Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism

Javier Garcia-Bernardo, Eelke Heemskerk & Frank Takes

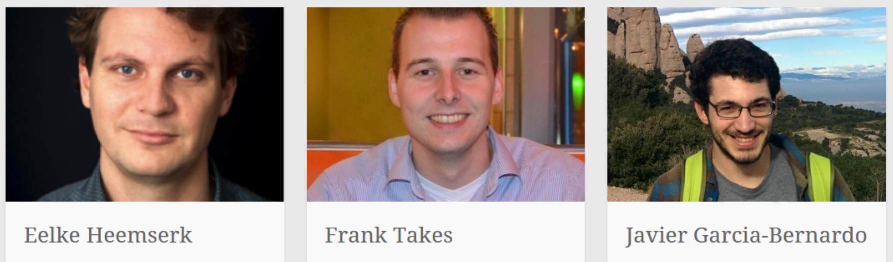
University of Amsterdam, The Netherlands

CSL colloquium
Amsterdam, December 11, 2015

UNIVERSITEIT VAN AMSTERDAM

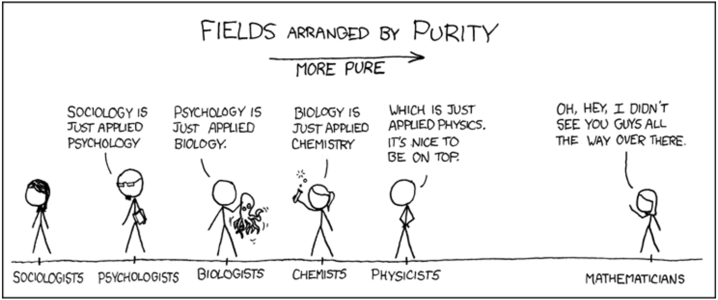
About us

About us



- Eelke Heemskerk: PI. Political Science PhD.
- Frank Takes: Post-doc. Computer Science PhD.
- Javier Garcia-Beranrdo: PhD. Computer Science M.Sc.
- Nick Hogan: M.Sc. Anthropology B.Sc.
- Roberto Lucchese: M.Sc. Computer Science B.Sc.
- Jouke Huijzer: M.Sc. Political Science B.Sc.
- Coming next March: 2xPhD candidates and 1xPost-doc.

About us



FIELDS ARRANGED BY PURITY
MORE PURE
SOCIOLOGY IS JUST APPLIED PSYCHOLOGY
PSYCHOLOGY IS JUST APPLIED BIOLOGY.
BIOLOGY IS JUST APPLIED CHEMISTRY
WHICH IS JUST APPLIED PHYSICS. IT'S NICE TO BE ON TOP.
OH, HEY, I DIDN'T SEE YOU GUYS ALL THE WAY OVER THERE.
SOCIOLOGISTS
PSYCHOLOGISTS
BIOLOGISTS
CHEMISTS
PHYSICISTS
MATHEMATICIANS

CSL at UVM (Computational Story Lab)

Figure: The mascot, roboctopus.

- Vermont Complex Systems Center (@uvmcomplexity)
- Great people
- Awesome projects
- New masters in Complex Systems and Data Science (Deadline May 31st)

CSL at UVM (Computational Story Lab)

Corporate networks

Corporate networks

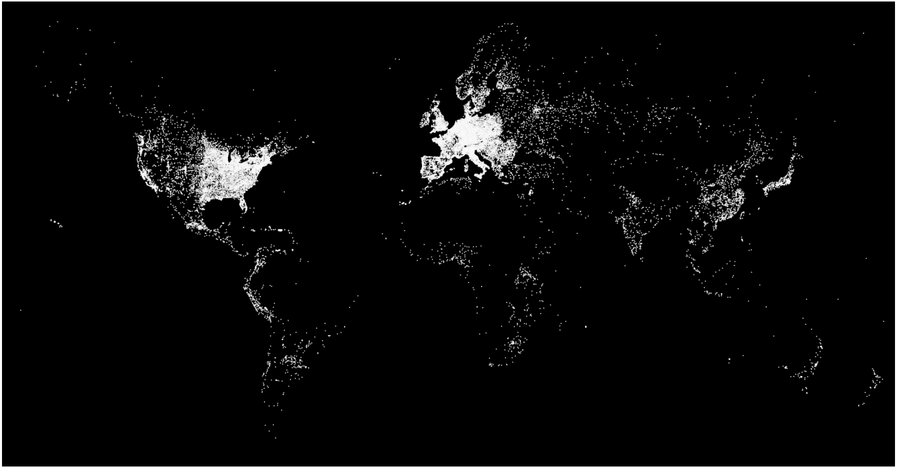
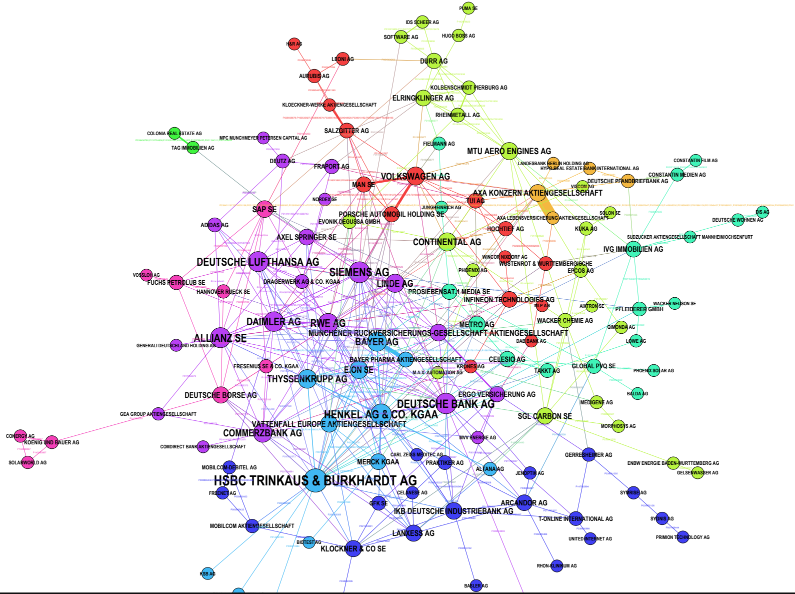


Figure: 400, 000 largest firms globally, plotted based on their latitude/longitude.

