

# Network structure and outcomes

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# References

- **Overviews:**
  - Jackson (2010),  
<https://class.coursera.org/networksonline-001>
  - Goyal (2012)
- **Network industries: Economides (1996), Economides and Encaoua (1996)**

## 1 Introduction

## 2 Describing Networks

## 3 Network structure & outcomes

Fershtman and Gandal (2011)

Claussen, Falck, and Grohsjean (2012)

Related Subsequent Work

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# Section 1

## Introduction

# Introduction 1

- Network: nodes & links between them
- Questions:
  - How does network structure affect behavior?
  - How are networks formed?
- Focus on networks that are not owned by a single entity
  - i.e. not on network industries where a single firm owns and controls its network (telecom, electricity, airlines, etc)
  - Relatively new area, little empirical work

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# Networks in IO

- R&D collaboration
- Trade
- Buyer-supplier
- Consumer information & targeting

## Section 2

# Describing Networks

- Nodes  $\in \{1, \dots, N\} = \mathcal{N}$
- Adjacency matrix  $G$ ,  $N \times N$  matrix with  $g_{ij}$  representing connection between  $i$  and  $j$
- Graph  $\equiv (\mathcal{N}, G)$ 
  - Undirected  $\equiv$  symmetric  $G$
  - Directed  $\equiv$  asymmetric  $G$
  - Unweighted (or discrete)  $\equiv g_{ij} \in \{0, 1\}$
  - Weighted  $\equiv$  not discrete



# Summary statistics 1

- Distance between two nodes = shortest path between them ( $\infty$  if no connected path)
- Diameter = largest distance between nodes
- Clustering
  - of graph is portion of  $j$  and  $k$  connected given  $j$  and  $k$  both connected to  $i$
  - of node  $i$  is the portion of time  $j$  and  $k$  are connected directly given  $j$  and  $k$  are connected to  $i$
  - average clustering of graph = average across nodes of node clustering
- Degree of a node = number of links
  - Directed graphs: in-degree & out-degree
  - Degree centrality =  $\frac{\text{degree}}{N-1}$
  - Network density = fraction of possible links present  
=  $\frac{\text{average degree}}{N-1}$
  - Degree distribution = CDF of node degree

## Summary statistics 2

- **Centrality measures:**
  - Degree, closeness, betweenness, decay
  - Eigenvector, Katz, Bonacich

## Section 3

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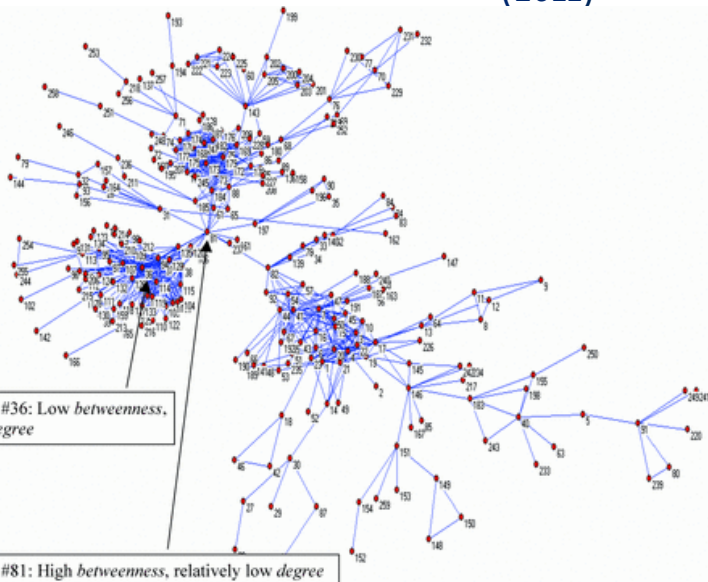
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- Question: how does network structure affect some outcome?
- Reduced form work: regress outcome on node or network summary statistics

# Example: Fershtman and Gandal (2011)

- Knowledge spillovers in open-source projects
- Data:
  - Sourceforge
  - Contributor network: linked if participated in same project
  - Project network: linked if have common contributors
- Question: how important are project vs contributor spillovers for project success?
  - Project spillover = developers learn from working on a particular project
  - Contributor spillover = developers learn from working with other developers
- Related paper: [Claussen, Falck, and Grohsjean \(2012\)](#)

# Example: Fershtman and Gandal (2011)



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# Example: Fershtman and Gandal (2011)

**Table:** The Distribution of Contributors per Project and Projects per Contributor

Project Network		Contributor Network	
Contributors	N Projects	Projects	N Contributors
1	77,571	1	123,562
2	17,576	2	22,690
3-4	11,362	3-4	10,347
5-9	6,136	5-9	3,161
10-19	1,638	10-19	317
20-49	412	20-49	26
≥ 50	56	≥50	1
Total projects	114,751	Total contributors	160,104

# Example: Fershtman and Gandal (2011)

Table: Distribution of Component Size

Component Size (Contributors)	Components (Subnetworks)
55,087	1
196	1
65-128	2
33-64	27
17-32	152
9-16	657
5-8	2,092
3-4	4,810
2	8,287
1	47,787



# Example: Fershtman and Gandal (2011)

Table: Distribution of Degree

Degree	Number of Contributors
0	47,787
1	22,133
2	14,818
3-4	20,271
5-8	20,121
9-16	16,228
17-32	10,004
33-64	5,409
65-128	2,040
129-256	802
257-505	491

# Empirical specification

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- Degree centrality as measure of direct connections
- Closeness centrality =  $C_C(i) = \frac{N-1}{\sum_{j \in \mathcal{N}} d(i,j)}$  – conditional on degree measures indirect connections
- $S_i$  = success = number of downloads

$$S_i = \alpha + \gamma C_C(i)/(N - 1) + \beta \text{degree}_i + \text{controls}$$

