

MAPPING AND MEASURING EXTENDED SUPPLY CHAIN STRUCTURES

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Agenda

- (i) Data source: Bloomberg SPLC.
- (ii) Supply chain mapping procedure: An illustrated application.
- (iii) Things to be careful with.
- (iv) Possible novel research opportunities.

DATA SOURCE

Data source: Bloomberg SPLC

- Multiple data sources;
- Cogs, capex, sga and R&D;
- Data checked and quantified;
- > 1 mln contracts and over 123,000 firms globally (10x Compustat)
- Used in reputable management Journals (AMJ, MS).

However...

In 2016, average explained Revenue% is 28%

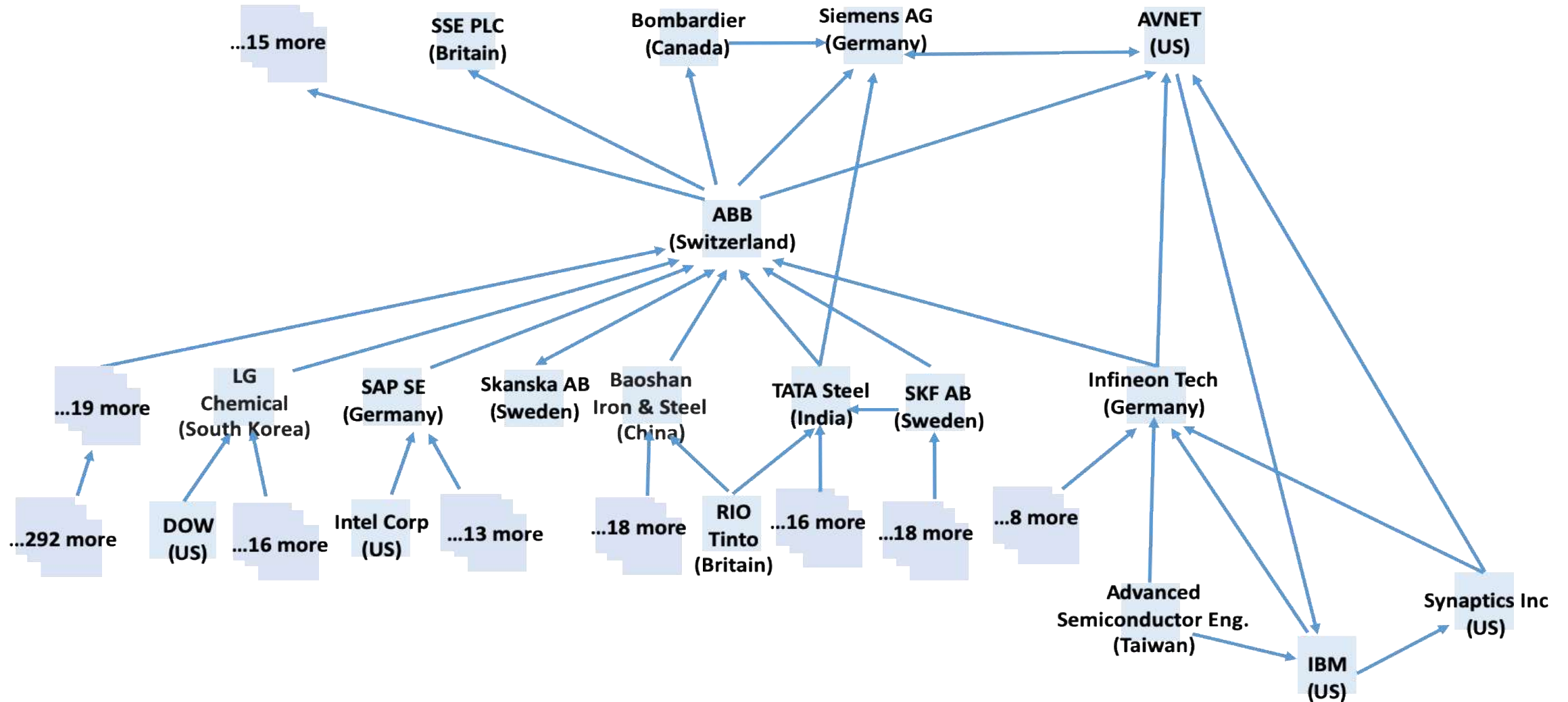
In 2017, about 34%

In 2018, about 40%.



SUPPLY CHAIN MAPPING PROCEDURE: An illustrated application

Observational unit. The multi-tier supply chain of a focal firm.



Step 1

Identify focal firms in the 2015 Forbes2000 list.

.....> List of 617 focal firms.

Step 2

Apply a disproportionate stratified random sampling with industry-country strata.

.....> Representative list of 280 focal firms.

Step 3

- (a) Identify customers, suppliers and sub-suppliers from the Bloomberg SPLC database;
- (b) Search and match redundant tickers (e.g., ABB Ltd appears as 'ABB SS Equity' on the Stockholm Stock Exchange and as 'ABBN VX Equity' on Swiss Stock Exchange).
- (c) Remove supply chain members that are not involved in COGS relationships, so to approximate 'physical' multi-tier supply chains;

->
- 245 focal firms;
 - 4803 supply chain members;
 - 20504 contractual relationships.

Step 4

- (a) Isolate 245 multi-tier supply chains from a large network
- (b) Remove outliers that could distort empirical results:

.....> Final sample of 189 multi-tier supply chains.