Corporate networks

Figure: Global board interlock network.


PUMA SE
IDS SCHEER AG
SOFTWARE AG
HUGO BOSS AG
H&R AG
LEONI AG
DURR AG
AURUBIS AG
KOLBENSCHMIDT PIERBURG AG
KLOECKNER-WERKE AKTIENGESELLSCHAFT
ELRINGKLINGER AG
RHEINMETALL AG
COLONIA REAL ESTATE AG
MPC MUNCHMEYER PETERSEN CAPITAL AG
SALZGITTER AG
TAG IMMOBILIEN AG
FIELMANN AG
MTU AERO ENGINES AG
DEUTZ AG
FRAPORT AG
LANDESBANK BERLIN HOLDING AG
HYPO REAL ESTATE BANK INTERNATIONAL AG
CONSTANTIN FILM AG
CONSTANTIN MEDIEN AG
VOLKSWAGEN AG
MAN SE
DEUTSCHE PFANDBRIEFBANK AG
VISCOM AG
AXA KONZERN AKTIENGESELLSCHAFT
NORDEX SE
TUI AG
JUNGHEINRICH AG
SAP SE
PORSCHE AUTOMOBIL HOLDING SE
SOLON SE
DIS AG
EVONIK DEGUSSA GMBH
AXA LEBENSVERSICHERUNG AKTIENGESELLSCHAFT
DEUTSCHE WOHNEN AG
ADIDAS AG
HOCHTIEF AG
KUKA AG
AXEL SPRINGER SE
SUDZUCKER AKTIENGESELLSCHAFT MANNHEIM/OCHSENFURT
CONTINENTAL AG
IVG IMMOBILIEN AG
WINCOR NIXDORF AG
DEUTSCHE LUFTHANSA AG
WUSTENROT & WURTTEMBERGISCHE
PHOENIX AG
EPCOS AG
VOSSLOH AG
SIEMENS AG
FUCHS PETROLUB SE
DRAGERWERK AG & CO. KGAA
LINDE AG
HANNOVER RUECK SE
PROSIEBENSAT.1 MEDIA SE
INFINEON TECHNOLOGIES AG
MLP AG
AIXTRON SE
WACKER NEUSON SE
PFLEIDERER GMBH
DAIMLER AG
RWE AG
WACKER CHEMIE AG
METRO AG
QIMONDA AG
MUNCHENER RUCKVERSICHERUNGS-GESELLSCHAFT AKTIENGESELLSCHAFT
ALLIANZ SE
DAB BANK AG
LOWE AG
BAYER AG
GENERALI DEUTSCHLAND HOLDING AG
BAYER PHARMA AKTIENGESELLSCHAFT
CELESIO AG
FRESENIUS SE & CO. KGAA
GLOBAL PVQ SE
KRONES AG
E.ON SE
TAKKT AG
PHOENIX SOLAR AG
M.A.X. AUTOMATION AG
THYSSENKRUPP AG
BALDA AG
DEUTSCHE BORSE AG
ERGO VERSICHERUNG AG
MEDIGENE AG
DEUTSCHE BANK AG
GEA GROUP AKTIENGESELLSCHAFT
HENKEL AG & CO. KGAA
SGL CARBON SE
MORPHOSYS AG
VATTENFALL EUROPE AKTIENGESELLSCHAFT
CONERGY AG
KOENIG UND BAUER AG
COMMERZBANK AG
MVV ENERGIE AG
COMDIRECT BANK AKTIENGESELLSCHAFT
SOLARWORLD AG
CARL ZEISS MEDITEC AG
GERRESHEIMER AG
ENBW ENERGIE BADEN-WURTTEMBERG AG
MERCK KGAA
PRAKTIKER AG
MOBILCOM-DEBITEL AG
ALTANA AG
GELSENWASSER AG
JENOPTIK AG
HSBC TRINKAUS & BURKHARDT AG
FREENET AG
CELANESE AG
SYMRISE AG
ARCANDOR AG
GFK SE
IKB DEUTSCHE INDUSTRIEBANK AG
T-ONLINE INTERNATIONAL AG
SYGNIS AG
MOBILCOM AKTIENGESELLSCHAFT
UNITED INTERNET AG
PRIMION TECHNOLOGY AG
LANXESS AG
BIOTEST AG
KLOCKNER & CO SE
RHON-KLINIKUM AG
KSB AG
BASLER AG

Corporate network analysis

- Apply techniques from (social) **network analysis** to corporate data
- **Nodes** represent around 200 million firms across the globe
- **Edges** could denote different relationships:
  - (Undirected) **board interlocks**: shared senior level directors
  - (Directed) ownership ties based on shareholder information
- Node attributes: country, sector, performance indicators, number of employees, ...
- Edge attributes: number of interlocks, type of shares, number of shares, ultimate share percentage, ...
- Data source: ORBIS database. Longitudinal
- Computer: 1.5TB RAM (ready early February)

CORPNET

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

erc
European Research Council
Established by the European Commission

CORPNET
University of Amsterdam

CORPNET

Universiteit van Amsterdam

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

European Research Council
Established by the European Commission

CORPNET
University of Amsterdam

- **Nature**: Map and analyze the network.

CORPNET

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

- **Nature**: Map and analyze the network.
- **Origins**: Uncover generating mechanisms

CORPNET

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

European Research Council
Established by the European Commission

CORPNET
University of Amsterdam

- **Nature**: Map and analyze the network.
- **Origins**: Uncover generating mechanisms
- **Power**: Understand how it operates: "nearly 4/10 of the control over the economic value of transnational companies (TNCs) in the world is held, via a complicated web of ownership relations, by a group of 147 TNCs in the core, which has almost full control over itself" (Vitali et al., 2011)

CORPNET

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

European Research Council
Established by the European Commission

CORPNET
University of Amsterdam

- Previous work: **community detection** and **centrality** analysis on the largest $400,000$ firms (nodes) and $1,700,000$ interlocks (edges)

CORPNET

- **CORPNET** — Corporate Network Governance: Power, Ownership and Control in Contemporary Global Capitalism
- *What are the* **features**, **origins** *and* **power** *political consequences of corporate governance networks in modern economic life?*

