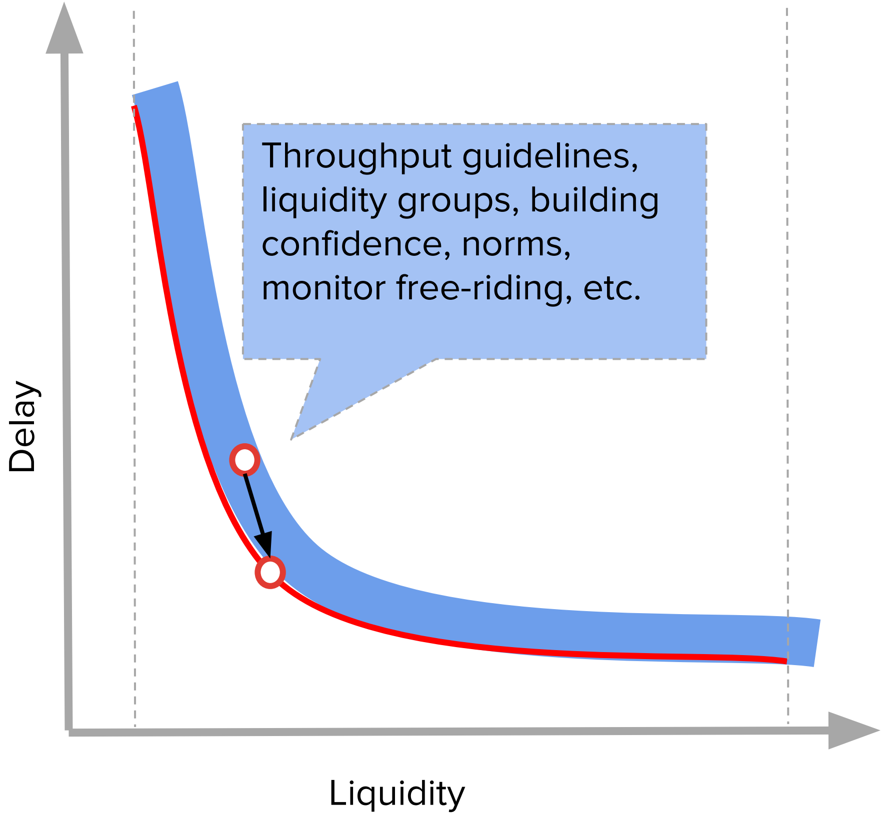
Galbiati and Soramaki (2011). J. of Econ. Dynamics and Control



Bech and Garratt (2003, 2006)

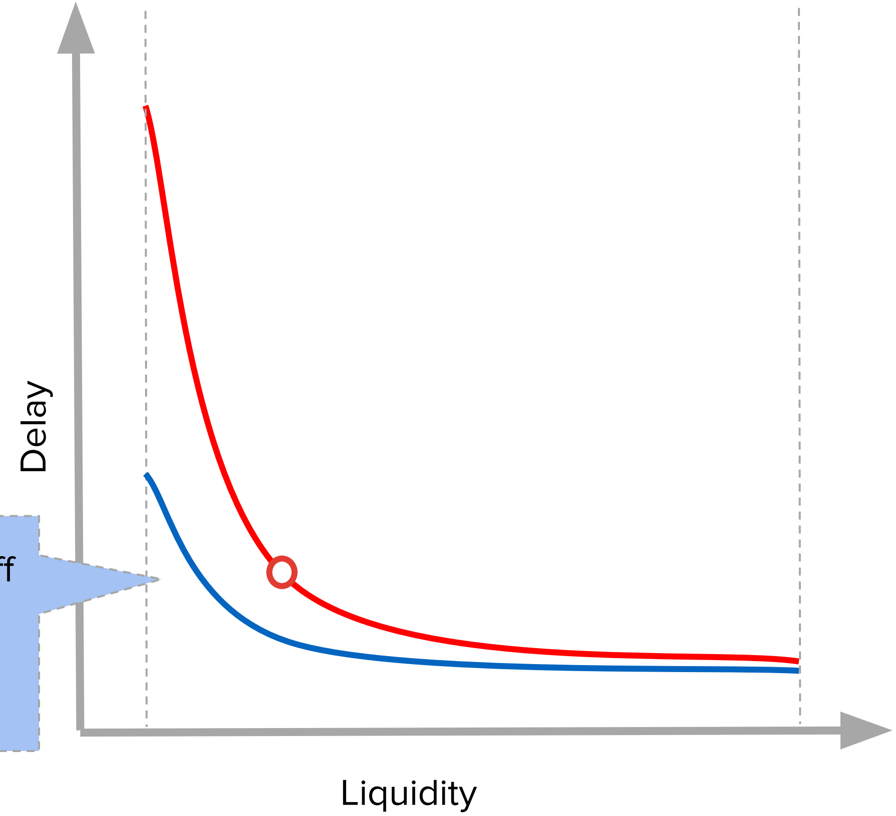


How do we foster co-operation?