The Forbes logo, consisting of the word "Forbes" in a white, serif font on a black rectangular background.

Bloomberg SPLC data



Bloomberg SPLC data

MAGNA INTL Equity - SPLC - Related Functions Menu

MG CN C\$ ↑ 79.63 +0.74 T79.61/79.62X 2x1
At 11:37 d Vol 495,929 0 79.22T H 79.92T L 78.86T Val 39.436M

7201 JP Equity Actions Supply Chain Analysis
Viewing 7201 JP
Analyze Latest Sales Surprise % JPY Display Name As of 07/10/18
Show As 7) Chart 8) Table View Quantified Suppliers
Add Column 18 Fields
Group By None W Stats...

Name	Country	Fund Tkr	Market Cap	Sales Surprise	Revenue Relationship	Account Value (Q) As Type	% Cost Source	As Of Date
2) Nissan Motor Co Ltd	JP	7201 JP	4.24T	5.55%				
2) Nissan Shatai Co Ltd	JP	7222 JP	151.26B	—	98.50%	137.53B COGS	5.61% +2018A CF	06/26/2018
2) Hitachi Ltd	JP	6501 JP	3.73T	0.56%	2.78%	58.07B COGS	2.56% Estimate	10/21/2017
2) Bridgestone Corp	JP	5108 JP	3.15T	-1.93%	5.27%	50.08B COGS	2.09% Estimate	06/11/2018
2) Komatsu Ltd	JP	6301 JP	3.08T	6.21%	0.38%	2.17B CAPEX	1.86% Estimate	06/06/2017
2) Adient PLC	US	AONT US	514.33B	4.79%	8.63%	39.46B COGS	1.65% Estimate	03/23/2018
2) ZF Friedrichshafen AG	DE	1003Z GR	—	—	1.24%	39.09B COGS	1.63% Estimate	05/22/2018
2) Valeo SA	FR	FR FP	1.53T	-0.09%	6.22%	37.57B COGS	1.57% Estimate	04/11/2018
2) Kasai Kogyo Co Ltd	JP	7256 JP	52.35B	—	66.40%	36.93B COGS	1.57% +2017A CF	06/23/2017
2) Continental AG	DE	CON GR	5.21T	-1.77%	2.50%	37.45B COGS	1.56% Estimate	03/21/2018
2) Unipres Corp	JP	5949 JP	102.28B	1.55%	40.50%	32.50B COGS	1.38% +2017A CF	06/23/2017
2) Denso Corp	JP	6902 JP	4.19T	2.76%	1.90%	25.38B COGS	1.08% +2018Q3 CF	02/02/2018
2) Faurecia SA	FR	ED FP	1.11T	23.02%	3.50%	23.02B COGS	0.96% Estimate	03/08/2018
2) Lear Corp	US	LEA US	1.41T	5.48%	3.46%	21.50B COGS	0.94% Estimate	06/13/2018
2) Autoliv Inc	SE	ALV US	1.01T	0.65%	7.00%	21.35B COGS	0.93% Estimate	06/20/2018
2) Alphabet Inc	US	GOOGL US	89.65T	2.41%	0.10%	3.48B SG&A	0.91% Estimate	05/22/2018
2) FANUC Corp	JP	6954 JP	4.37T	1.49%	0.75%	960.89M CAPEX	0.83% Estimate	06/08/2017
2) Clarion Co Ltd	JP	6796 JP	85.39B	1.21%	37.30%	18.17B COGS	0.77% +2017A CF	06/26/2017
2) Aisin Seiki Co Ltd	JP	7259 JP	1.47T	3.58%	1.92%	18.40B COGS	0.75% +2018C3 CF	02/02/2018

300) Edit Panel 301) Expand Panel

385 DPA 11:57 1ST LEAD Kashmir gunfight kills two rebels and one protester By In
384 BN 11:57 Michael Flynn Is Jeered by Protesters After Court Appearance (1)
BN 11:57 +SETH KLARMAN'S BAUPOST ISSUES STATEMENT

More time trading, less time KYCing. KYC



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A2 7201 JP Equity

	A	B	C	D	E	F
		CUR MKT CAP	SALES SURPRISE_LAST_QTR	SUPPLY_CHAIN_REVENUE_PERCENTAGE	RELATIONSHIP_AMOUNT	SUPPLY_CHAIN_CO
1	7201 JP Equity	4.36617E+12	-0.656494895			
2						
3						
4						
5	7201 JP Equity	4.36617E+12	-0.656	#N/A Field Not Applicable	#N/A Field Not Applicable	#N/A Field Not App
6	7248 JP Equity	2.06024E+11	1.975			
7	7222 JP Equity	1.64473E+11	#N/A N/A	84.00	213062.5478	COGS
8	5108 JP Equity	3.26298E+12	-7.277	97.70	116049.3	COGS
9	6501 JP Equity	2.33795E+12	4.814	5.69	52769.87802	COGS
10	LT IN Equity	1.20631E+12	-3.601	1.97	49183.42861	COGS
11	ED FP Equity	4948442687	-3.086	0.56	2353.671978	CAPEX
12	CON GR Equity	37311116129	-1.821	4.78	27843.62907	COGS
13	7256 JP Equity	44213623632	#N/A N/A	2.87	36249.0459	COGS
14	5949 JP Equity	90410588335	-1.264	68.10	36584.00154	COGS
15	FR FP Equity	11053239314	1.965	42.90	33044.25	COGS
16	6954 JP Equity	3.29508E+12	0.725	6.43	29164.14231	COGS
17	6301 JP Equity	1.75926E+12	-2.496	0.74	1300.894208	CAPEX
18	6796 JP Equity	86236976425	-2.202	0.24	1065.775744	CAPEX
19	5401 JP Equity	2.06077E+12	-3.414	41.20	20459.09606	COGS
20	1003Z GR Equity	#N/A N/A	#N/A N/A	1.47	18463.14189	COGS
21	5411 JP Equity	8.90628E+11	-5.987	2.49	25930.66712	COGS
22	IBM US Equity	1.41391E+11	2.226	1.72	14748.0576	COGS
23	ALV US Equity	11054207671	4.108	0.11	2800.956799	SGA
24	6902 JP Equity	3.53539E+12	2.023	8.04	17105.98471	COGS
25	JCI US Equity	26447018296	0.146	1.60	17978.35162	COGS
26	ORCL US Equity	1.63546E+11	-1.228	1.38	15896.67101	COGS
27				0.05	457.7658527	CAPEX