European Research Council
Established by the European Commission

CORPNET
University of Amsterdam

- Previous work: **community detection** and **centrality** analysis on the largest $400,000$ firms (nodes) and $1,700,000$ interlocks (edges)
- Focus in the first few months of the CORPET project: **data quality** of the 200 million firm dataset

Community detection

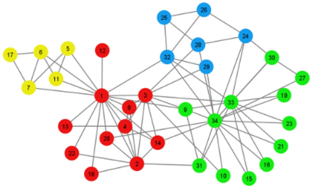
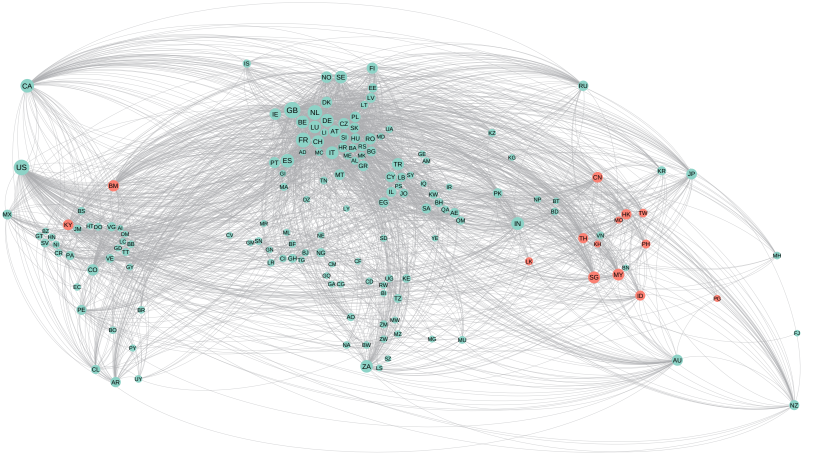


Figure: Communities: node subsets connected more strongly with each other
Image credits: Waltman & van Eck, CWTS Leiden

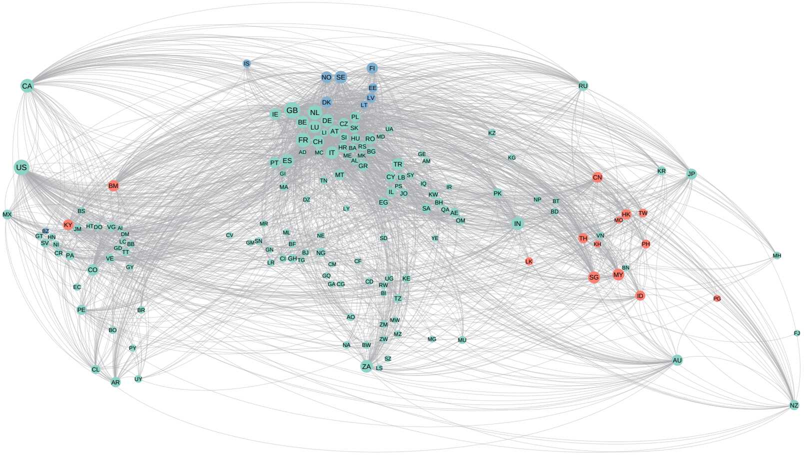
- Country network: aggregate firms from the same country
- E.M. Heemskerk and F.W. Takes, The Corporate Elite Community Structure of Global Capitalism, in *New Political Economy* 21(1): 90–118, 2016. `dx.doi.org/10.1080/13563467.2015.1041483`

