Networks and the Geography of Innovation

Balázs Lengyel

Agglomeration, Networks, and Innovation Research Lab
HUN-REN Centre for Economic- and Regional Studies
Corvinus University of Budapest

We live in small world network.

Diffusion of viruses and information is fast

Brockman D., Helbing D (2013) Science

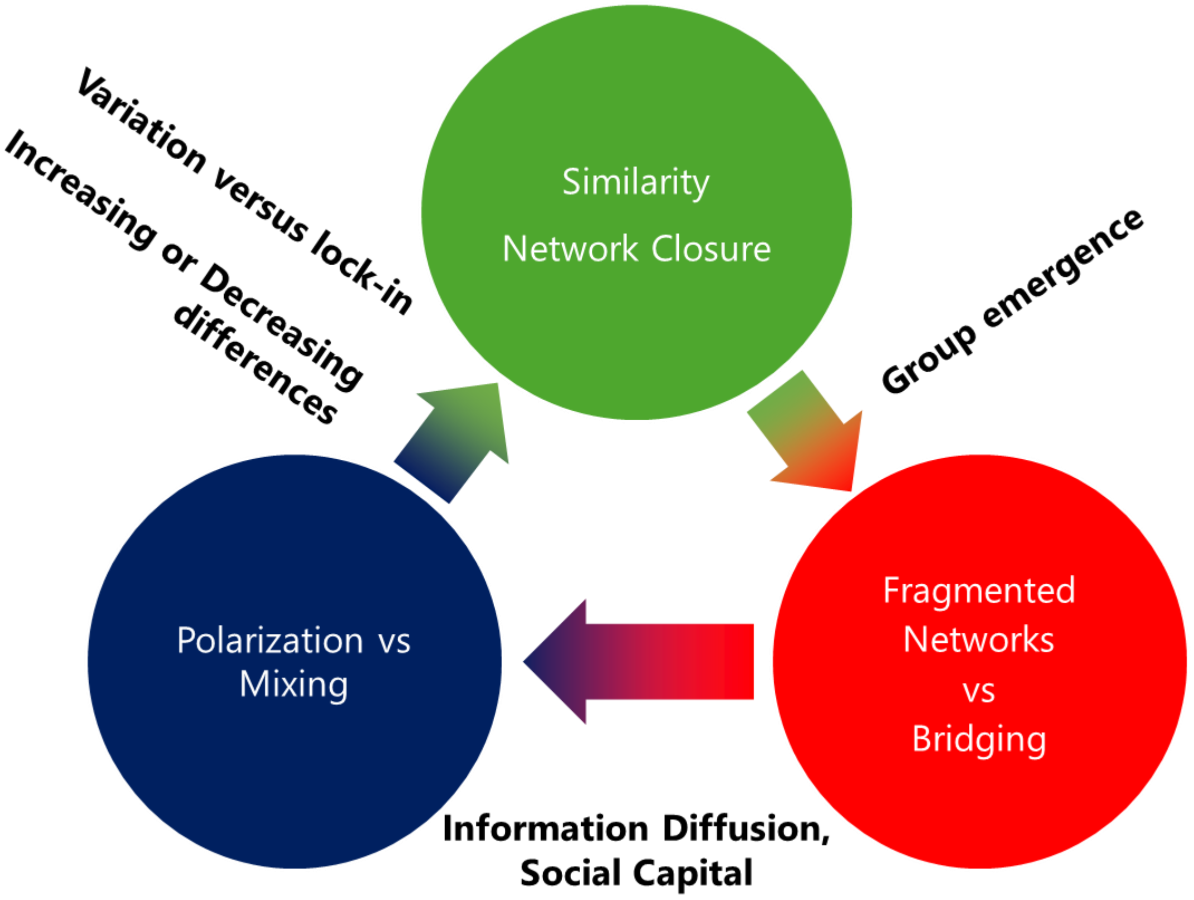
The global society is segregated

Why do we observe growing inequalities
if diffusion of ideas and knowledge
is very quick
in small-world networks?

Prosperous areas next to a slum in Mumbai.