7201 JP Equity 7248 JP Equity 7222 JP Equity 5108 JP Equity 6501 JP Equity LT IN

Ready

Bloomberg SPLC data

2016Dec(B)-Gephi-20180806_104316

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General

Conditional Formatting Format as Table Cell Styles

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	A	B	C	D	E	F	G	H	I
1	ID	SUPPLIER	BUYER	DIRECTION	TRANSACTION	SUPPLIER_REVENUE_PERCENTAGE	BUYER_COST_PERCENTAGE	COST_ACCOUNT_TYPE	SOURCE_OF_RELATIONSHIP
2	0	TMO US Equity	THC US Equity	DIRECTED	9.126744	0.221350998	5.215282917	CAPEX	Estimate (TMO US)
3	1	MDT US Equity	THC US Equity	DIRECTED	87.995688	1.209728956	2.025682926	COGS	Estimate (MDT US)
4	2	MDRX US Equity	THC US Equity	DIRECTED	9.028845	2.612513065	0.188572004	SGA	Estimate (MDRX US)
5	3	STJ US Equity	THC US Equity	DIRECTED	55.7182	3.951644897	1.256896019	COGS	Estimate (THC US)
6	4	CERN US Equity	THC US Equity	DIRECTED	57.43622	4.723521233	1.240254998	SGA	Estimate (CERN US)
7	5	BSX US Equity	THC US Equity	DIRECTED	42.326728	2.241882086	0.954810023	COGS	Estimate (THC US)
8	6	CTSH US Equity	THC US Equity	DIRECTED	5.725864	0.169911996	0.123641998	COGS	Estimate (CTSH US)
9	7	GNRC US Equity	THC US Equity	DIRECTED	0.753911	0.205215007	0.367760986	CAPEX	Estimate (GNRC US)
10	8	HRC US Equity	THC US Equity	DIRECTED	13.077735	2.278748035	0.295008987	COGS	Estimate (HRC US)
11	9	SN/ LN Equity	THC US Equity	DIRECTED	11.275834	0.992591023	0.254361004	COGS	Estimate (SN/ LN)
12	10	PLCM US Equity	THC US Equity	DIRECTED	0.068376	0.023572	0.032873001	CAPEX	Estimate (PLCM US)
13	11	PEGA US Equity	THC US Equity	DIRECTED	1.264138	0.668869972	0.027296999	SGA	Estimate (PEGA US)
14	12	ZBRA US Equity	THC US Equity	DIRECTED	0.223433	0.025419001	0.004825	COGS	Estimate (ZBRA US)
15	13	VRSN US Equity	THC US Equity	DIRECTED	0.507933	0.176639006	0.011171	SGA	Estimate (VRSN US)
16	14	CRVW US Equity	THC US Equity	DIRECTED	0.19273125	15	0.004355	COGS	2015A CF (CRVW US)
17	15	FDX US Equity	TMO US Equity	DIRECTED	33.9628	0.261675	1.382455945	COGS	Estimate (FDX US)
18	16	GLW US Equity	TMO US Equity	DIRECTED	9.797281	0.390796989	0.42098999	COGS	Estimate (GLW US)
19	17	7731 JP Equitv	TMO US Equitv	DIRECTED	0.802780476	0.048170999	0.659162998	CAPEX	Estimate (7731 JP)

Customers/Suppliers relationships list and network:

	Population:	Final Sample:	
	<i>Focal firms</i>	<i>Focal firms</i>	<i>Supply chain members</i>
Capital goods - 2010	68	38	674
Food, Beverage and Tobacco - 3020	86	32	252
Technology Hardware and Equipment - 4520	66	25	504
Automobiles and components - 2510	30	24	280
Materials - 1510	196	22	620
Pharma & Biotech - 3520	44	19	209
Consumer Durables & Apparel - 2520	20	13	175
Health Care Equipment - 3510	46	9	131
Household and Personal Products - 3030	39	6	37
Semiconductors - 4530	22	1	254
Others	0	0	1667
Total	617	189	4803
United States	185	66	1091
Japan	99	46	914
Taiwan	21	11	413
United Kingdom	19	9	123
China/Hong Kong	64	9	762
France	19	8	85
Germany	25	8	94
South Korea	15	8	492
Switzerland	16	6	43
Sweden	12	4	51
Brazil	11	2	36
Finland	5	2	22
Mexico	7	2	31
Others	119	8	646
Total	617	189	4803