Corporate Network Communities

Communities, resolution = 2.0

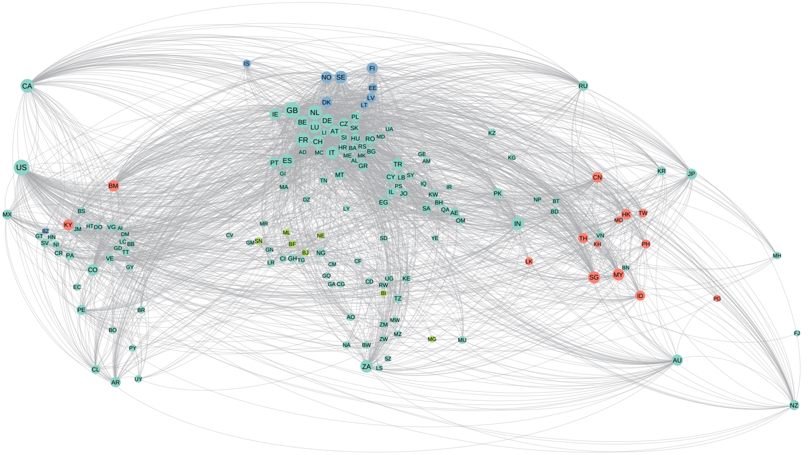


Communities, resolution = 1.75

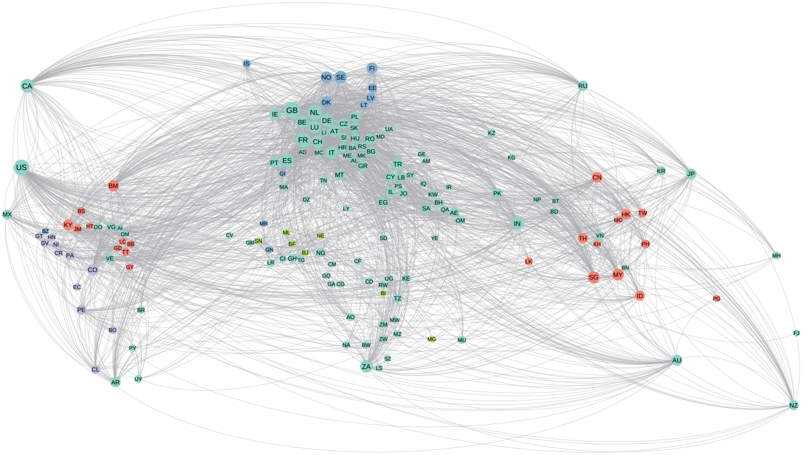


Universiteit van Amsterdam

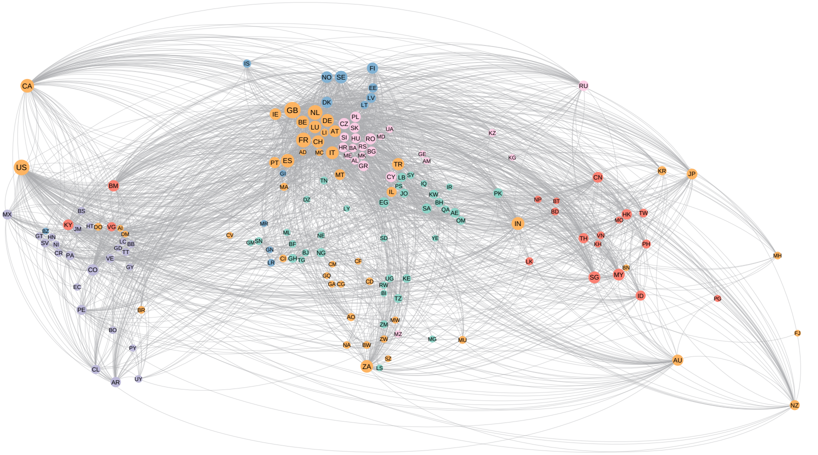
Communities, resolution = 1.55



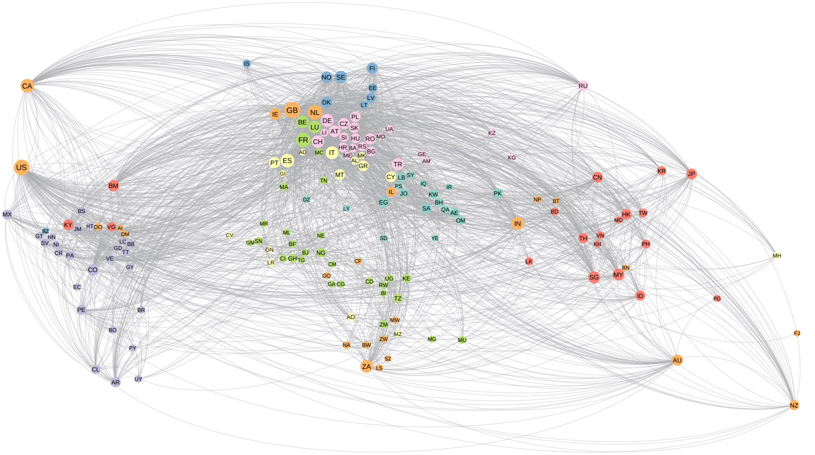
Communities, resolution = 1.5



Communities, resolution = 1.0



Communities, resolution = 0.5



Appearing Communities

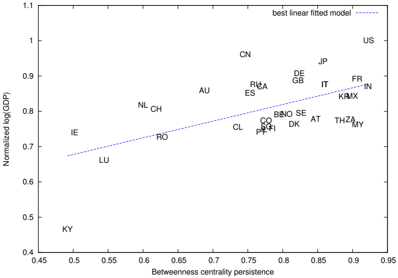
- Clearly a layered / nested community structure
- Some communities are more distinct than other
- The China / Asian cluster separates itself the first. At the highest level of fragmentation it actually includes Western oriented Asian countries as Japan and Korea as well.
- Europe is divided along geographical lines, even when we only consider border crossing ties!
- Although it may look like Europe is integrating, community detection reveals clear dividing lines

Appearing Communities

- Carroll and Fennema concluded that by 1996 the transnational corporate elite network is best described as a superstructure that rests upon rather resilient national bases (Carroll & Fennema, 2002).
- Our results suggest a multi-level structure.
- In this regional fragmented corporate elite, the transatlantic connection remains particularly strong.

Centrality analysis

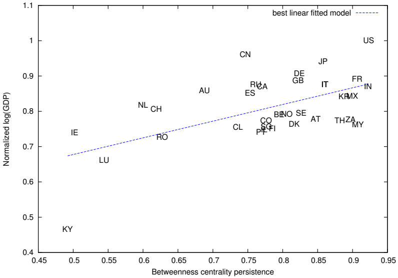
- F.W. Takes and E.M. Heemskerk, Centrality in the Global Network of Corporate Control, *forthcoming*, 2016.



- Main result: large differences between countries in terms of **centrality persistence**, measuring national vs. global power of a country's firms

Centrality analysis

- F.W. Takes and E.M. Heemskerk, Centrality in the Global Network of Corporate Control, *forthcoming*, 2016.



- Main result: large differences between countries in terms of **centrality persistence**, measuring national vs. global power of a country's firms
- Outliers due to cliques with high degree nodes of administrative interlock ties

Data quality

Data quality

- Data quality
  - Accuracy: the data is true
  - Consistency: data remains clear and verifiable over time
  - Integrity: data has not suffered from corruption
  - **Completeness**: do we have all the data?
- We "found" that the Spanish market size was ten times larger than the US market: one outlier in the data.
- Other problems are more subtle, such as the size bias: Larger companies are added first to the database.