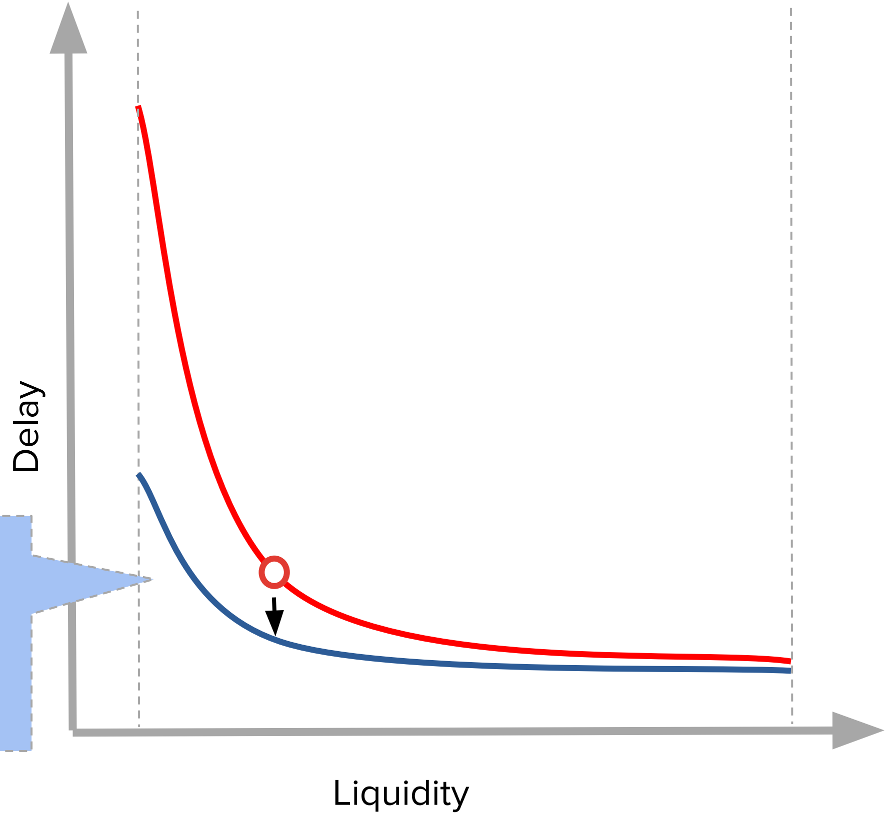
Liquidity Saving Mechanisms (LSMs)

Leinonen and Soramaki (2011).
Bank of Finland WP



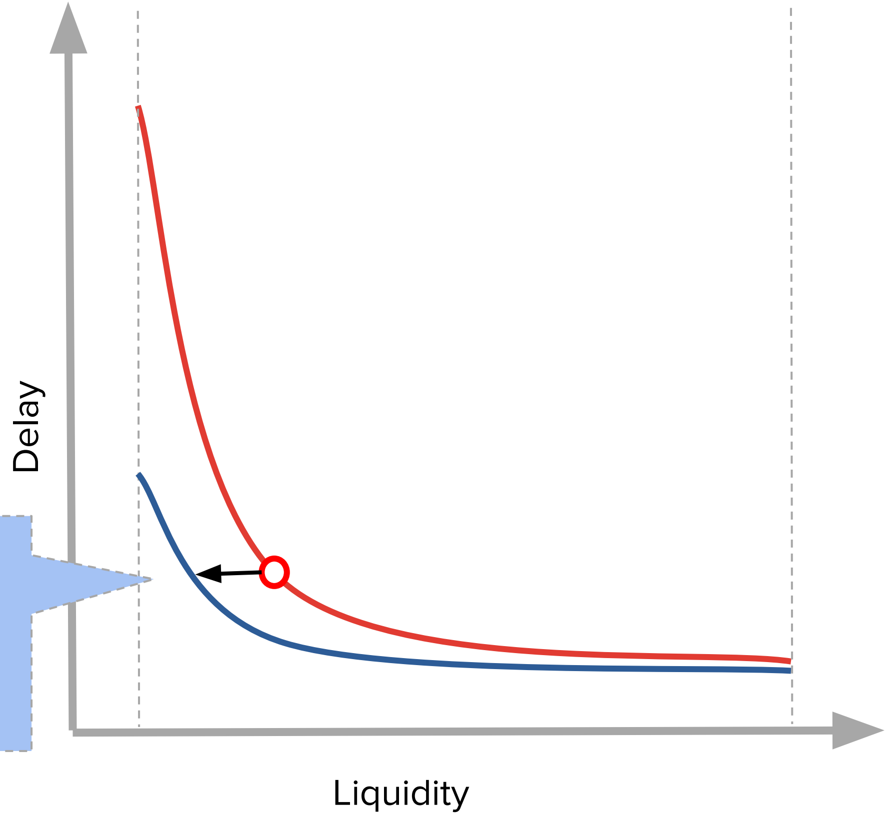
We can find new trade-off curves using different system designs