# Results - project network

**Table: Regression Results: Dependent Variable: ldownloads**

Independent variables	Regression 1 Coefficient	(All 66,511 Projects) T-Statistic	Regression 2 Coefficient	(Giant Component: 18,697) T-Statistic
Constant	0.72	17.76	1.45	3.62
lyears_since	1.42	60.66	1.68	31.08
lcount_topics	0.23	9.07	0.18	3.59
lcount_trans	0.35	11.73	0.45	8.15
lcount_aud	0.36	10.44	0.44	5.85
lcount_op_sy	0.11	5.95	0.18	5.00
ds_1	1.96	60.57	2.01	31.90
ds_2	0.60	17.58	0.78	11.50
ds_3	0.89	25.83	0.66	9.95
ds_4	1.86	57.21	1.80	29.27
ds_5	2.72	79.97	2.61	40.96
ds_6	2.12	27.07	2.03	15.35
inactive	0.45	6.11	0.39	2.75
lcpp	0.46	18.71	0.87	29.34
ldegree	0.19	9.45	0.079	2.10
giant_comp	0.21	3.86		
lgiant_cpp	0.44	12.05		
lgiant_degree	0.05	1.26		
lcloseness			0.69	3.21
Number of observations	66,511		18,697	
Adjusted R <sup>2</sup>	0.41		0.40	

# Contributor effects

- Regress downloads on average contributor degree and average contributor closeness centrality (and controls)
- Result:
  - Coefficient on log average closeness = 0.12, with  $t = 1.59$
  - Coefficient on log average degree =  $-0.019$ , with  $t = -0.72$
- Including both contributor and project measures, project ones significant, contributor ones not

## Robustness

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Dept Variable: Ldownloads Independent variables	≥ 2yr, Coef	≥ 200dl T Stat	< 3.6yr, Coef	≥ 200dl T Stat	≥ 2yr, Coef	≥ 200dl T Stat
Constant	5.75	13.35	6.21	14.55	8.51	16.29
lyears_since	1.08	11.18	0.91	11.40	1.06	10.97
lcount_topics	0.06	1.31	0.06	1.12	0.06	1.23
lcount_trans	0.42	9.61	0.44	8.83	0.41	9.39
lcount_aud	0.21	2.65	0.46	5.62	0.18	2.28
lcount_op_sy	0.26	7.91	0.26	6.62	0.26	7.94
ds_1	0.46	6.83	0.75	6.23	0.46	6.88
ds_2	0.57	7.31	0.52	4.80	0.57	7.68
ds_3	0.27	4.35	0.23	2.72	0.28	4.44
ds_4	0.19	3.45	0.18	2.41	0.18	3.24
ds_5	0.75	12.99	0.54	6.92	0.73	12.80
ds_6	0.73	7.00	0.45	3.06	0.72	6.89
Inactive	0.018	0.12	0.02	0.11	0.041	0.28
lcpp	0.76	22.21	0.63	19.30	0.59	15.38
ldegree	0.19	5.07	0.0038	0.09	0.019	0.43
lcloseness	0.71	3.28	0.54	2.37	0.45	2.08
lbetweenness					0.30	9.21
Number of observations	6,397		4,086		6,397	
Adjusted R <sup>2</sup>	0.28		0.25		0.29	

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# Limitations

- How to interpret results?
  - Network structure affects downloads
  - Downloads affect contributions, which affects network structure
- Why closeness centrality and degree? (they do explore robustness to other measures, but none of them theoretically motivated)

# Claussen, Falck, and Grohsjean (2012)

- Developer networks in electronic games
- Panel data 1972-2007 on games & developers
- Construct network of developers 1995-2007
- Developers linked in year  $t$  if worked together anytime between 1972 and  $t$
- Look at relationship between revenue (or rating) & degree centrality & closeness centrality

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$$S_{igdpt} = \alpha_i + \alpha_d + \alpha_p + \alpha_t + \beta_1 D_{igdpt-1} + \beta_2 C_{igdpt-1} + CV_{igdpt} \gamma + \epsilon_{igdpt}$$

- Developer  $i$
- Game  $g$
- Developing firm  $d$
- Publisher  $p$
- Year  $t$



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**Table 1**  
Summary statistics.

Variable	N	Mean	SD	Min	Max
ln(revenue)	151,677	14.958	1.701	4.264	19.440
Critics' score	146,675	0.007	0.781	-3.831	2.223
Degree centrality $D_{igdpt}$	148,627	0.001	0.002	0.000	0.041
Closeness centrality $C_{igdpt}$	148,627	0.205	0.038	0.052	0.338
Leading position	151,677	0.213	0.410	0	1
Tenure	151,677	3.871	4.254	0	28
Team size	151,677	65.780	53.234	1	297
Licensed game	151,677	0.362	0.480	0	1

# Claussen, Falck, and Grohsjean (2012)

**Table 3**

Baseline regression results with revenue as success measure.