Average operating revenue

Universiteit van Amsterdam

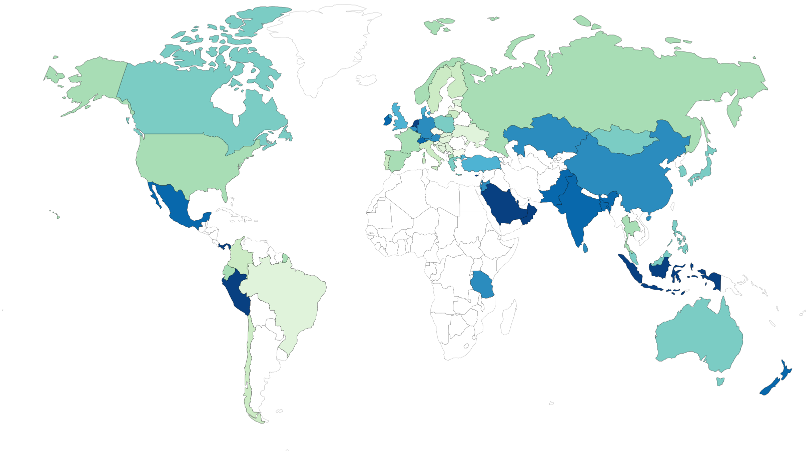


Figure: Observed average revenue per country for 200 million firms

Why we care about the average

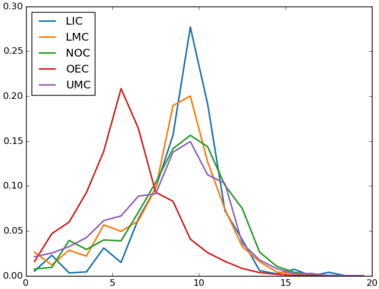


Figure: Distribution of log(revenue) for different regions

Why we care about the average

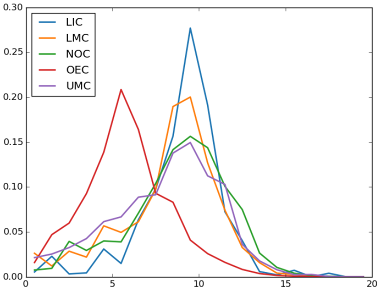


Figure: Distribution of log(revenue) for different regions

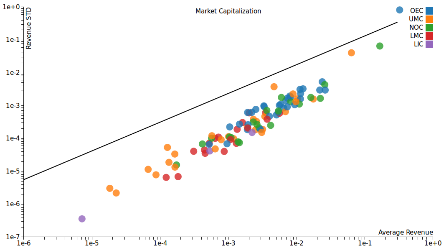


Figure: Average revenue within country vs Standard deviation of the revenue

Why we care about the average

- The distribution of firm operating revenues follows a lognormal distribution for 95% of firms, with consistent variance across countries. Can be described with the average.

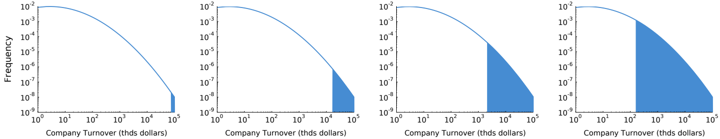
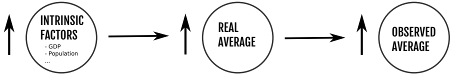


Figure: Lognormal distribution and addition of firms

Data quality

- Assess firm data quality based on comparing intrinsic factors of countries using:
  - Worldbank data on GDP per capita for each country
  - Eurostat data on the number of firms in each county
  - Distribution of sum of revenues per country in our data

Data quality



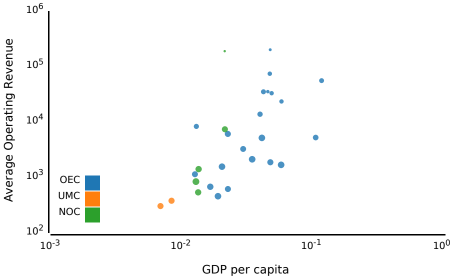


Figure: Richer countries have larger firms

Data quality

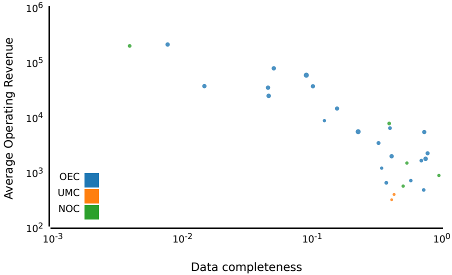


Figure: Richer countries have better quality

Data quality

- Rich countries have higher average revenue, but better quality, which decrease the observed average (hard to decouple).
- We are interested in the real average (given complete data):
  1. Real average $\propto \frac{\text{GDP}}{number\ \ of\ \ firms}$
  2. Calculate the effect of intrinsic factors and extrapolate to other countries
  3. Calculate the quality of our global firm data

Data quality

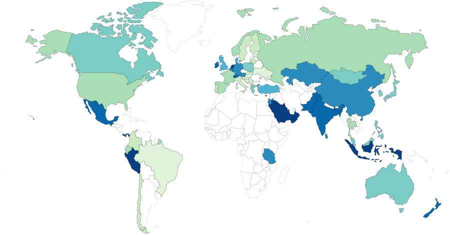


Figure: Observed average revenue

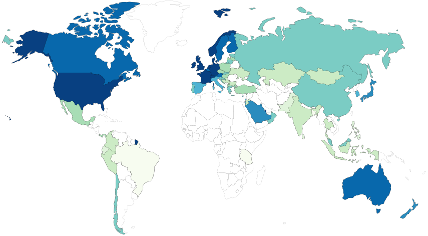


Figure: Estimated average revenue

Data quality

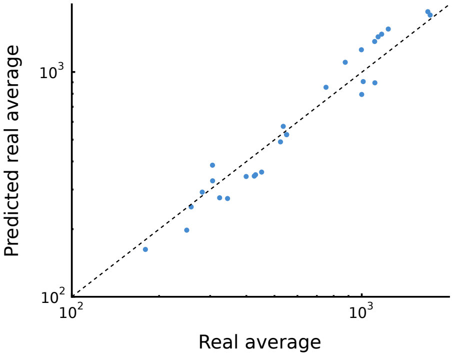


Figure: Pretty good job at predicting

Data quality

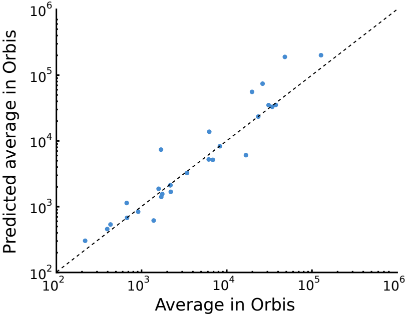


Figure: $\log(predicted\ \ observed) = 3.15 \log(estimated\ \ real) + \log(completeness) - 1.05$

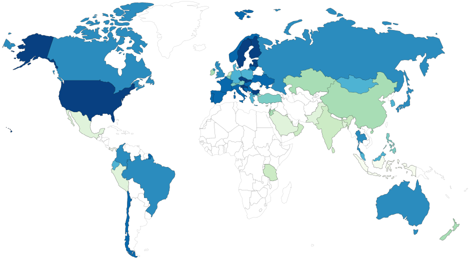
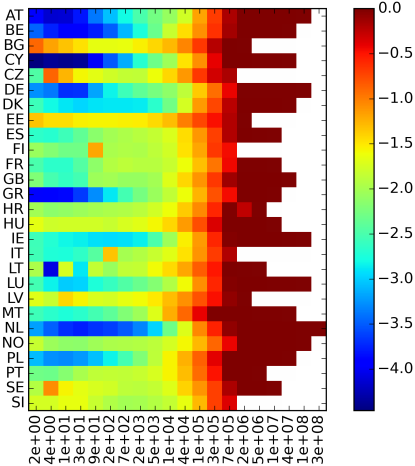