Network fragmentation and inequalities

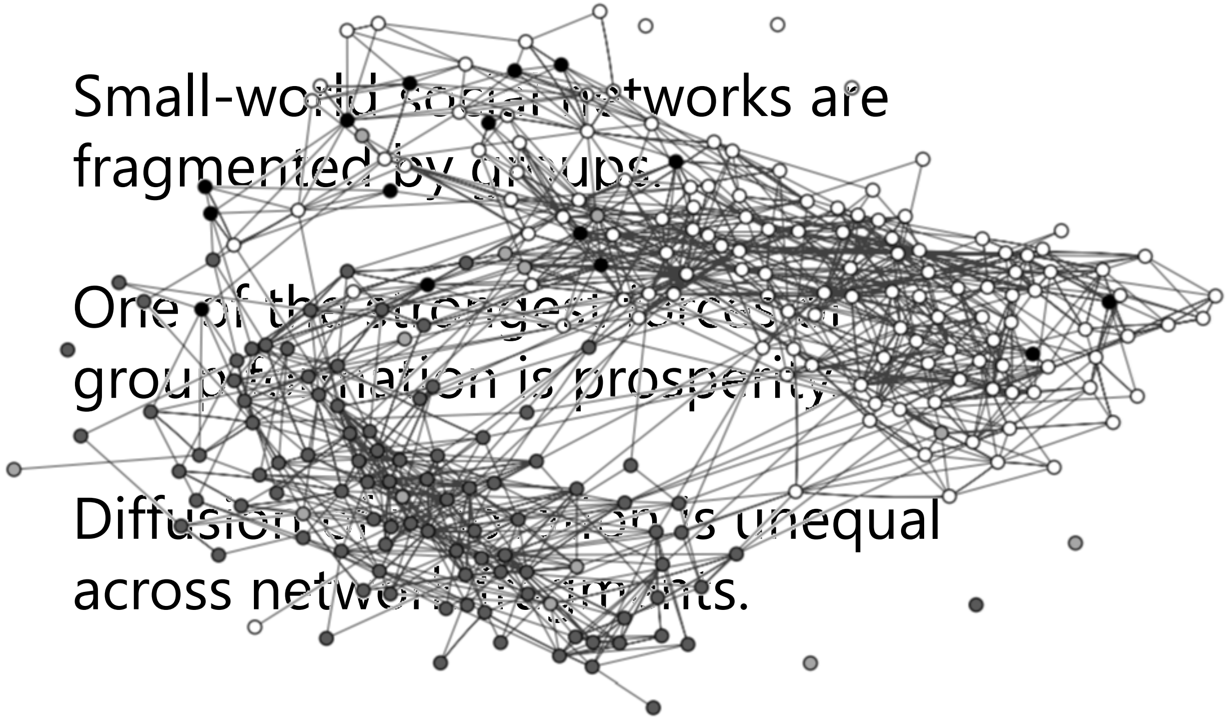
DiMaggio-Garip (2012) Annual Review of Sociology



Small-world social networks are fragmented by groups.

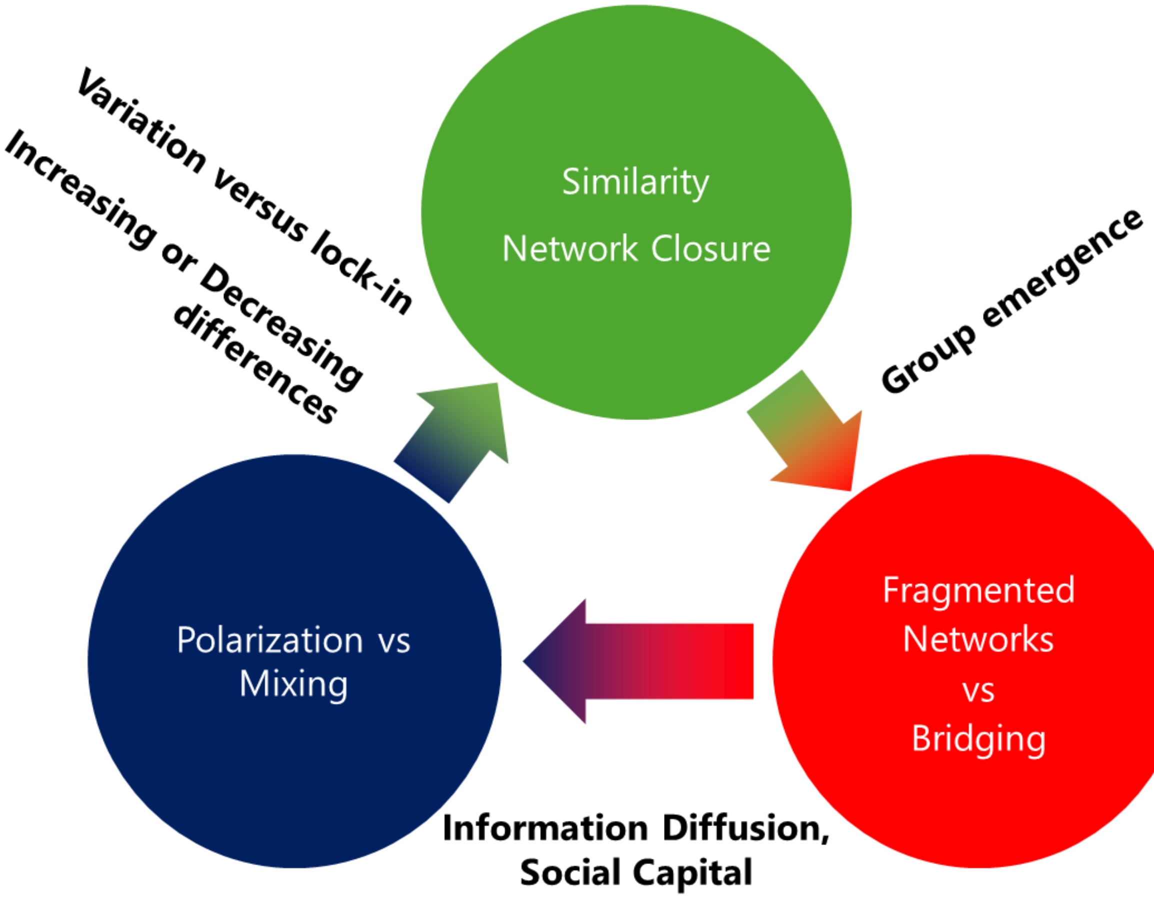
One of the strongest forces of group formation is prosperity.