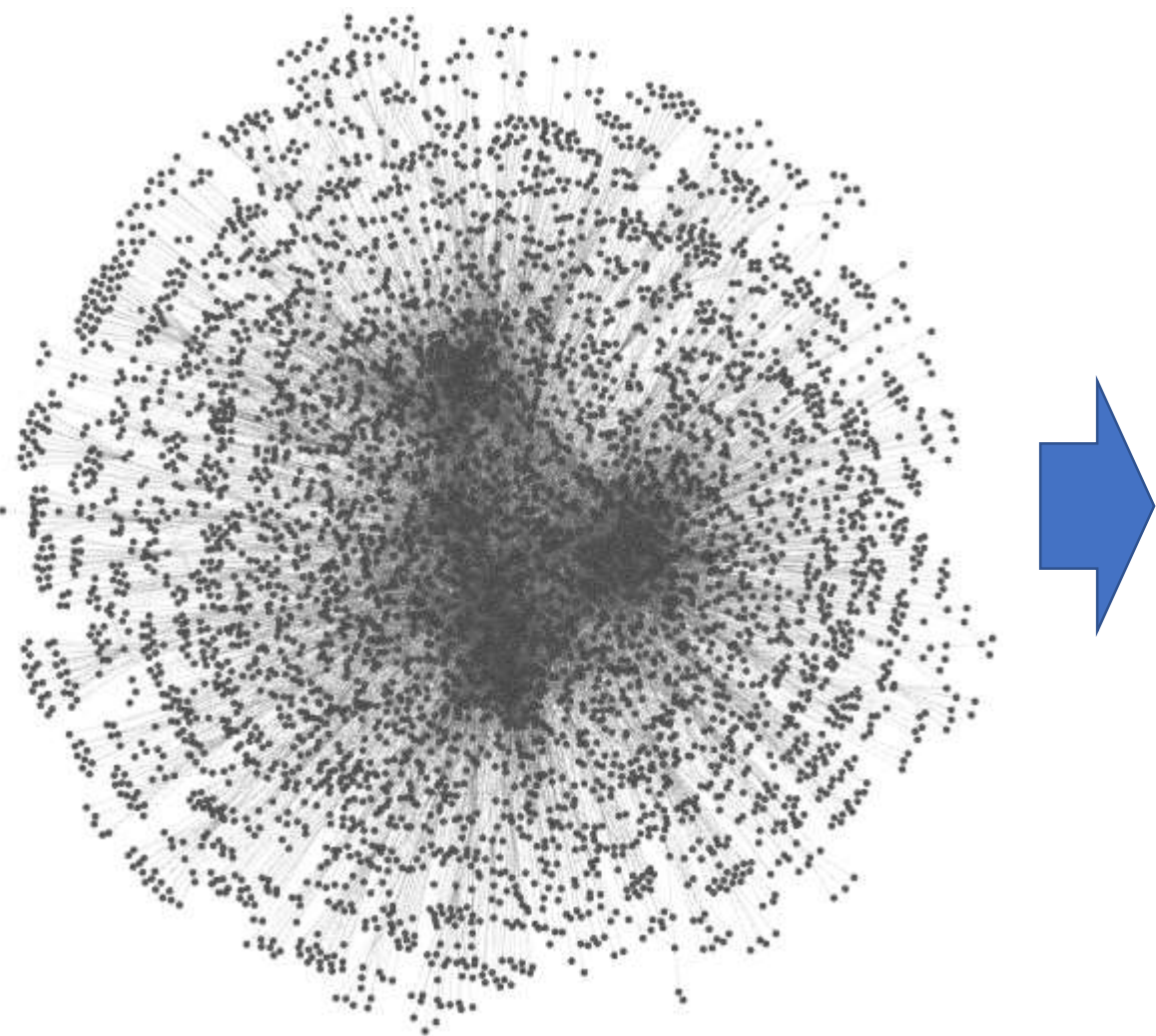
Legend:

- Supply chain member;
- Contractual relationship.



Note: data cleaning did not introduce relevant biases (35 retailers, 56 focal firms with poor data quality)

Isolating Multi-tier SCs

[illegible]

Isolating Multi-tier SCs

a) Generic sub-matrix identifying potential supply chain members:

	A	B	C
A	0	X1	X2
B	X3	0	X4
C	X5	X6	0

b) Sub-matrixes that identify legitimate sub-suppliers of a generic focal firm 'A'

$A \leftarrow B \leftarrow C$

	A	B	C
A	0	0	0
B	1	0	0
C	0	1	0

$A \leftarrow B \leftrightarrow C$

	A	B	C
A	0	0	0
B	1	0	1
C	0	1	0

$A \leftrightarrow B \leftarrow C$

	A	B	C
A	0	1	0
B	1	0	0
C	0	1	0

$A \leftrightarrow B \leftrightarrow C$

	A	B	C
A	0	1	0
B	1	0	1
C	0	1	0

c) Sub-matrixes that identify firms to be excluded from the multi-tier supply chain of a generic focal firm 'A':