	(3-1)	(3-2)	(3-3)	(3-4)
Dependent variable: ln(revenue)				
Degree centrality $D_{igdpt}$	8.494* (4.468)	8.029* (4.342)	7.281** (3.321)	6.512* (3.644)
Closeness centrality $C_{igdpt}$	-0.137 (0.201)	-0.307 (0.217)	-0.105 (0.155)	-0.223 (0.174)
Co-worker degree c. $\bar{D}_{-igdpt}$			40.20 (60.77)	56.53 (45.38)
Co-worker closeness $\bar{C}_{-igdpt}$			-0.548 (3.059)	-3.122 (2.567)
Tenure	0.0170 (0.0618)	0.0612 (0.0886)	0.0236 (0.0664)	0.0676 (0.0932)
Team size	0.00447*** (0.000937)	0.00396*** (0.000990)	0.00446*** (0.000938)	0.00394*** (0.000991)
Licensed game	0.192*** (0.0720)	0.172** (0.0771)	0.193*** (0.0721)	0.171** (0.0774)
Network measures lagged	No	Yes	No	Yes
Observations	151,484	94,597	151,443	94,388
Number developers	56,944	30,993	56,937	30,956
Within-developer $R^2$	0.635	0.638	0.635	0.638
Between-developer $R^2$	0.802	0.742	0.798	0.736
Overall $R^2$	0.736	0.689	0.734	0.684

Notes: Fixed-effect OLS point estimates with standard errors clustered at the project

# Gandal and Stettner (2016)

## “Network dynamics and knowledge transfer in virtual organisations”

- Panel data of Sourceforge contributions
- Look for direct & indirect spillovers
- Programmers who work on many projects positively impact success beyond their effect on connectivity in the network

# Athey and Ellison (2014)

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## “Dynamics of Open Source Movements”

- Dynamic model of open source contributions and commercial competitors
- Theory paper, not empirical

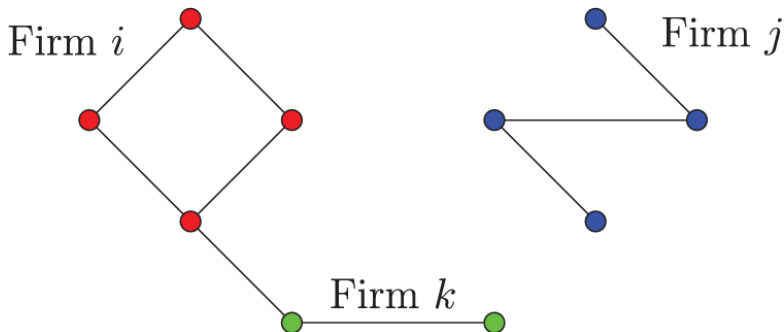
# Knowledge Spillovers through Networks of Scientists

## Zacchia (2019)

- Weighted network of publicly traded companies
- Links = proportion of firms' inventors that have former patent collaborations
- Main endogeneity concern: common unobservables
- IV motivated by model of firm interaction

# Network Among Inventors

- Inventor  $m$  and  $n$  linked ( $p_{(mn)t} = 1$ ) if  $m$  and  $n$  collaborated on any past patent



# Network Among Firms

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$$c_{(ij)t}^f = f \left( \frac{\text{inv. of } i \text{ connected to } j \text{ at } t + \text{inv. of } j \text{ connected to } i \text{ at } t}{\text{inv. of } i \text{ at } t + \text{inv. of } j \text{ at } t} \right)$$

- Symmetric
- $0 \leq c_{(ij)t}^f \leq 1$
- In empirical results,  $f(\cdot) = \sqrt{\cdot}$  and  $g_{(ij)t} = c_{(ij)t}^{\sqrt{\cdot}}$