Figure: Actual completeness of our data

Completeness per country



Conclusion

- Big corporate network data provides great insight in firm power and control across the globe
- Topological properties, centrality analysis and community detection all show regional patterns in the global network
- Interpretation of measures is crucial and depends on data quality
- We understand the completeness of our 200 firm dataset, now we can assess the effect on the network

Projects and ideas

Revolting doors

Revolting doors

Figure: 24 high-level former politicians in the energy sector

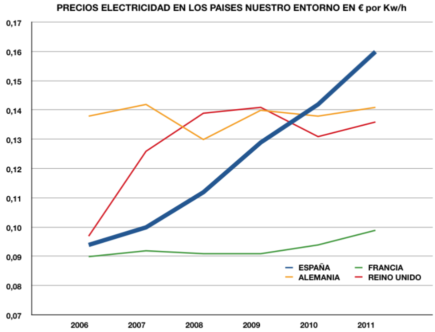
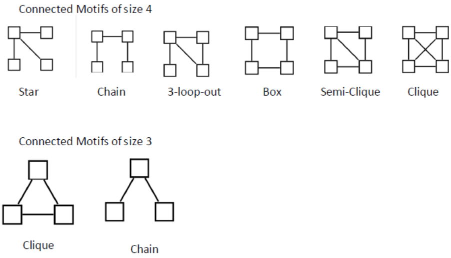


Figure: Price of the electricity for Spain (blue), France (green), Germany (yellow) and UK (red)

What can be done: See how revolting doors affect economy.

Motifs in networks



- Cliques are over-represented: "Triadic closure"
- What can be done: Find other motifs, relate them to functions in the network.

Last names

- What are the elite families?

Last names

- What are the elite families?

2823	horowitz	0.000035	0.000589	4.382193e+11	16.925534
2600	gupta	0.000039	0.000623	4.605060e+11	16.181555
2752	mehta	0.000036	0.000476	3.402674e+11	13.251747
4214	hollander	0.000021	0.000272	1.935952e+11	12.945244
977	kaplan	0.000109	0.001405	9.993748e+11	12.885862
3748	frankel	0.000025	0.000306	2.161069e+11	12.432170
2951	freedman	0.000033	0.000385	2.684805e+11	11.635076
3119	lieberman	0.000031	0.000340	2.338258e+11	10.961698
956	goldberg	0.000111	0.001042	6.899919e+11	9.379767
3047	scully	0.000032	0.000272	1.753170e+11	8.548746
1700	hirsch	0.000063	0.000498	3.145199e+11	7.974270
2839	haddad	0.000035	0.000272	1.708891e+11	7.879714
641	stein	0.000161	0.001201	7.414170e+11	7.476160
1570	gold	0.000068	0.000476	2.873987e+11	7.037540
2045	weinstein	0.000051	0.000351	2.100484e+11	6.858198
1356	healy	0.000079	0.000544	3.250415e+11	6.847610
2701	reddy	0.000037	0.000249	1.484878e+11	6.790080
1161	stern	0.000091	0.000589	3.437826e+11	6.451354
1256	rubin	0.000085	0.000532	3.066906e+11	6.255854
1761	gerber	0.000061	0.000362	2.046825e+11	5.981301
1923	sharma	0.000055	0.000328	1.852137e+11	5.961625
1156	shapiro	0.000092	0.000521	2.873413e+11	5.688276
2307	hassan	0.000044	0.000249	1.363710e+11	5.599909
301	cohen	0.000323	0.001767	9.552407e+11	5.465592
805	levy	0.000131	0.000714	3.843564e+11	5.426666
1609	grossman	0.000066	0.000351	1.871815e+11	5.320299
980	richter	0.000108	0.000532	2.714213e+11	4.911191
1891	goddard	0.000056	0.000272	1.373582e+11	4.837191
2107	epstein	0.000049	0.000238	1.201519e+11	4.834733
1334	siegel	0.000081	0.000385	1.933025e+11	4.784112

Figure: US overrepresented

Last names

- What are the elite families?

2823	horowitz	0.000035	0.000589	4.382193e+11	16.925534
2600	gupta	0.000039	0.000623	4.605060e+11	16.181555
2752	mehta	0.000036	0.000476	3.402674e+11	13.251747
4214	hollander	0.000021	0.000272	1.935952e+11	12.945244
977	kaplan	0.000109	0.001405	9.993748e+11	12.885862
3748	frankel	0.000025	0.000306	2.161069e+11	12.432170
2951	freedman	0.000033	0.000385	2.684805e+11	11.635076
3119	lieberman	0.000031	0.000340	2.338258e+11	10.961698
956	goldberg	0.000111	0.001042	6.899919e+11	9.379767
3047	scully	0.000032	0.000272	1.753170e+11	8.548746
1700	hirsch	0.000063	0.000498	3.145199e+11	7.974270
2839	haddad	0.000035	0.000272	1.708891e+11	7.879714
641	stein	0.000161	0.001201	7.414170e+11	7.476160
1570	gold	0.000068	0.000476	2.873987e+11	7.037540
2045	weinstein	0.000051	0.000351	2.100484e+11	6.858198
1356	healy	0.000079	0.000544	3.250415e+11	6.847610
2701	reddy	0.000037	0.000249	1.484878e+11	6.790080
1161	stern	0.000091	0.000589	3.437826e+11	6.451354
1256	rubin	0.000085	0.000532	3.066906e+11	6.255854
1761	gerber	0.000061	0.000362	2.046825e+11	5.981301
1923	sharma	0.000055	0.000328	1.852137e+11	5.961625
1156	shapiro	0.000092	0.000521	2.873413e+11	5.688276
2307	hassan	0.000044	0.000249	1.363710e+11	5.599909
301	cohen	0.000323	0.001767	9.552407e+11	5.465592
805	levy	0.000131	0.000714	3.843564e+11	5.426666
1609	grossman	0.000066	0.000351	1.871815e+11	5.320299
980	richter	0.000108	0.000532	2.714213e+11	4.911191
1891	goddard	0.000056	0.000272	1.373582e+11	4.837191
2107	epstein	0.000049	0.000238	1.201519e+11	4.834733
1334	siegel	0.000081	0.000385	1.933025e+11	4.784112