$A \rightarrow B \rightarrow C$

	A	B	C
A	0	1	0
B	0	0	1
C	0	0	0

$A \rightarrow B \leftrightarrow C$

	A	B	C
A	0	1	0
B	0	0	1
C	0	1	0

$A \rightarrow B \leftarrow C$

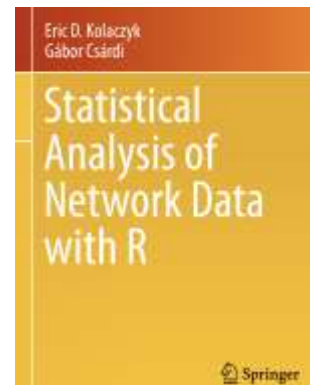
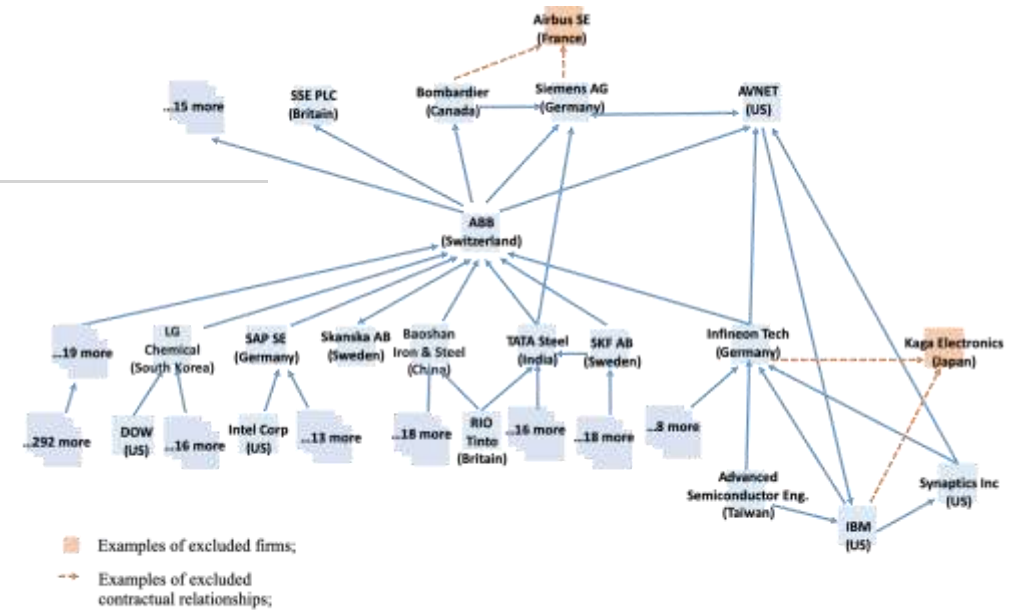
	A	B	C
A	0	1	0
B	0	0	0
C	0	1	0

$A \leftrightarrow B \rightarrow C$

	A	B	C
A	0	1	0
B	1	0	1
C	0	0	0

$A \leftarrow B \rightarrow C$

	A	B	C
A	0	0	0
B	1	0	1
C	0	0	0



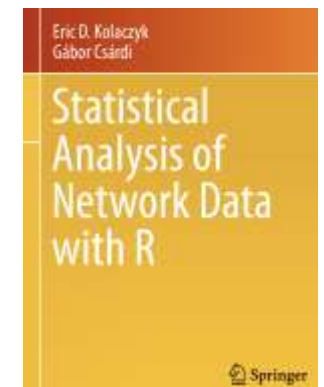
Examples of SC structural measures

Geographical Heterogeneity: $1 - \sum_k p_k^2$ where p_k is the proportion of focal firm's suppliers that fall in category k ($k=77$ countries) (Jackson et al., 1991; Richard et al., 2004)

Industrial Heterogeneity: $1 - \sum_k p_k^2$ where p_k is the proportion of focal firm's suppliers that fall in category k ($k=78$ Industry groups) (Jackson et al., 1991; Richard et al., 2004)

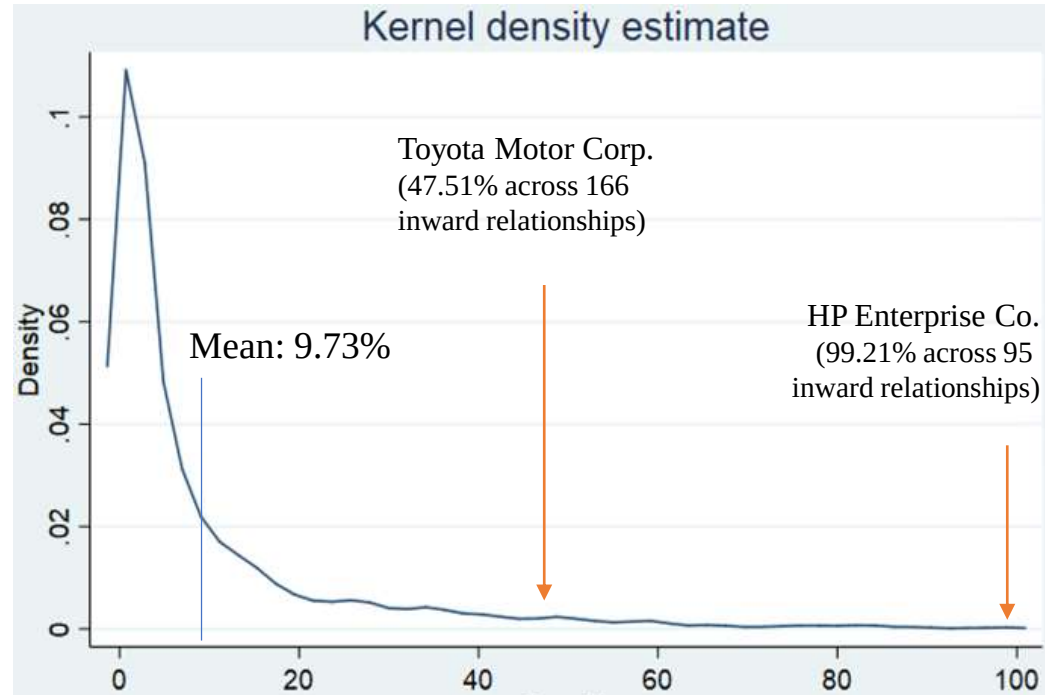
Density: $E/V(V-1)$, where E is the number of contractual relationships and $|V|$ is the number of suppliers (Wasserman and Faust, 1994)