Diffusion of information is unequal across network fragments.



Currarini, Pin, Jackson (2009) Econometrica

Network fragmentation and innovation



Similar specialization in knowledge increases link probability.

- Increases understanding and specialization

Local collaboration networks can become too cohesive and locked-in into technologies – Grabher (1993), Boschma & Frenken (2010), Giuliani (2013), Balland et al. (2016)

Bridging is on purpose

- To collect new knowledge.

In this class

1. Network concepts and tools to study

2. Economic relevance and the geography of social and collaboration networks

3. Data Lab

4. Case studies
    1. collaboration networks and innovation in regions
    2. role of networks in diffusion of innovation (EXTRA)

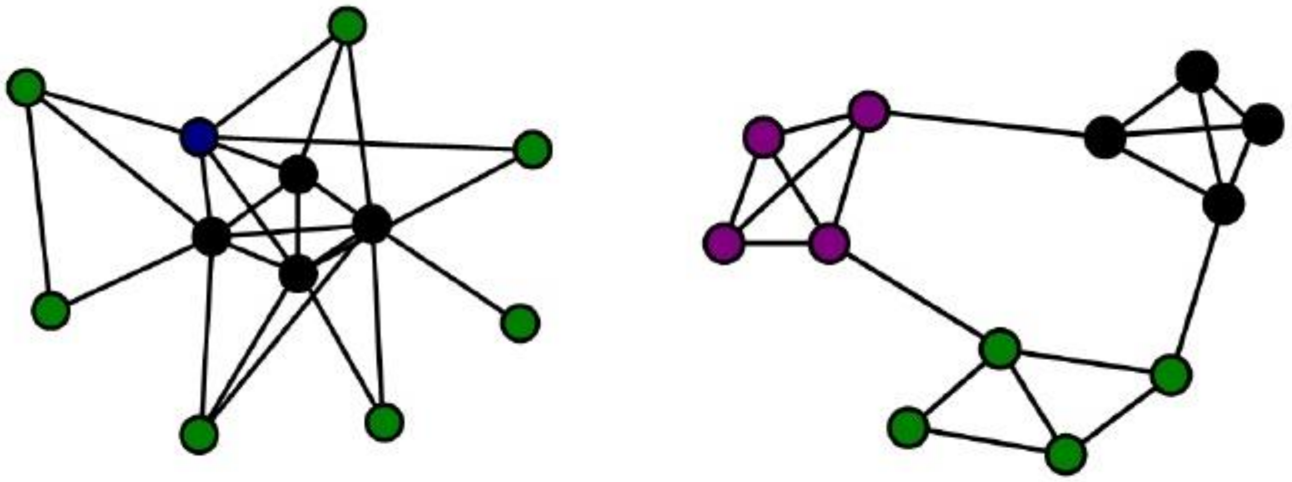
1. Network concepts and tools

Network definition

The network consists of a certain number of elements (actor, individual, organization) and the relationships between them (friendship, sales, professional support, etc.).