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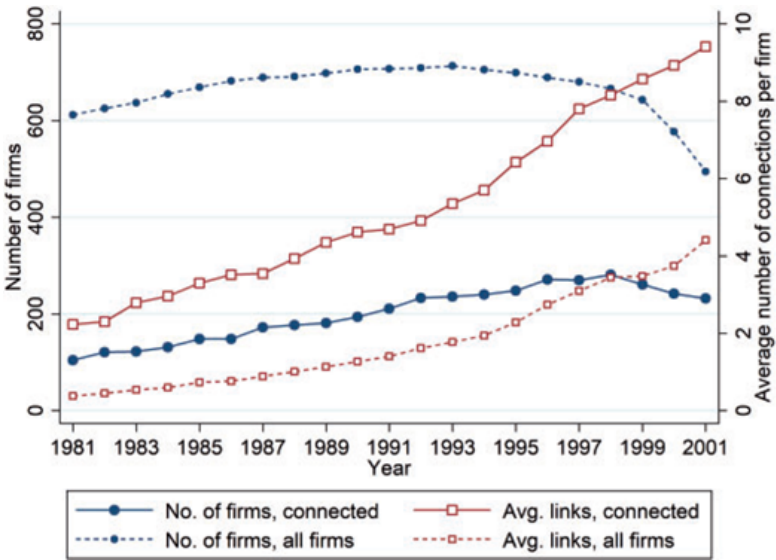
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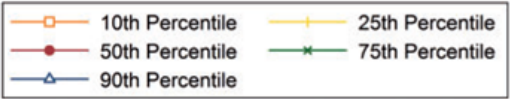
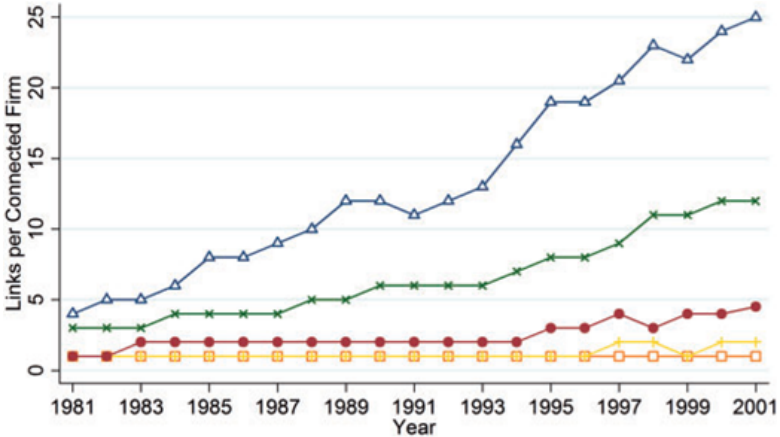
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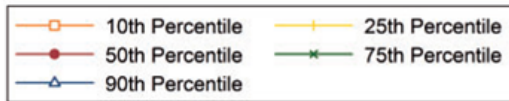
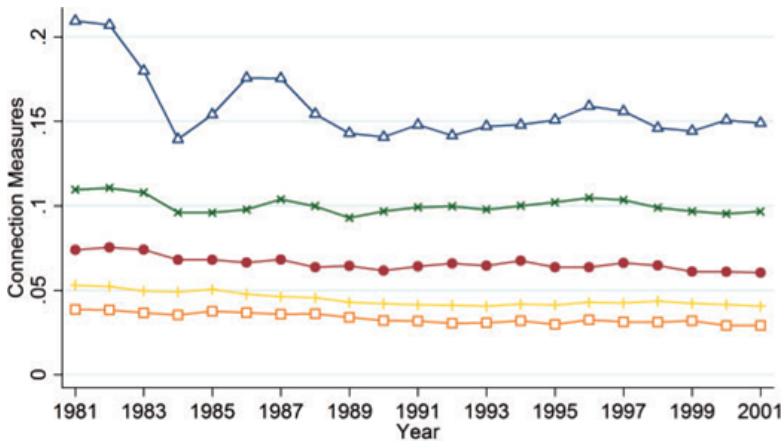
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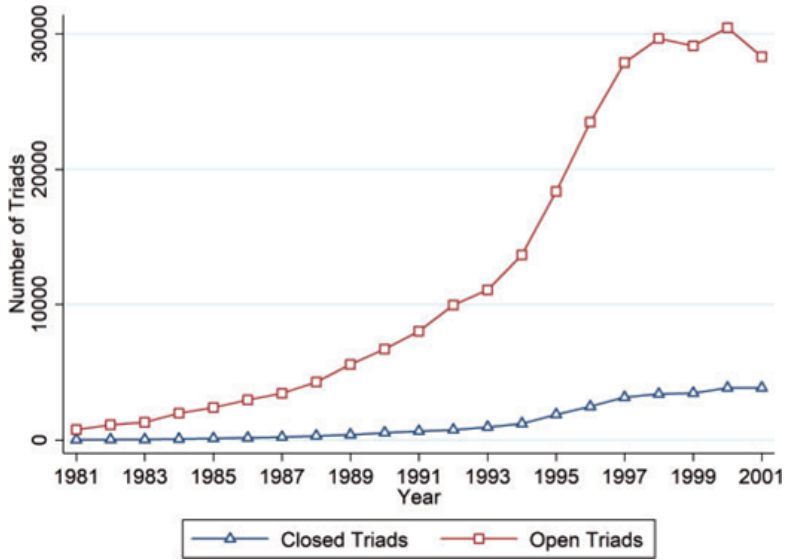
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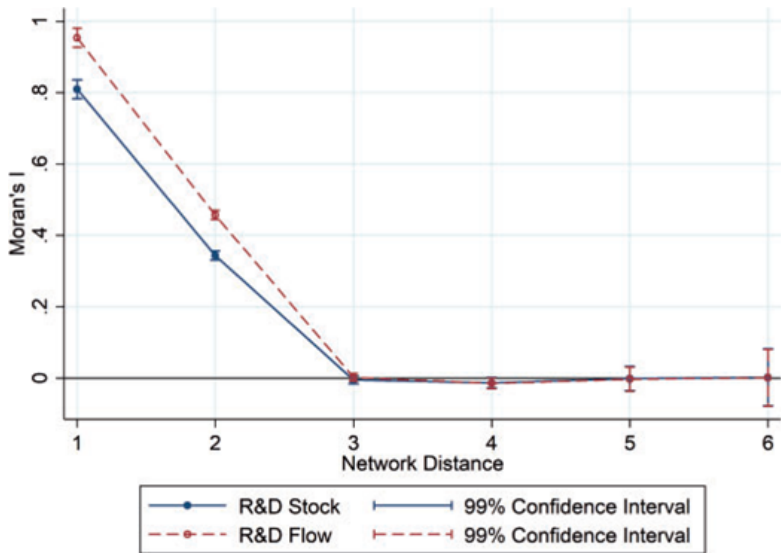
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**TABLE 1**

Summary statistics, 1981–2001

	No network	Quartile of $\sum_{it} \bar{g}_{it}$			
		1	2	3	4
$Y_{it}$ : real sales (Millions 1996\$)	751	1,066	1,383	2,172	10,462
	(3,792)	(2,357)	(2,504)	(4,533)	(20,058)
$V_{it}/A_{it}$ : Tobin's $q$	1.886	1.885	2.573	2.734	3.410
	(2.031)	(1.839)	(3.080)	(3.306)	(4.118)
$P_{it}$ : patent stock (cit. weighted)	7.453	16.09	24.65	74.03	652.0
	(48.17)	(44.75)	(50.91)	(143.8)	(1322.1)
$E_{it}$ : employees (thousands)	4.068	6.940	9.328	12.40	57.09
	(12.52)	(15.80)	(16.63)	(22.43)	(96.80)
$Y_{it}/E_{it}$ : labour productivity	135.6	134.5	157.1	156.5	192.4
	(80.06)	(106.6)	(95.43)	(117.7)	(153.3)
$Y_{it}/K_{it}$ : capital productivity	6.932	5.308	5.142	4.941	4.184
	(6.083)	(3.167)	(3.992)	(3.292)	(2.883)
$Y_{it}/S_{it}$ : productivity of R&D	39.31	19.71	51.10	11.12	4.342
	(134.1)	(70.47)	(479.9)	(34.46)	(3.932)
$Y_{it}/J_{it}$ : Jaffe measure ( $i, t$ )	80.28	107.7	140.0	211.6	962.5
	(407.7)	(238.5)	(264.9)	(435.4)	(1787.8)
$Y_{it}/\prod_j S_{jt}^{g_{ijt}}$ : $Y$ to spillover pool		953.9	846.2	577.6	198.9
		(2,224.0)	(1,762.1)	(1,858.7)	(1,339.6)
No. of observations	4,363	1,854	1,819	1,949	2,028