Clustering: $G^{-1} \sum_{i=1}^G C_i^D$, with $C_i^D = \text{closed triads}_i^D / \text{open triads}_i^D$ (Fagiolo, 2007)

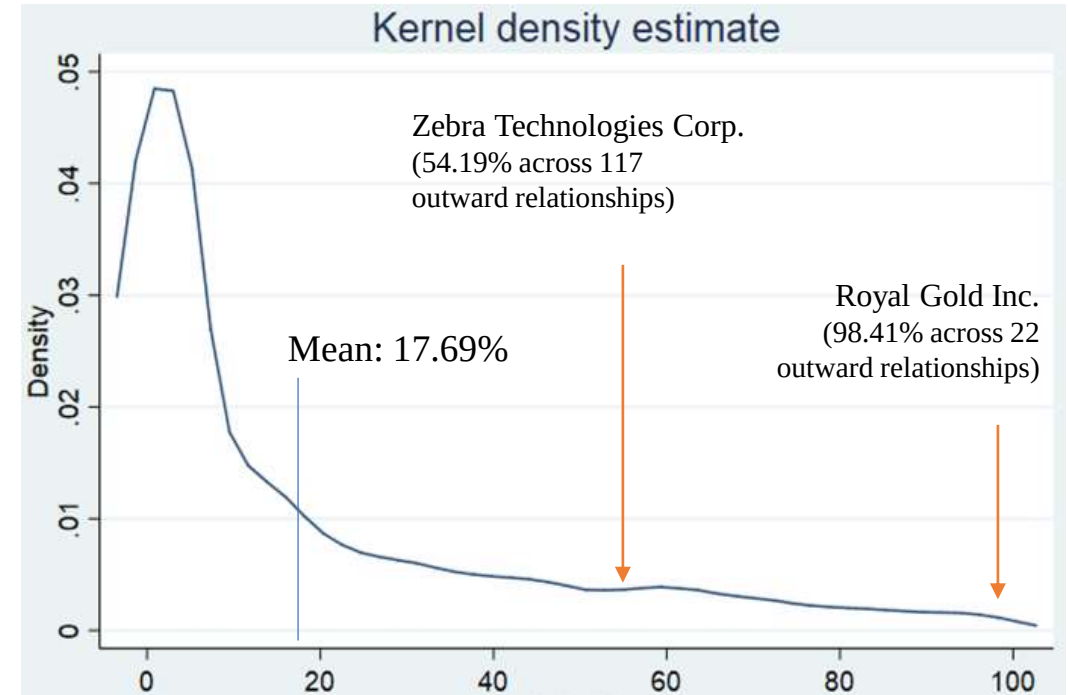


**THINGS TO BE
CAREFUL
WITH...**

SC data coverage and biases related to the selection mechanism:



(a) Customer's known-spend%
(b) (n = 3225)



(b) Supplier's known-revenues%
(n = 3114)

**POSSIBLE NOVEL
RESEARCH
OPPORTUNITIES**

Examples of novel research opportunities

Investigate how **supply chain structure** influences a firm's:

- Innovation capability (Bellamy et al., 2014)
- Financial performance (Lu and Shang, 2017)

Investigate how **supply chain structure** influences a supply chain-level phenomenon (Carter and Washispack, 2018):

- Evolution of structures of supply chains (Park et al., 2018)
- Supply chain innovations (Carnovale and Yeniyurt, 2015)
- Suppliers' and sub-suppliers' collective ESG disclosure

How to measure a collective SC-level phenomenon

Collective Supply Chain Disclosure: $\frac{\sum_{j=1}^N D_j}{N}$
where D_j is a supplier's disclosure index



Tests for reliability: $ICC(2) = (MSB-MSW)/MSB$

Test for non-independence: $ICC(1) = (MSB-MSW) / (MSB+(k-1)*MSW)$

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BACK-UP

Heterogeneity: a simplified illustration

Categorical Heterogeneity

- Blau / Herfindhal / Hirschman index
 - P_k is proportion of ego's alters that fall in category k