Dots: Node, vertex

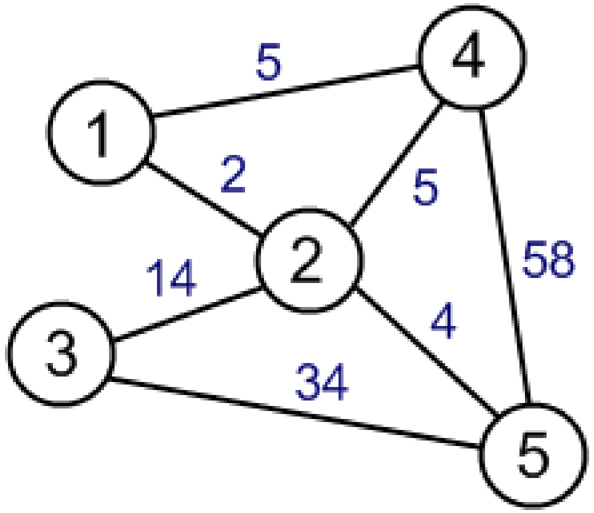
Lines: edge, tie



Edge characteristics

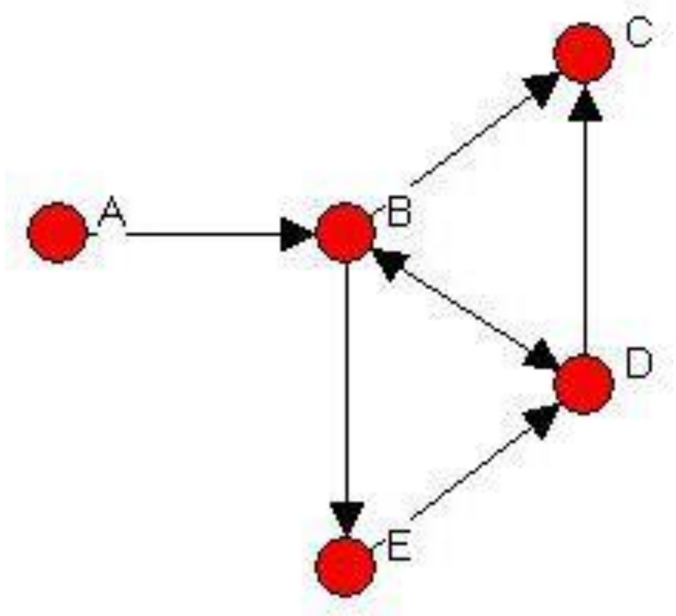
Weighted – unweighted

Friendship vs. the quality of friendship
Meetings vs. frequency of meetings

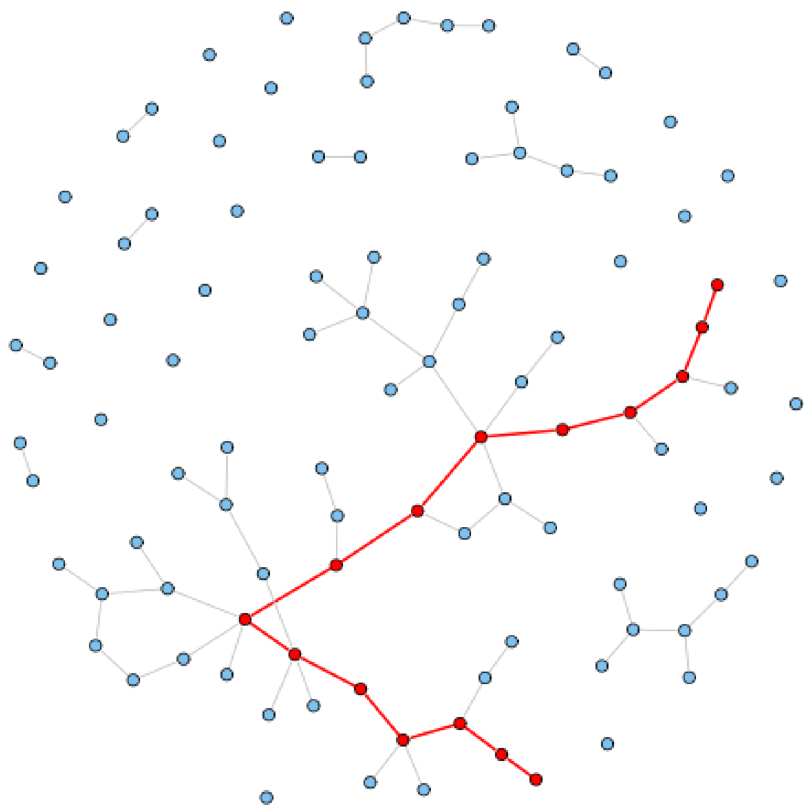


Directed-undirected

Collaboration vs. information diffusion



Path



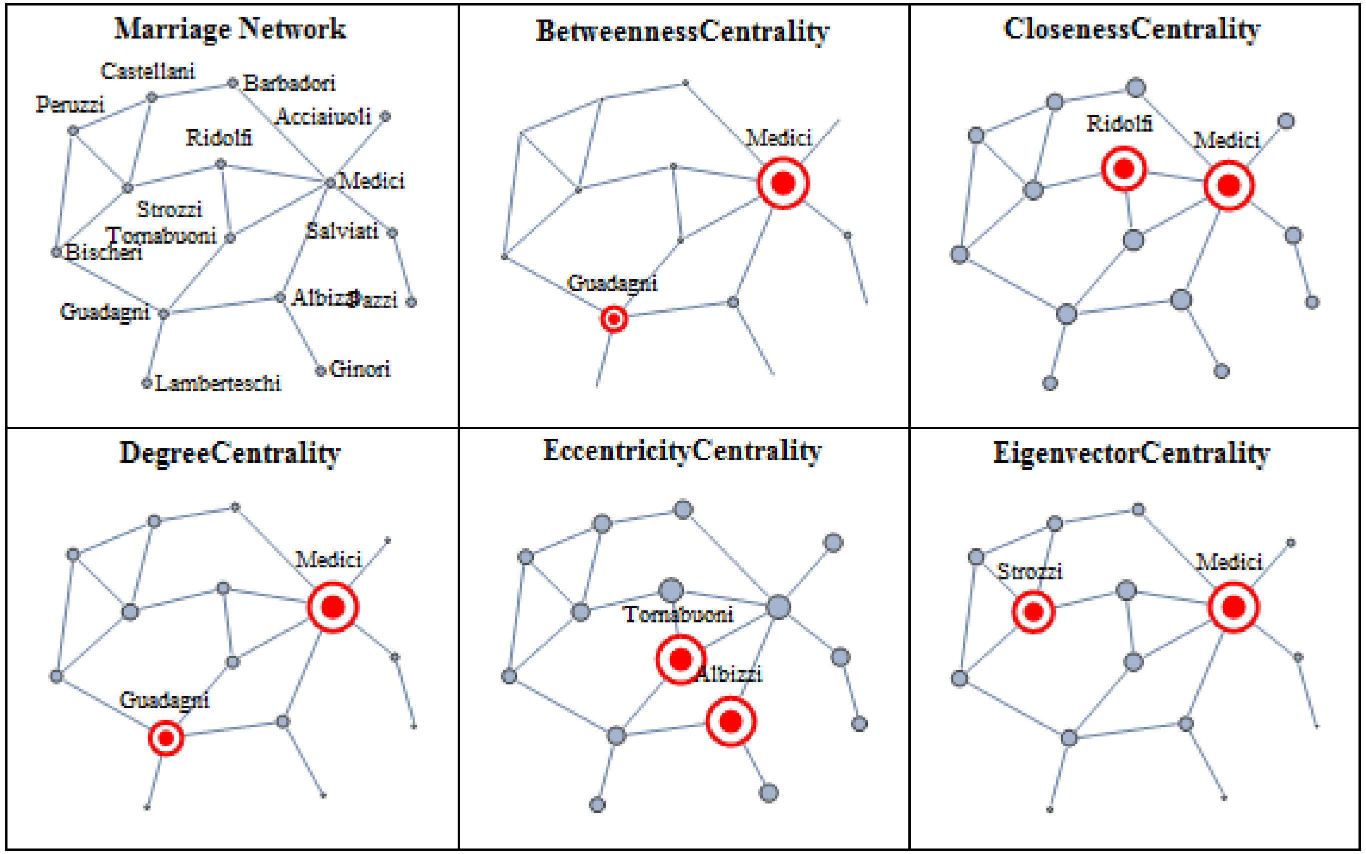
- Path: The set of edges that we can get from one node to any other node
- Distance: the number of steps needed to get from one node to another in the network
- Shortest path: the path between two nodes that includes the fewest steps

Network features: centrality of nodes

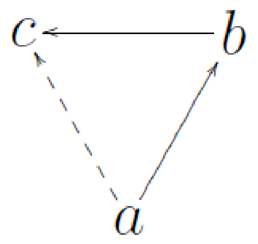
Degree centrality: The number of connections of nodes. For directed networks, we distinguish indegree and outdegree.