Liquidity Saving Mechanisms (LSMs)



Which will allow the system to settle faster with a given amount of liquidity

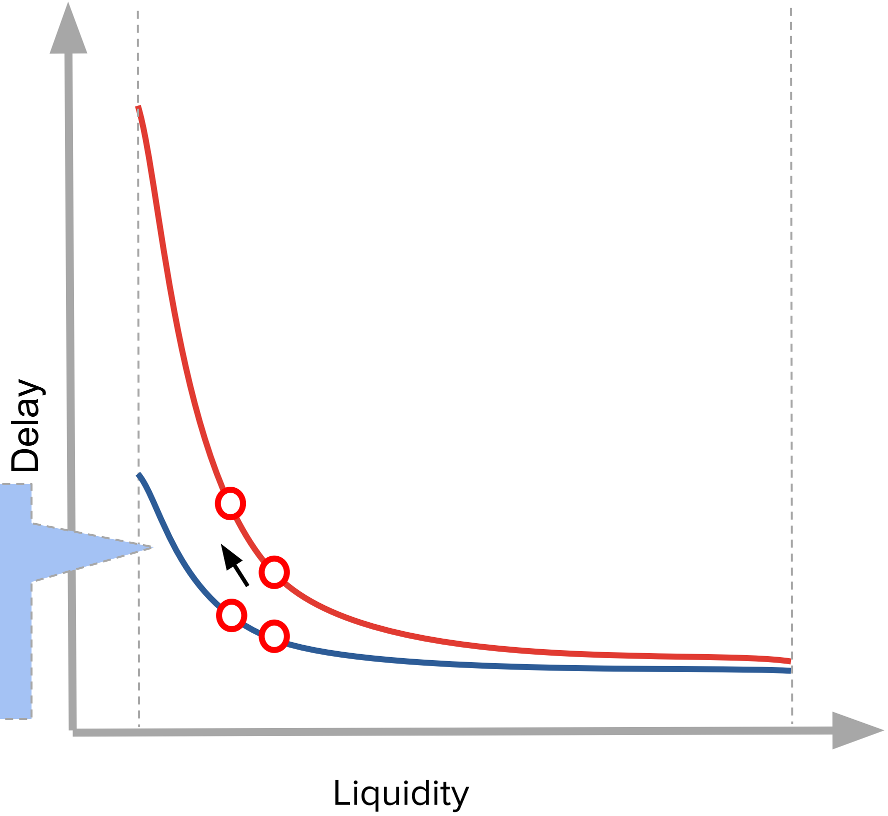
Liquidity Saving Mechanisms (LSMs)