# Econometric Model

$$\log Y_{it} = \alpha_i + \sum_{q=1}^Q \beta_q \log X_{itq} + \gamma \log S_{it} + \delta \sum_{j=1}^N g_{(ij)t} \log S_{jt} + \tau_t + v_{it}$$

- Output  $Y_{it}$
- Inputs  $X_{itq}$
- R&D stock  $S_{it}$  (depreciated past sum of R&D expenditures)
- $\delta$  = strength of R&D spillovers

# Endogeneity

- $E[\log S_{jt} v_{it}] \neq 0$  from e.g.  $v_{jt}$  correlated with  $v_{it}$ , or  $S_{jt}$  chosen with some knowledge of  $v_{it}$
- Endogenous connections  $E[g_{(ij)t} v_{it}] \neq 0$

# Analytic Framework

- Firms  $\mathcal{I}$  with connection  $\mathcal{G}$
- Knowledge capital

$$\tilde{S}_i = s_i^\gamma \left( \prod_j s_j^{g_{ij}} \right)^\delta$$

- R&D cost  $e^{\tilde{\omega}_i} S_i$
- Cobb-Douglas Production as above
- Firms maximize profits (output minus linear input costs minus R&D costs)



- Unique Bayes-Nash equilibrium with

$$\log S_i^* = \frac{\log \gamma + \sum_q \beta_q (\log \beta_q - \log \xi_q - \log \gamma)}{1 - \gamma - \sum_q \beta_q} b_i^*(\mathcal{G}; \vartheta) + s_i^*(\Omega_i; \mathcal{G})$$

where

- $\vartheta = \frac{\delta}{1 - \gamma - \sum_q \beta_q}$
- $b_i^*(\mathcal{G}; \vartheta)$  is Katz-Bonacich network centrality
- $\Omega_i$  is firm's information set and

$$s_i^*(\Omega_i; \mathcal{G}) = \frac{\omega_i - (1 - \sum_q \beta_q) \bar{\omega}_i + \log E[\prod_j e^{g_{ij} \delta s_j^*(\Omega_j, \mathcal{G})} | \Omega_i]}{1 - \gamma - \sum_q \beta_q}$$

## Identifying Assumptions

- Correlation of  $\log S_{jt}$  with unobservables of  $i$  happens through  $s_i^*(\Omega_i; \mathcal{G})$  due to  $\omega_{it}$  and  $\omega_{jt}$  possibly being correlated and  $\Omega_i$  potentially being informative about  $\omega_{jt}$
- Assumption 1:  $\exists C > 0$  such that if distance from  $i$  to  $j$  is greater than  $C$ , then  $\text{Cov}(\omega_i, \omega_j | d_{ij} > C) = 0$  and  $\text{Cov}(\bar{\omega}_i, \bar{\omega}_j | d_{ij} > C) = 0$
- Assumption 2:  $\exists L > 0$  such that  $d_{ij} > L$  implies  $(\omega_j, \bar{\omega}_j) \notin \Omega_i$
- Implies:

$$\text{Cov}(\omega_i, \log S_j | d_{ij} > C + L) = 0$$

$$\text{Cov}(\log S_i \log S_j | d_{ij} \leq C + 2L) \leq 0$$

$$\text{Cov}(\log S_i \log S_j | d_{ij} > C + 2L) = 0$$

- Use  $\log S_k$  as instrument for  $\log S_j$  when  $k$  and  $j$  are distance  $C + L < D \leq C + 2L$  apart

TABLE 2  
*Production function, ordinary least squares estimates, 1981–2001*

	(1)	(2)	(3)	(4)	(5)
Private R&D ( $\gamma$ )	0.0455*** (0.0108)	0.0438*** (0.0105)	0.0568*** (0.0118)	0.0554*** (0.0128)	0.0515*** (0.0142)
R&D spillovers ( $\delta$ )	0.0159*** (0.0023)	0.0147*** (0.0024)	0.0114*** (0.0024)	0.0118*** (0.0025)	0.0116*** (0.0028)
Geographic spillovers		0.0035 (0.0021)	0.0027 (0.0020)	0.0023 (0.0023)	0.0015 (0.0019)
Capital	0.2071*** (0.0143)	0.2061*** (0.0145)	0.2035*** (0.0194)	0.2020*** (0.0213)	0.2023*** (0.0198)
Labour	0.6550*** (0.0241)	0.6580*** (0.0249)	0.6634*** (0.0351)	0.6613*** (0.0359)	0.6622*** (0.0363)
Jaffe tech. proximity		0.1352** (0.0581)	0.0361 (0.0583)	0.0026 (0.0766)	0.0179 (0.0805)
Fixed effects	YES	YES	YES	YES	YES
Only network	NO	NO	YES	YES	YES
No. of communities (Community $\times$ Year Effects)	0	0	0	10	20
No. of observations	12,503	12,503	7,607	7,607	7,607