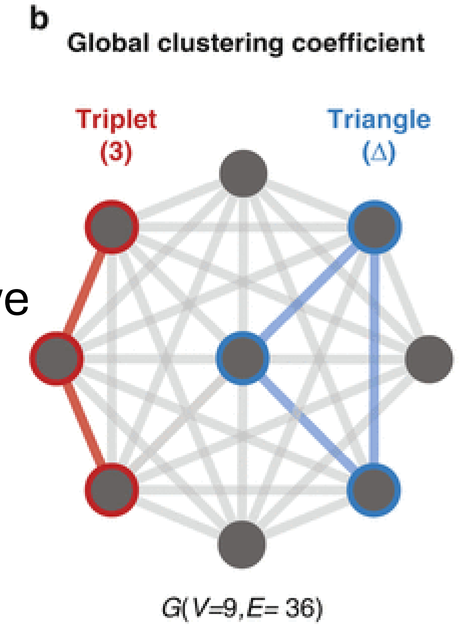
Betweeness centrality: the number of shortest paths that pass through the vertex.

Closeness centrality: the inverse of the sum of distances from the node to all other nodes.



Clustering





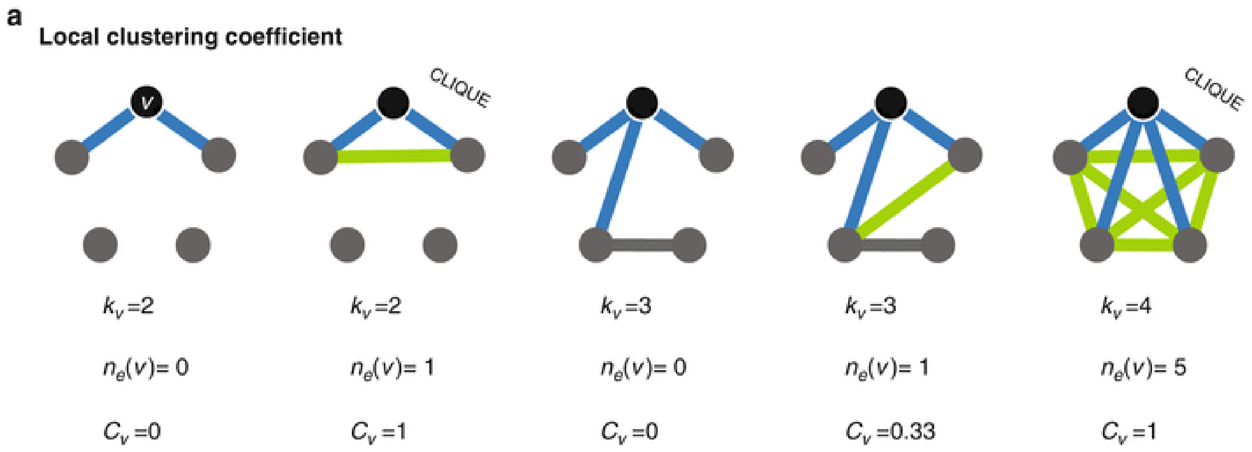
- Transitivity: if 'a' knows 'b' and 'b' knows 'c'-t, then 'a' is likely to know 'c' as we
  - Note that we concentrate on tiadic relations in this measure!

- Global clustering: how many triads are closed out of all possible triads?

- Local clustering: for all *j,k* neighbor-pairs of *I, how many times does the j-k* edge materialize?