Or operate with less liquidity for a given amount of delays

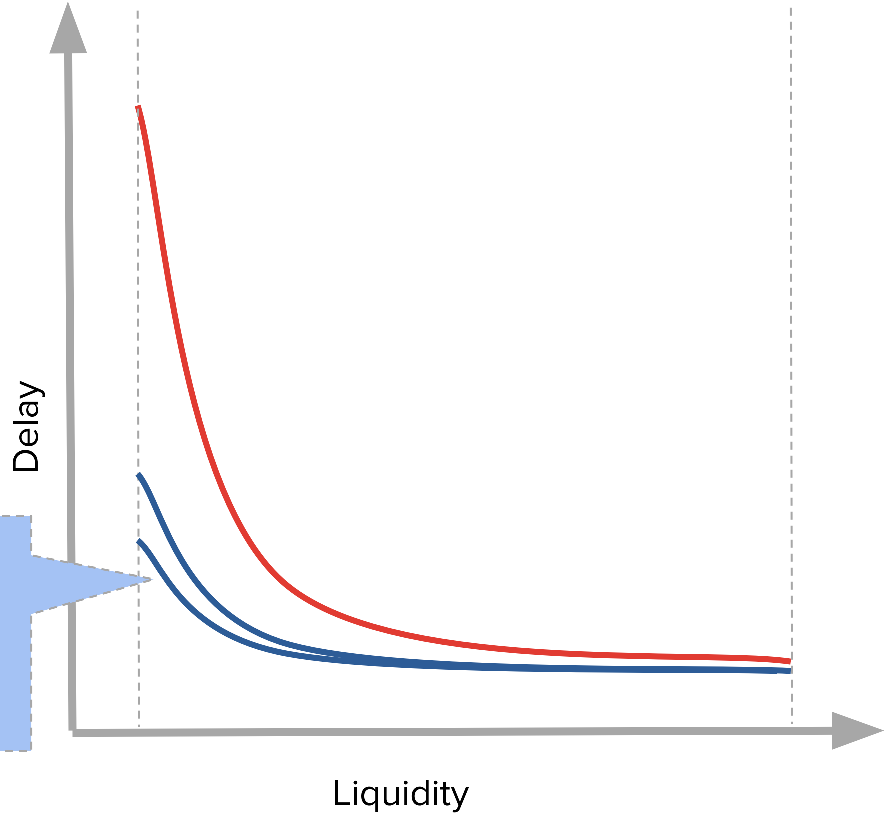
How about stress situations?

Bech and Soramaki (2002). E-money & Payment Systems Review



Stress situations reduce liquidity in the system. LSM help alleviate the impact.

Which LSM is the best?



Need to simulate ...

Bypass FIFO

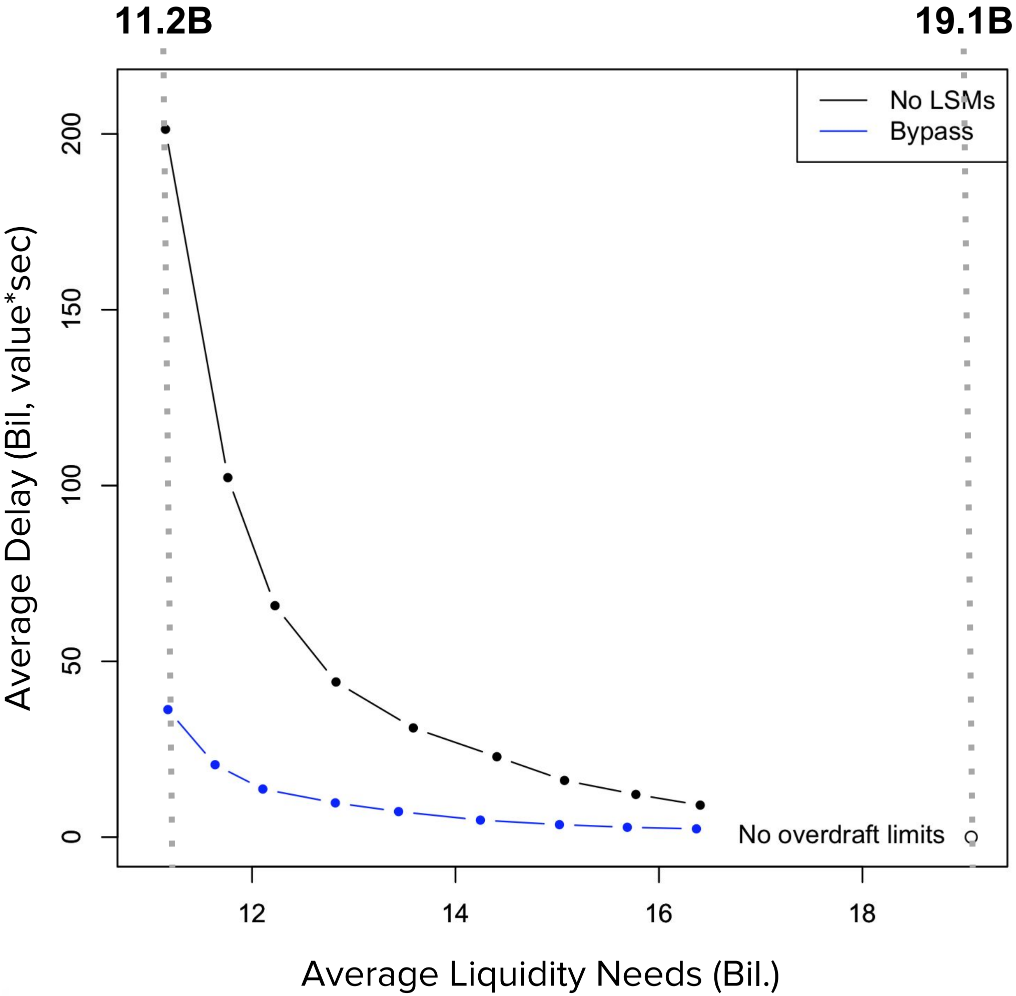
Simulations with Payments Canada for modernization of Canada's Payment System