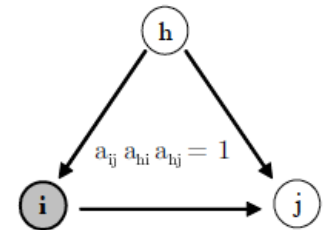
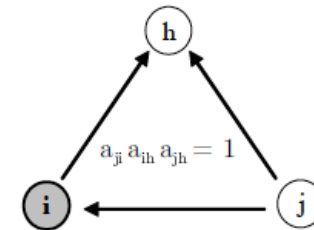
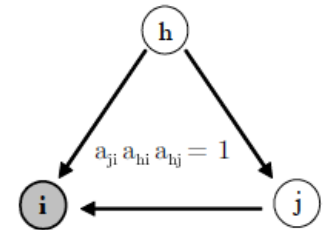
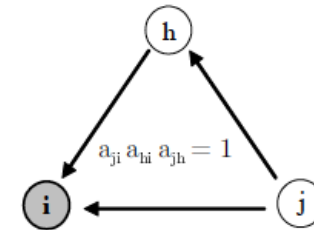
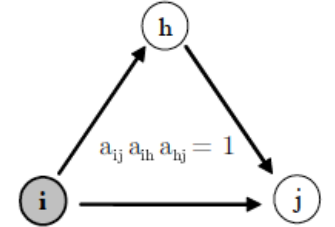
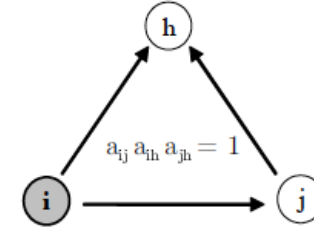
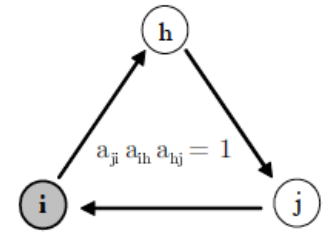
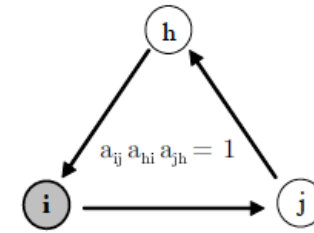
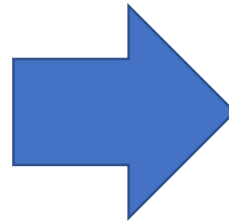
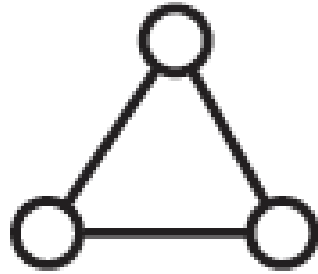
$$H = 1 - \sum_k p_k^2$$

- $H = 0$ if all alters in one category
- $H = 1 - 1/K$ if all categories have equal frequency (can't reach 1.0)
- Agresti's IQV
 - Divide H by $1 - 1/K$ so that measure runs between 0 and 1
 - Gives amount of diversity given the number of categories
 - H could be seen as best measure of diversity, because it is not satisfied until the number of categories $\rightarrow \infty$, which would imply massive diversity

Bill	freq	prop	prop^2	K =	2
Male	14	0.875	0.765625	H =	0.219
Female	2	0.125	0.015625	IQV =	0.438
	16	1	0.78125		
Jane					
Male	8	0.5	0.25	H =	0.5
Female	8	0.5	0.25	IQV =	1
	16	1	0.5		

$$IQV = \frac{H}{1 - 1/K}$$

Clustering in directed binary networks:



PHYSICAL REVIEW E 76, 026107 (2007)

Clustering in complex directed networks

Giorgio Fagiolo*

Sant'Anna School of Advanced Studies, Laboratory of Economics and Management, Piazza Martiri della Libertà 33, I-56127 Pisa, Italy

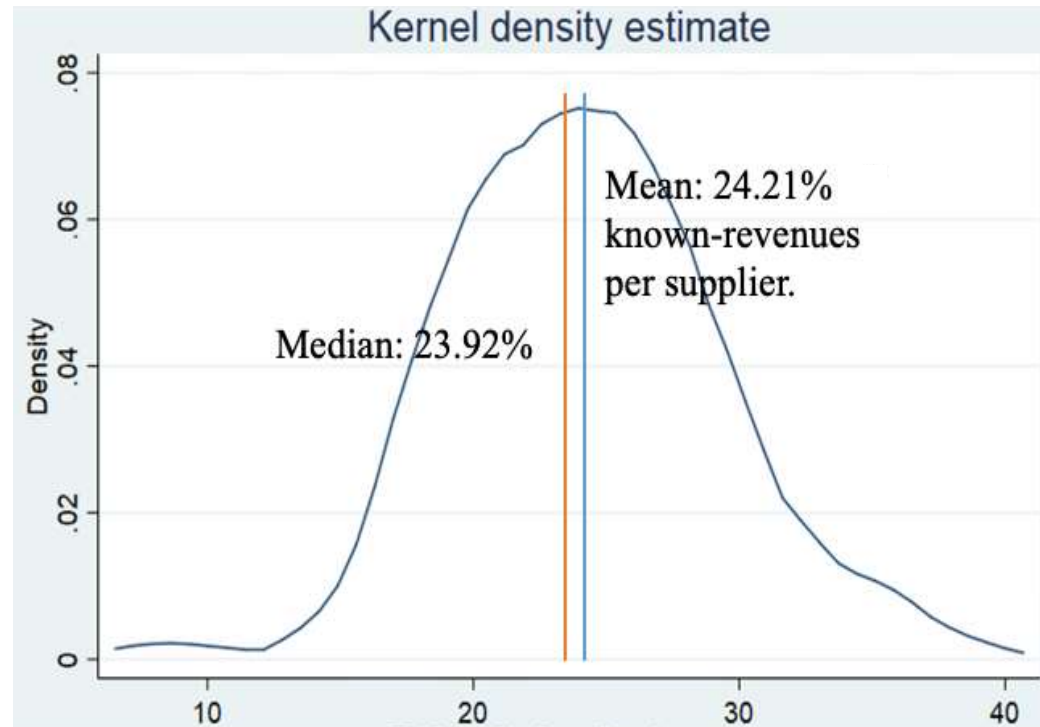
(Received 6 February 2007; published 16 August 2007)