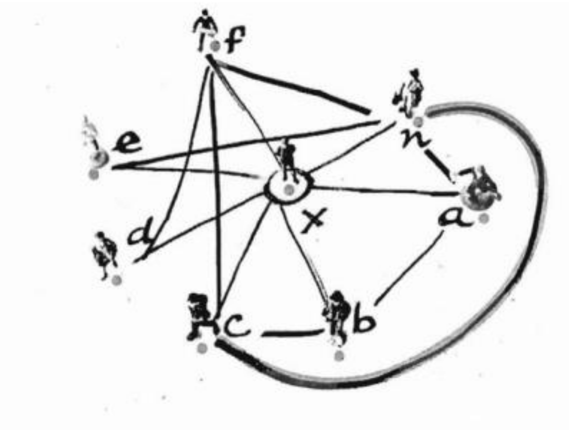
  (one can sum this up

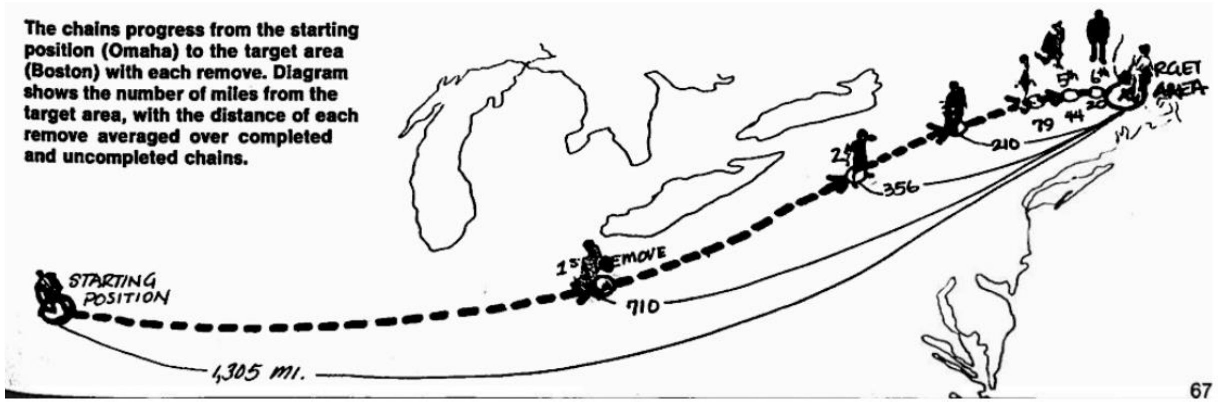
  for the full network)



Stanley Milgram: 6 degrees of separation / The Experimenter (2015)

Small-world networks





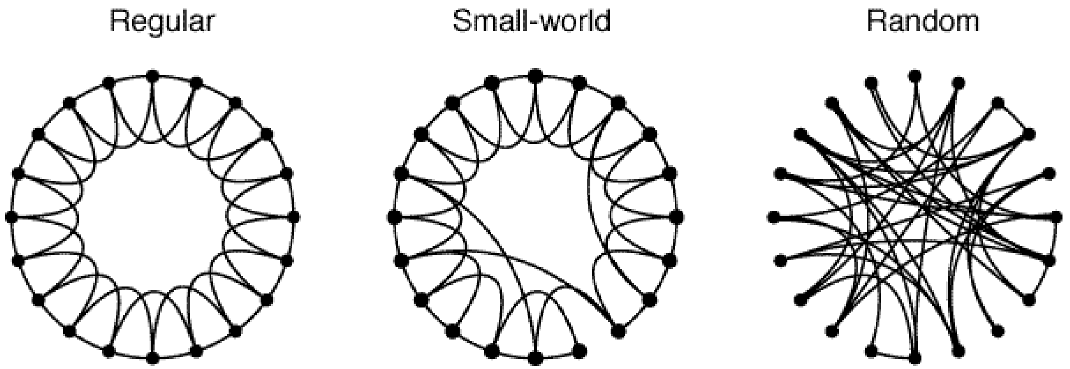
Milgram, S. (1967) The Small-world Problem. *Psychology Today*, 1, 1, 61-67.