Problem: FIFO order may 'block' settlement if a large payment is at the front of the queue.

Bypass FIFO tries to settle payments down the queue and selects the first one that it finds.

Example: A has liquidity available 200. A has queued payment: 300, 150 and 100.

Payment 150 can be settled.



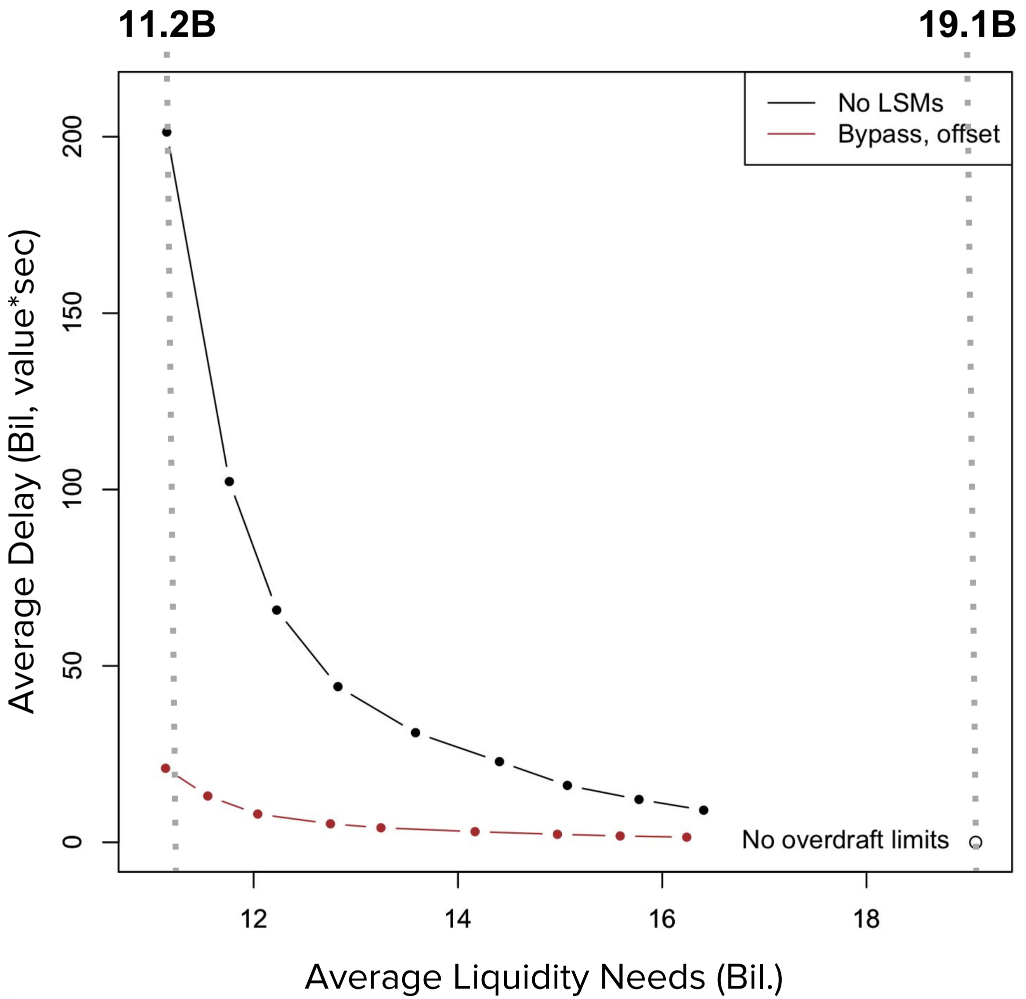
Bilateral Offset

Problem: Liquidity may be unnecessarily used when receiver has payments to sender in its own queue.