Many empirical networks display an inherent tendency to cluster, i.e., to form circles of connected nodes. This feature is typically measured by the clustering coefficient (CC). The CC, originally introduced for binary, undirected graphs, has been recently generalized to weighted, undirected networks. Here we extend the CC to the case of (binary and weighted) *directed* networks and we compute its expected value for random graphs. We distinguish between CCs that count all directed triangles in the graph (independently of the direction of their edges) and CCs that only consider particular types of directed triangles (e.g., cycles). The main concepts are illustrated by employing empirical data on world-trade flows.

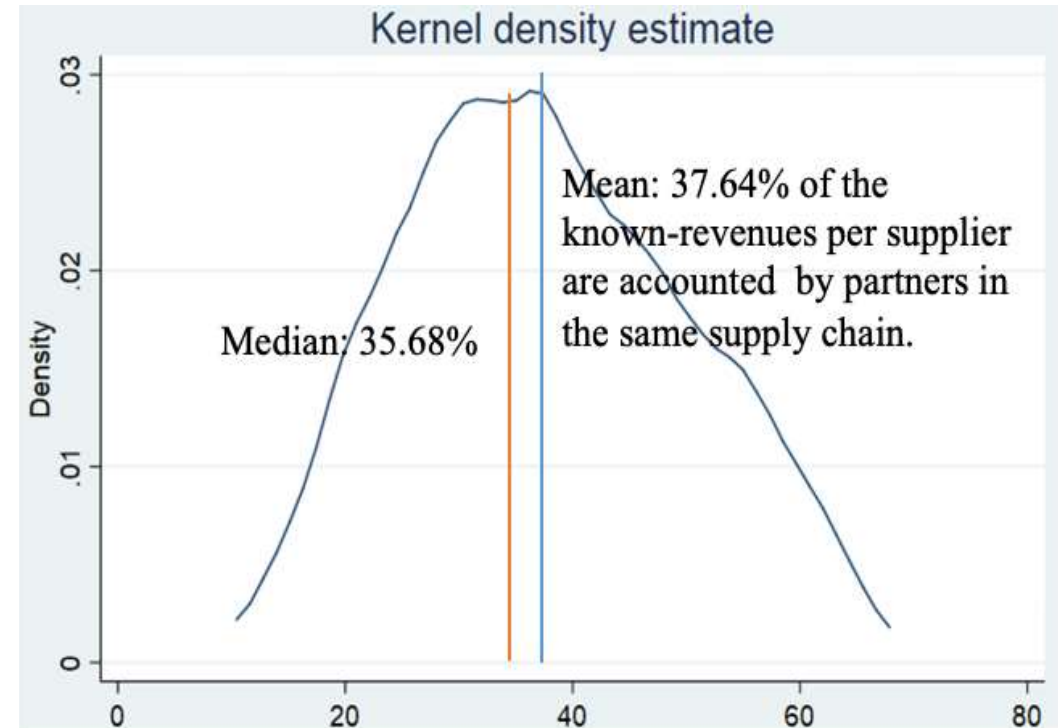
DOI: [10.1103/PhysRevE.76.026107](https://doi.org/10.1103/PhysRevE.76.026107)

PACS number(s): 89.75.-k, 89.65.Gh, 87.23.Ge, 05.70.Ln

Robustness checks:



(a) Supply chain data coverage (n = 189)



(b) Supply chain independence (n = 189)

Robustness checks:

	(1) Robustness: Data coverage		(2) Robustness: Independence	
	Coefficient	Robust Std Errors	Coefficient	Robust Std Errors
SCGeographicalH	0.603***	0.191	0.356**	0.165
SCIndustrialH	0.191	0.274	-0.568***	0.197
SCDensity	1.10***	0.264	0.502***	0.179
SCClustering	-0.440**	0.206	-0.384***	0.089
<i>SCHorizontal</i>	-0.014	0.092	0.080	0.081
<i>SCVertical</i>	-0.240**	0.106	-0.038	0.082
<i>SCOrgSize</i>	-0.027	0.198	0.078	0.163
<i>IndustryClock</i>	-0.427*	0.227	-0.209	0.226
<i>FFDisclosure</i>	0.153**	0.072	0.138**	0.061
<i>IndustryRepRisk</i>	0.071	0.098	-0.011	0.078
<i>SCRegPressure</i>	-0.035	0.131	0.201**	0.088
Constant	0.428**	0.198	0.312	0.216
Observations	95		95	
R-squared	0.497		0.598	

Note: *p <0.1; **p<0.05; ***p<0.01.

STEP 3b: Bloomberg ESG?

- Multiple data sources;
- 120 ESG indicators;
- Data checked and standardized;
- Over 10,000 public firms globally;
- ESG data integrated with financials;
- History from 2007;
- Used by more than 12,600 customers;
- Widely used in reputable accounting Journals.

Strengths: higher coverage than Sustainalytics and Thomson ASSET4;

Limits: predominantly medium/large Mkt Cap. In our dataset, 34% have ESG=0 and Mkt Cap <2bln. However, randomly distributed across SCs.