*Notes:* The table reports OLS estimates of model (4.11). Columns 1 and 2 are estimated over the entire original sample of 736 firms in the time interval 1981–2001. Estimates in columns 3, 4, and 5 restrict the sample to firms with at least one non-zero connection ( $g_{(ij)t} \neq 0$ ) in any year  $t$ ; all observations of these firms are also included for years with no connections. All estimates include firm and year fixed effects. Columns 4 and 5 include additional community-by-year fixed effects, where communities are obtained via the Louvain algorithm with  $\varphi = 0.8$  (10 communities) in column 4 and  $\varphi = 0.6$  (20 communities) in column 5. Standard errors are clustered by the 20 “communities” obtained via the Louvain algorithm with  $\varphi = 0.6$  (small sample corrections are applied). All observations of the same individual firm in different years enter the same cluster. For estimates not restricted to the network, firms outside the network constitute single clusters. Asterisks denote conventional significance levels of  $t$ -tests (\*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ).

TABLE 3  
*Production function, first stage estimates, 1981–2001*

	(1)	(2)	(3)	(4)	(5)
Distance 2 instrument	0.0043*** (0.0002)	0.0044*** (0.0002)			
Distance 3 instrument		-0.0001* (0.0001)	0.0006*** (0.0001)	0.0005*** (0.0001)	0.0005*** (0.0001)
Private R&D	0.1598*** (0.0517)	0.1774*** (0.0488)	0.5022*** (0.1463)	0.4612*** (0.1436)	0.4357*** (0.1504)
Capital	0.1827 (0.1133)	0.1895 (0.1098)	0.6169** (0.2622)	0.5903** (0.2719)	0.5923** (0.2746)
Labour	-0.0761 (0.0921)	-0.0530 (0.0913)	-0.6482** (0.2412)	-0.6021** (0.2636)	-0.6541** (0.2631)
Jaffe tech. proximity	1.8439*** (0.4808)	1.8224*** (0.5123)	3.3663** (1.5953)	3.2740** (1.3777)	3.3672** (1.4690)
Fixed effects	YES	YES	YES	YES	YES
Only network	YES	YES	YES	YES	YES
No. of communities (Community × Year Effects)	0	0	0	10	20
<i>F</i> -statistic	255.17	219.47	24.92	32.06	19.18
No. of observations	7,607	7,607	7,607	7,607	7,607

*Notes:* The table reports OLS “first stage” regressions of the spillover variable  $\sum_{j \neq i} g_{(ij)t} \log S_{jt}$  on selected instruments and all other right-hand side variables included in the regressions from Table 2. The sample is restricted to firms with at least one non-zero connection ( $g_{(ij)t} \neq 0$ ) in any year  $t$ ; all observations of these firms are also included for years with no connections. Columns 1 and 2 include, on the right hand side, the distance 2 instrument; columns 2 through 5 include the distance 3 instrument. All estimates include firm and year fixed effects. Columns 4 and 5 include additional community-by-year fixed effects, where communities are obtained via the Louvain algorithm with  $\varphi = 0.8$  (10 communities) in column 4 and  $\varphi = 0.6$  (20 communities) in column 5. Standard errors are clustered by the 20 “communities” obtained via the Louvain algorithm with  $\varphi = 0.6$  (small sample corrections are applied). All observations of the same individual firm in different years enter the same cluster. Asterisks denote conventional significance levels of  $t$ -tests (\* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ).

TABLE 4  
Production function, two stages least squares estimates, 1981–2001

	(1)	(2)	(3)	(4)	(5)
Private R&D ( $\gamma$ )	0.0560*** (0.0117)	0.0562*** (0.0118)	0.0510*** (0.0111)	0.0489*** (0.0127)	0.0464*** (0.0131)
R&D spillovers ( $\delta$ )	0.0127*** (0.0029)	0.0125*** (0.0030)	0.0204** (0.0084)	0.0230** (0.0088)	0.0211** (0.0095)
Geographic spillovers	0.0027 (0.0019)	0.0027 (0.0019)	0.0030 (0.0018)	0.0026 (0.0021)	0.0018 (0.0018)
Capital	0.2025*** (0.0200)	0.2027*** (0.0199)	0.1969*** (0.0225)	0.1944*** (0.0244)	0.1956*** (0.0234)
Labour	0.6642*** (0.0357)	0.6640*** (0.0356)	0.6692*** (0.0373)	0.6677*** (0.0382)	0.6685*** (0.0392)
Jaffe tech. proximity	0.0314 (0.0549)	0.0324 (0.0553)	0.0041 (0.0545)	-0.0364 (0.0669)	-0.0167 (0.0744)
Spillovers IV(s)	$D=2$	$D=2, 3$	$D=3$	$D=3$	$D=3$
Fixed effects	YES	YES	YES	YES	YES
Only network	YES	YES	YES	YES	YES
No. of communities					
(Community $\times$ Year Effects)	0	0	0	10	20
No. of observations	7,607	7,607	7,607	7,607	7,607

Notes: The table reports IV-2SLS estimates of model (4.11). All estimates are restricted to firms with at least one non-zero connection ( $g_{(ij)t} \neq 0$ ) in any year  $t$ ; all observations of these firms are also included for years with no connections. Models in columns 1 and 2 employ the distance 2 instrument; models in columns 3 through 5 employ the distance 3 instrument. All estimates include firm and year fixed effects. Columns 4 and 5 include additional community-by-year fixed effects, where communities are obtained via the Louvain algorithm with  $\varphi=0.8$  (10 communities) in column 4 and  $\varphi=0.6$  (20 communities) in column 5. Standard errors are clustered by the 20 “communities” obtained via the Louvain algorithm with  $\varphi=0.6$  (small sample corrections are applied). All observations of the same individual firm in different years enter the same cluster. Asterisks denote conventional significance levels of  $t$ -tests (\*\* $p < 0.05$ ; \*\*\* $p < 0.01$ ).