Bilateral Offset finds payments from receiver's queue that can be offset with sender's payment.

Example: A has 200 liquidity available and a payment of 500 to B. B has payments to A in queue: 300, 150 and 100.

Payment 500 can be settled offsetting 300 of the 500 against B's payment and the remaining 200 with available liquidity.

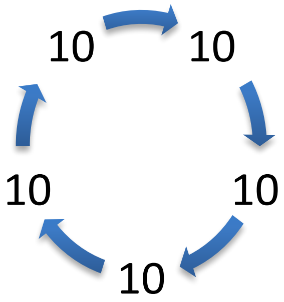


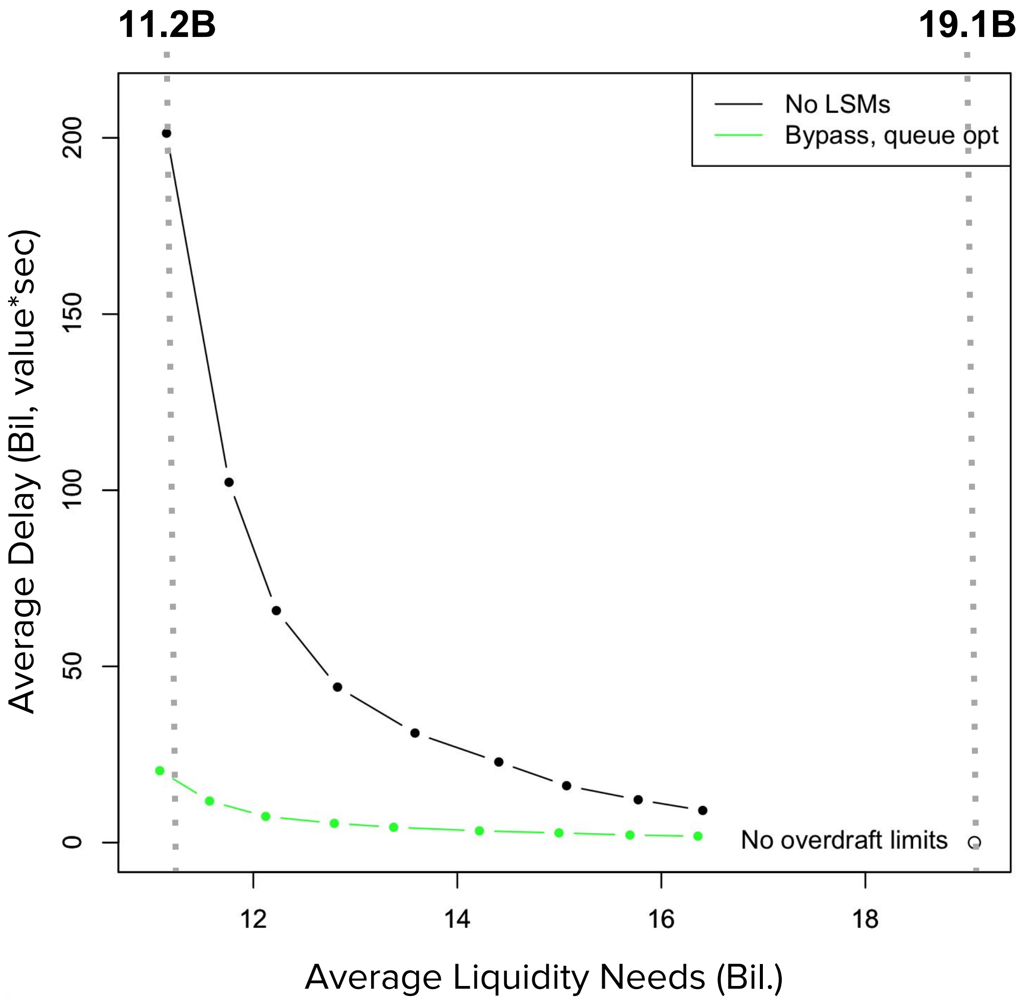
Queue Optimization

Problem: A system may become gridlocked

Queue optimization tries to find a subset of payments that can be settled by all banks with available liquidity through multilateral netting.

Example: A cycle where no bank has liquidity but all payments could be made simultaneously.