Figure: US overrepresented

...	...	...	...	...	...
179	pierce	0.000506	0.000261	2.999537e+11	0.514766
3	brown	0.005116	0.002583	3.196262e+12	0.504784
172	daniels	0.000514	0.000249	3.576335e+11	0.484440
45	roberts	0.001357	0.000646	9.885006e+11	0.475613
88	sanders	0.000819	0.000385	6.131644e+11	0.470291
104	patterson	0.000736	0.000340	5.764456e+11	0.461702
170	fernandez	0.000516	0.000238	4.067305e+11	0.460629
103	simmons	0.000748	0.000340	6.076401e+11	0.454599
112	wallace	0.000707	0.000306	6.453542e+11	0.432515
101	henderson	0.000779	0.000328	7.520451e+11	0.421784
151	hicks	0.000570	0.000238	5.619529e+11	0.417680
126	mcdonald	0.000653	0.000272	6.483840e+11	0.416437
133	woods	0.000626	0.000261	6.220029e+11	0.416304
2	williams	0.005687	0.002356	5.711752e+12	0.414313
71	ward	0.000942	0.000385	9.739485e+11	0.408833
18	jackson	0.002469	0.000963	2.822774e+12	0.389909
10	wilson	0.002903	0.001076	3.677759e+12	0.370715
119	bryant	0.000681	0.000249	8.862143e+11	0.365819
106	hamilton	0.000720	0.000249	1.044657e+12	0.345913
5	jones	0.005052	0.001552	9.102967e+12	0.307186
61	rogers	0.001091	0.000306	2.302062e+12	0.280245
28	walker	0.001858	0.000510	4.062537e+12	0.274293
57	nguyen	0.001150	0.000238	3.888380e+12	0.206914
31	young	0.001727	0.000295	7.671501e+12	0.170500
33	sanchez	0.001636	0.000249	8.446397e+12	0.152348
15	hernandez	0.002619	0.000396	1.363259e+13	0.151403
29	perez	0.001811	0.000272	9.534061e+12	0.150119
9	rodriguez	0.002981	0.000442	1.596607e+13	0.148176
8	garcia	0.003182	0.000408	2.052576e+13	0.128163
23	gonzalez	0.002216	0.000272	1.509750e+13	0.122693

Figure: US underrepresented

Last names

- What are the elite families?

2823	horowitz	0.000035	0.000589	4.382193e+11	16.925534
2600	gupta	0.000039	0.000623	4.605060e+11	16.181555
2752	mehta	0.000036	0.000476	3.402674e+11	13.251747
4214	hollander	0.000021	0.000272	1.935952e+11	12.945244
977	kaplan	0.000109	0.001405	9.993748e+11	12.885862
3748	frankel	0.000025	0.000306	2.161069e+11	12.432170
2951	freedman	0.000033	0.000385	2.684805e+11	11.635076
3119	lieberman	0.000031	0.000340	2.338258e+11	10.961698
956	goldberg	0.000111	0.001042	6.899919e+11	9.379767
3047	scully	0.000032	0.000272	1.753170e+11	8.548746
1700	hirsch	0.000063	0.000498	3.145199e+11	7.974270
2839	haddad	0.000035	0.000272	1.708891e+11	7.879714
641	stein	0.000161	0.001201	7.414170e+11	7.476160
1570	gold	0.000068	0.000476	2.873987e+11	7.037540
2045	weinstein	0.000051	0.000351	2.100484e+11	6.858198
1356	healy	0.000079	0.000544	3.250415e+11	6.847610
2701	reddy	0.000037	0.000249	1.484878e+11	6.790080
1161	stern	0.000091	0.000589	3.437826e+11	6.451354
1256	rubin	0.000085	0.000532	3.066906e+11	6.255854
1761	gerber	0.000061	0.000362	2.046825e+11	5.981301
1923	sharma	0.000055	0.000328	1.852137e+11	5.961625
1156	shapiro	0.000092	0.000521	2.873413e+11	5.688276
2307	hassan	0.000044	0.000249	1.363710e+11	5.599909
301	cohen	0.000323	0.001767	9.552407e+11	5.465592
805	levy	0.000131	0.000714	3.843564e+11	5.426666
1609	grossman	0.000066	0.000351	1.871815e+11	5.320299
980	richter	0.000108	0.000532	2.714213e+11	4.911191
1891	goddard	0.000056	0.000272	1.373582e+11	4.837191
2107	epstein	0.000049	0.000238	1.201519e+11	4.834733
1334	siegel	0.000081	0.000385	1.933025e+11	4.784112

Figure: US overrepresented

...	...	...	...	...	...
179	pierce	0.000506	0.000261	2.999537e+11	0.514766
3	brown	0.005116	0.002583	3.196262e+12	0.504784
172	daniels	0.000514	0.000249	3.576335e+11	0.484440
45	roberts	0.001357	0.000646	9.885006e+11	0.475613
88	sanders	0.000819	0.000385	6.131644e+11	0.470291
104	patterson	0.000736	0.000340	5.764456e+11	0.461702
170	fernandez	0.000516	0.000238	4.067305e+11	0.460629
103	simmons	0.000748	0.000340	6.076401e+11	0.454599
112	wallace	0.000707	0.000306	6.453542e+11	0.432515
101	henderson	0.000779	0.000328	7.520451e+11	0.421784
151	hicks	0.000570	0.000238	5.619529e+11	0.417680
126	mcdonald	0.000653	0.000272	6.483840e+11	0.416437
133	woods	0.000626	0.000261	6.220029e+11	0.416304
2	williams	0.005687	0.002356	5.711752e+12	0.414313
71	ward	0.000942	0.000385	9.739485e+11	0.408833
18	jackson	0.002469	0.000963	2.822774e+12	0.389909
10	wilson	0.002903	0.001076	3.677759e+12	0.370715
119	bryant	0.000681	0.000249	8.862143e+11	0.365819
106	hamilton	0.000720	0.000249	1.044657e+12	0.345913
5	jones	0.005052	0.001552	9.102967e+12	0.307186
61	rogers	0.001091	0.000306	2.302062e+12	0.280245
28	walker	0.001858	0.000510	4.062537e+12	0.274293
57	nguyen	0.001150	0.000238	3.888380e+12	0.206914
31	young	0.001727	0.000295	7.671501e+12	0.170500
33	sanchez	0.001636	0.000249	8.446397e+12	0.152348
15	hernandez	0.002619	0.000396	1.363259e+13	0.151403
29	perez	0.001811	0.000272	9.534061e+12	0.150119
9	rodriguez	0.002981	0.000442	1.596607e+13	0.148176
8	garcia	0.003182	0.000408	2.052576e+13	0.128163
23	gonzalez	0.002216	0.000272	1.509750e+13	0.122693