# Conclusions

- $D = 2$  IV near OLS implies  $D = 2$  might be too small, i.e.  $C = 2$
- Marginal social return =  $(\gamma + \delta \bar{g}_i) \frac{Y_i}{S_i} = 114\%$  considerably greater than marginal private return =  $\gamma \frac{Y_i}{S_i} = 102\%$

# Acemoglu, Akcigit, and Kerr (2016)

## “Innovation network”

- Directed network of patent citations, 1975-2004
- Results:
  - Network stable over time
  - Past innovations (patents) in connected industries predict current patents
  - Impact of innovations are localized

Network structure and outcomes

Paul Schrimpff

Introduction

Describing Networks

Network structure & outcomes

Fershtman and Gandal (2011)

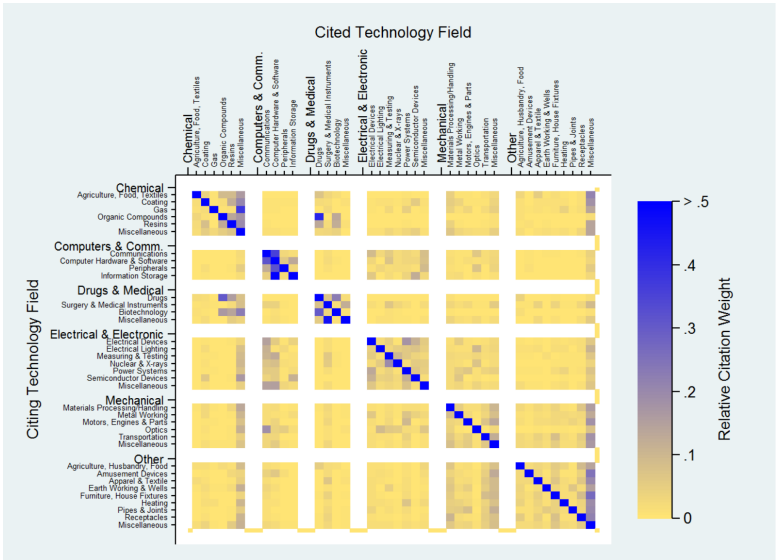
Claussen, Falck, and Grohsjean (2012)

Related Subsequent Work

Zacchia (2019)

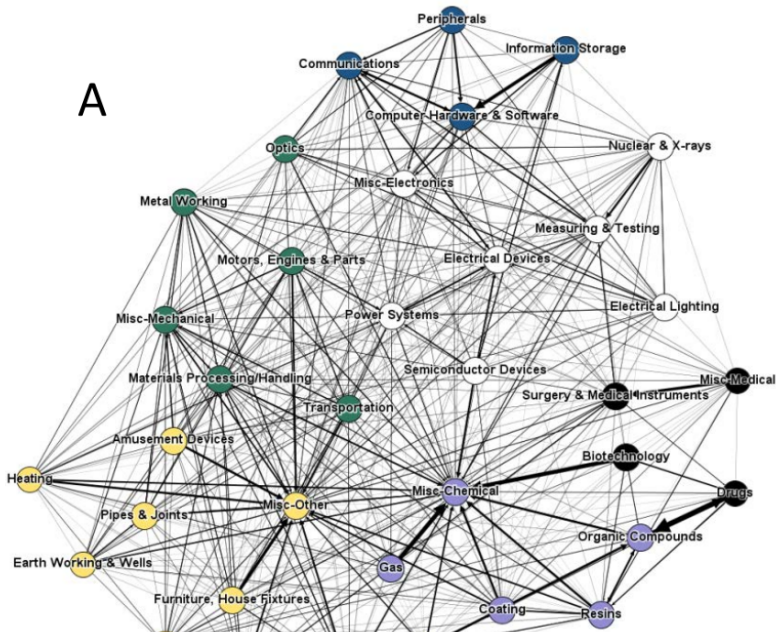
Acemoglu, Akgic, and Kerr (2016)

References





A



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Claussen, Falck, and Grohsjean (2012)

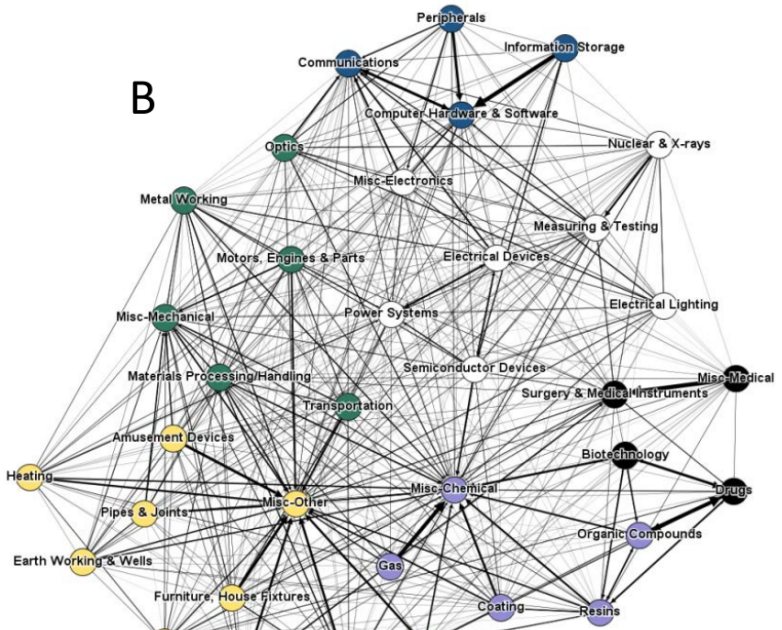
Related Subsequent Work

Zacchia (2019)