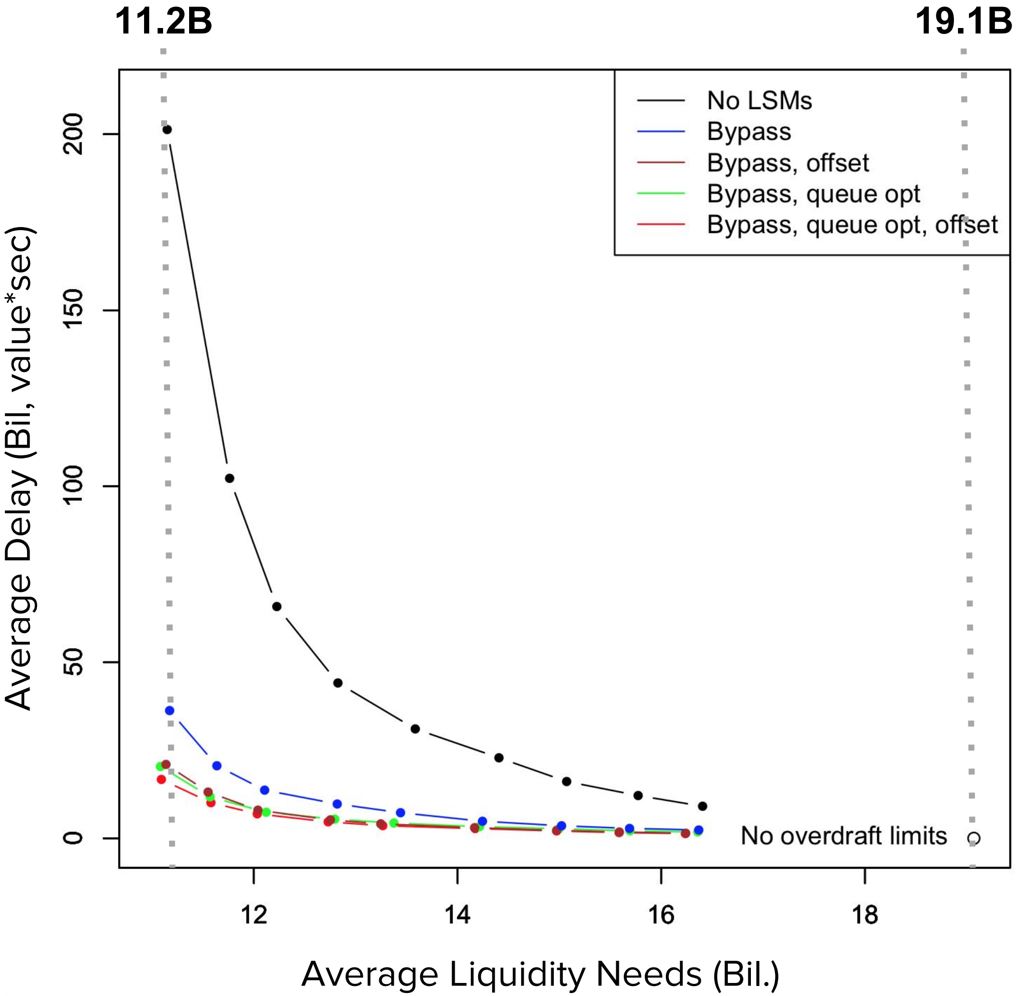
Summary

Bypass alone brings good benefits in reducing delays (or liquidity at a given delay level).

Other LSM's further improve on it.

Bypass + **Bilateral offset** and **Bypass** + **Queue Optimization** are equally efficient.

Having all LSM's running, brings best outcome from a liquidity-delay perspective



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Summary

Top Down Analysis

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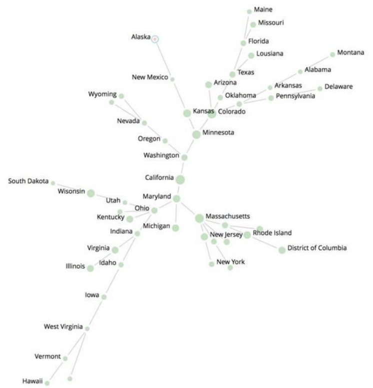
New Tools Give Better Picture, Literally, of Financial-System Risk

Researchers are using network analytics and advanced data modeling to identify weak spots in the system that otherwise might go unnoticed