Figure: US underrepresented

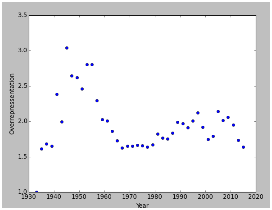


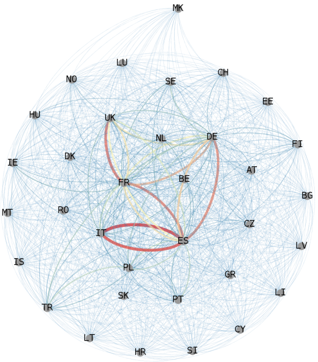
Figure: Overrepresentation in industry for the last names of congressmen

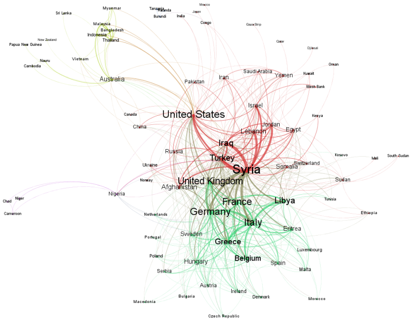
- What can be done: Find how last names are overrepresented for different fields (academia, business, politics, economy)

Last names

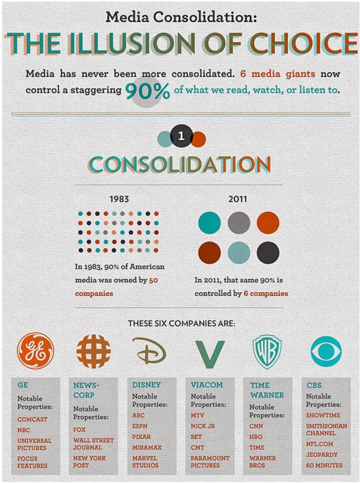
name	perc	perc2	CATALANITY	chiSq	perc3
garriga	0.000125	0.000399	76.475163	1.330853e+14	3.182386
vilanova	0.000112	0.000345	64.408641	1.112150e+14	3.083621
planas	0.000153	0.000446	75.057906	1.340273e+14	2.903358
sole	0.000289	0.000817	79.913169	2.378695e+14	2.826290
vila	0.000814	0.002246	61.755611	6.342631e+14	2.759836
jorda	0.000122	0.000325	46.420110	8.830136e+13	2.678109
rius	0.000113	0.000297	75.814902	7.811046e+13	2.621398
palacio	0.000163	0.000421	-20.793683	1.091496e+14	2.591856
roca	0.000652	0.001689	59.537106	4.368070e+14	2.589036
soler	0.001046	0.002583	42.069533	6.222004e+14	2.469568
giner	0.000235	0.000576	1.709732	1.368931e+14	2.448892
comas	0.000141	0.000331	71.873229	7.345977e+13	2.348692
vilar	0.000202	0.000472	16.666456	1.040648e+14	2.340618
uriarte	0.000135	0.000316	-84.223830	6.964932e+13	2.339333
gimeno	0.000496	0.001158	2.986512	2.542731e+14	2.335723
gilabert	0.000131	0.000304	32.098324	6.563229e+13	2.314886
simo	0.000115	0.000265	42.516089	5.711536e+13	2.308484
miralles	0.000340	0.000784	18.268128	1.682431e+14	2.305632

Migration



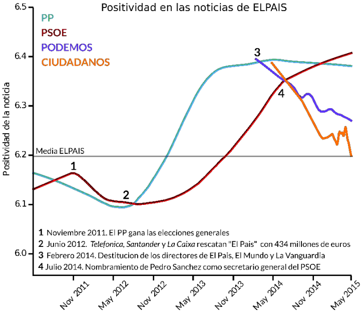


- What can be done: Networks of migration (erasmus, refugees, top executives)



- What can be done: Effect of independence in news (variety, positivity towards the system/government...).

Industry independence



Proxy votes

- Company/Fund A is a shareholder of Company B, C, D...
- Company/Fund A hires company X to manage what to vote in the meetings of those companies

- Particularly (maybe) important in the case of Exchange Trade Funds
- E.g. blackrock: Founded in 1988, it has $4.1 trillion in assets under management, making it bigger than any bank, insurance company, government fund or rival asset-management firm. It single-handedly manages almost as much money as all the worlds private-equity and hedge funds. Though its holdings are mostly equitiesit is the biggest shareholder in half of the worlds 30 largest companiesit also holds bonds, commodities, hedge funds, property and just about anything anyone would ever want to invest in. (The Economist)

- What's the effect of ETFs? Market coordination?

Others

- States as owners: Liberalism in first world vs. state ownership in emerging markets.
- Who rules: Cohesive transnational elite or competing elites?
- Old's boys club:
  - What determines who is linked to who?
  - Origins of inequality (Only 3% of top executives are women).

Prediction

- Predict crashes (network resilience) and cascades. When should we rescue the bank and when should we let it burn?
- Predict merges. What influence mergers and acquisitions?
- Predict performance based on network measures.

Thank you!

- **CORPNET** has a challenging yet exciting time ahead!
- We are open to collaboration, sharing data, resources and ideas!

- Find us on Twitter
  - CORPNET: *@uvaCORPNET*
  - Frank: *@franktakes*
  - Javier: *@javiergb_com*

CORPNET
University of Amsterdam

http://corpnet.uva.nl