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References

B



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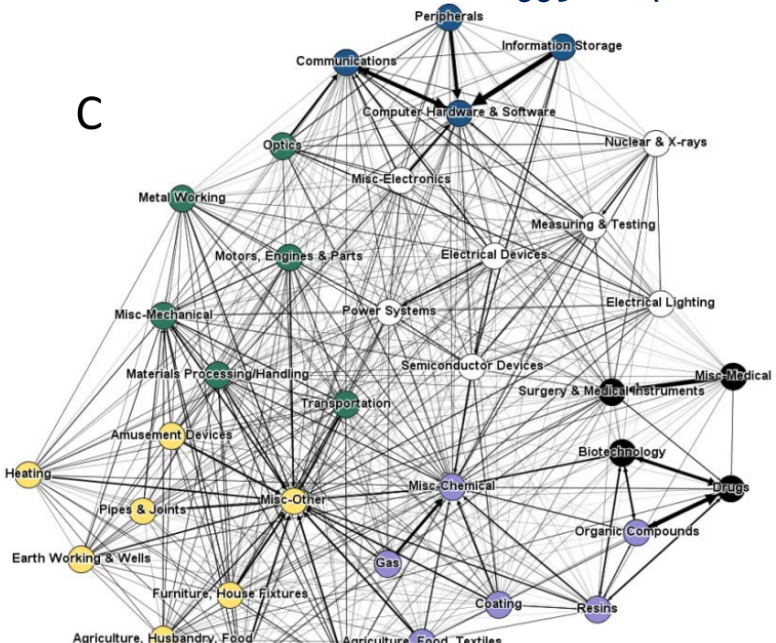
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 Related Subsequent Work  
 Zacchia (2019)  
 Acemoglu, Akgigit, and Kerr (2016)

References

1995-2004

C



# Predicting patents

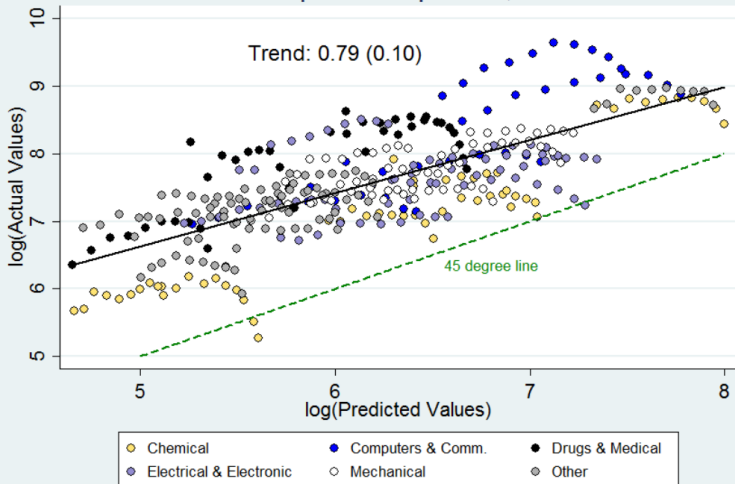
- Predicted patents in industry  $j$  from past citations:

$$\hat{P}_{j,t} = \sum_{k \neq j} \sum_{a=1}^{10} \frac{\text{Citations}_{j \rightarrow k, a}}{\text{Patents}_k} P_{k, t-a}$$

where

- $\text{Citations}_{j \rightarrow k, a}$  = citations of a patent in industry  $k$  that is  $a$  years old from  $j$
- $\text{Patents}_k$  = total patents in  $k$
- Both estimated using 1975-1994 data
- Predictions for 1995-2004

A: Actual vs. predicted patents, 1995-2004



**Appendix Table 2: Disaggregated analysis of innovation network**

	Full sample with >5 per annum			Restricted sample with >50 per annum		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable is log cumulative patent counts in patent class 1995-2004						
Log cumulative patents 1985-1994	0.678 (0.061)	0.732 (0.055)	0.840 (0.066)	0.785 (0.083)	0.806 (0.069)	0.905 (0.079)
Log expected patenting from network stimulus	0.345 (0.052)			0.265 (0.066)		
Log expected patenting from network stimulus due to top 10 upstream classes		0.298 (0.056)			0.294 (0.066)	
Log expected patenting from network stimulus due to next 10 upstream classes		0.067 (0.074)			-0.041 (0.091)	
Log expected patenting from network stimulus outside of top 20 upstream classes		-0.061 (0.054)			-0.032 (0.068)	
Log expected patenting from network stimulus within subcategory			0.077 (0.029)			0.043 (0.037)
Log expected patenting from network stimulus within rest of category			0.105 (0.037)			0.097 (0.047)
Log expected patenting from network stimulus outside of category			-0.004 (0.048)			0.012 (0.054)

Notes: See Appendix Table 1. In Columns 2 and 5, we separate the upstream stimulus provided by the ten most-important upstream classes, the next ten upstream classes, and those beyond. These upstream classes are defined by citation shares made by the focal class during the pre-1995 period. In two cases, the patent class cites fewer than ten upstream categories and is excluded. Columns 3 and 6 alternatively rely on the USPTO classification system of subcategories and categories, which is naturally cruder since it is less-tailored to an individual technology's citation patterns. The disaggregated results do not add up to the total network effect due to the log transformations.

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