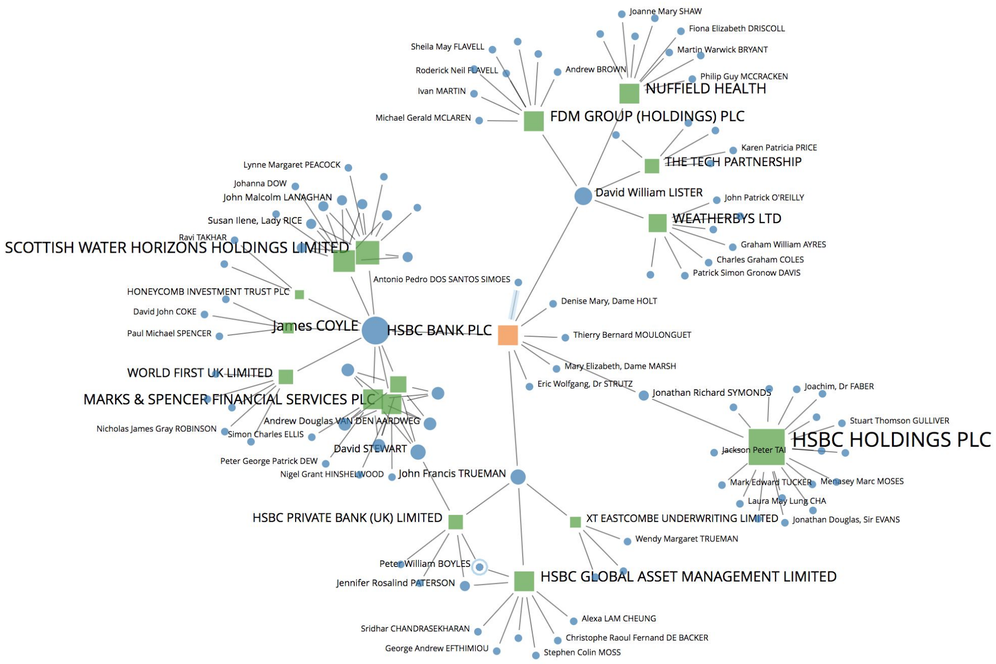


This sprawling tree shows housing prices in U.S. markets moving with little correlation in 2000. The tree has gotten shorter and shorter since, indicating higher correlation between markets.
PHOTO: FINANCIAL NETWORK ANALYTICS

Typical use cases:

- Systemic risk analysis
- System monitoring
- System design
- System stress testing
- Clustering/Classification
- Early warning
- Anomaly detection

Bottom Up Analysis



Typical use cases:

- Criminal investigation
- Terrorist networks
- Money laundering
- KYC & KYCC
- Fundamental investment analysis
- Supply chain analysis

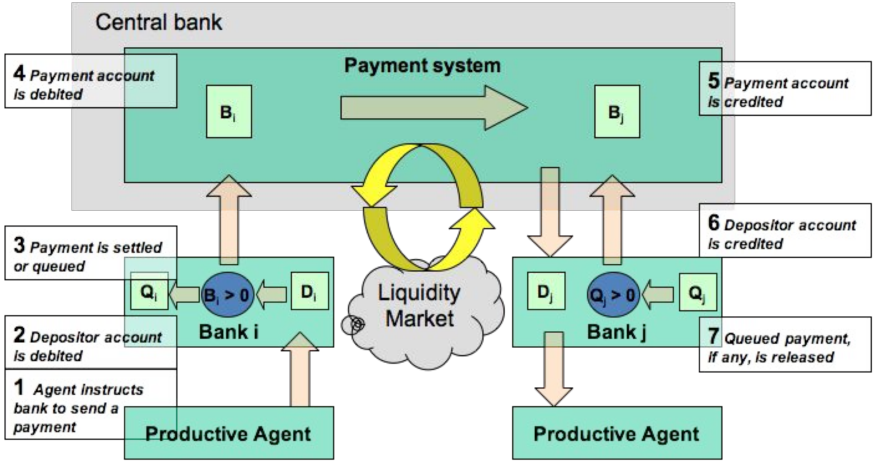
Network Features of Data

Typical use cases:

- AI/ML
- Fraud algorithms
- Recommendation engines
- Algorithmic investment

FNA Research: [Comparison of Graph Computing Platform Performance]()

Agent Based Models



Beyeler, Glass, Bech and Soramäki (2007), Physica A, 384-2, pp 693-718.

Typical use cases:

- Central Counterparty Clearing
- Payment Systems
- FX Settlement
- Financial Markets
- Housing Markets

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