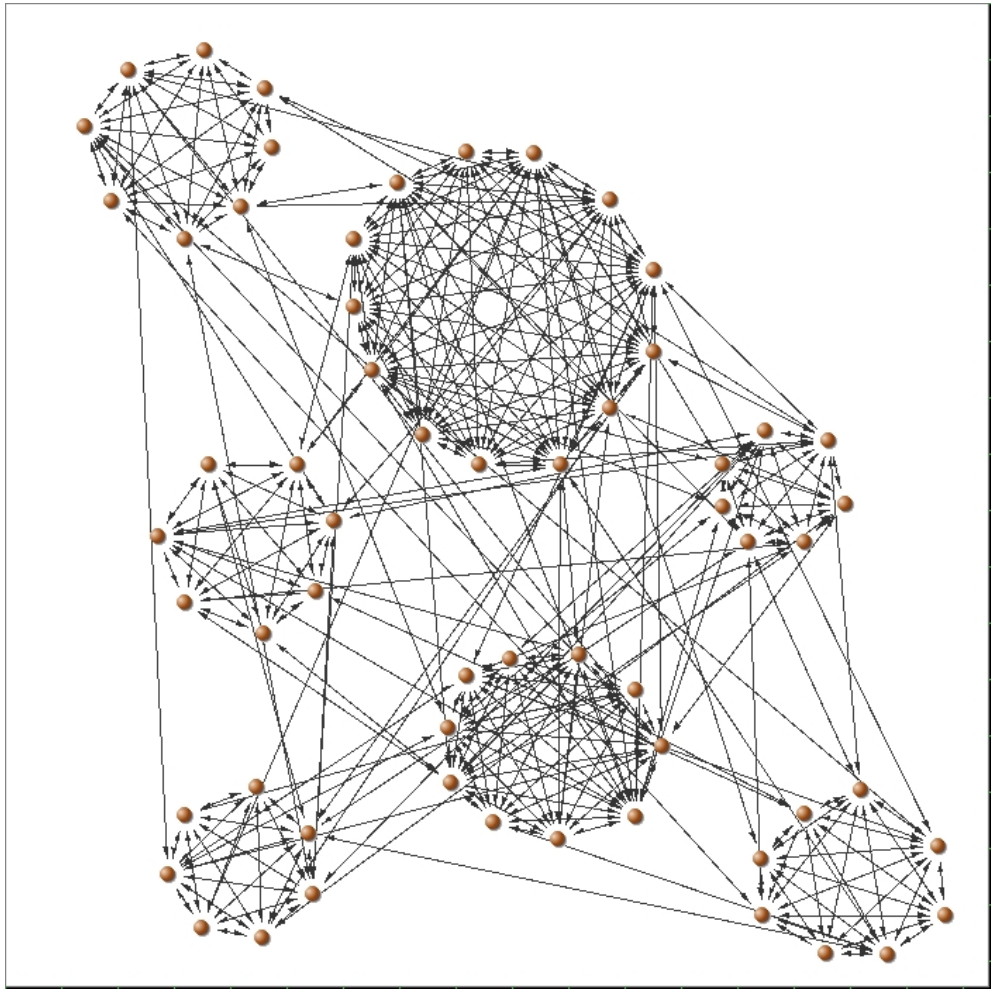
Small worlds

- Social networks cannot be described by random ties:

  Dense local relations and

  few bridges between isolated groups
- Small worlds
  - High clustering – due to dense local networks
  - Short paths – due to bridges

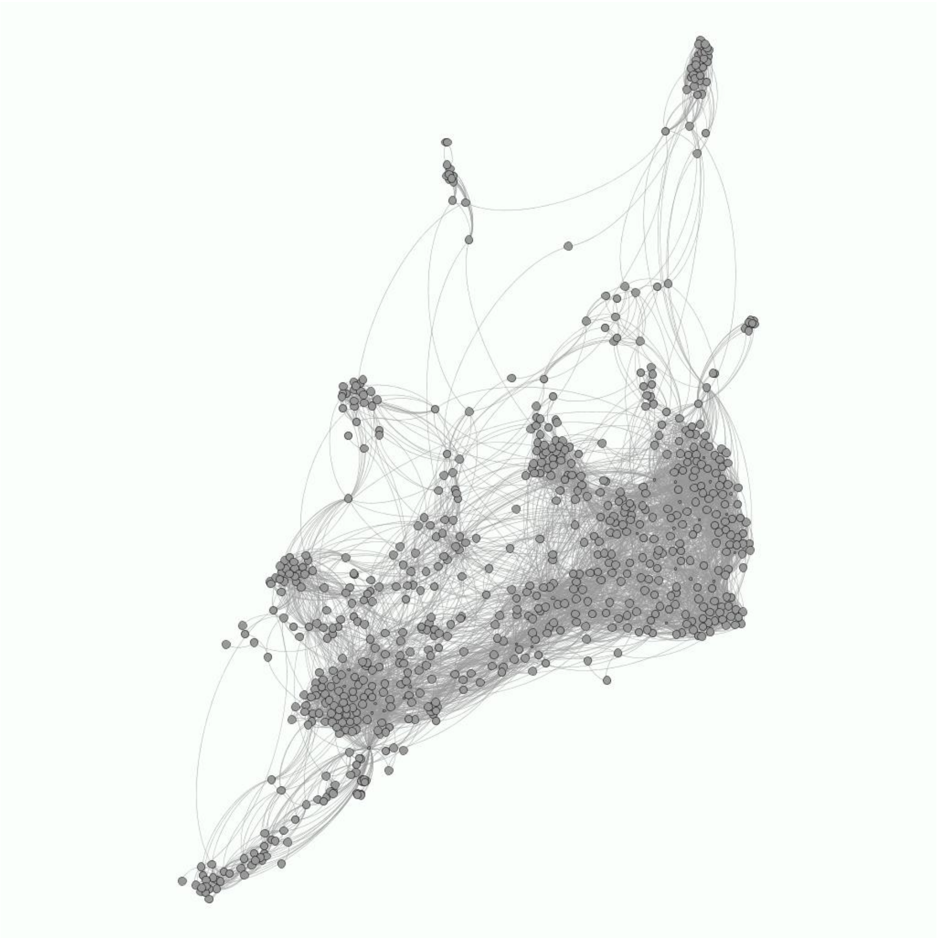




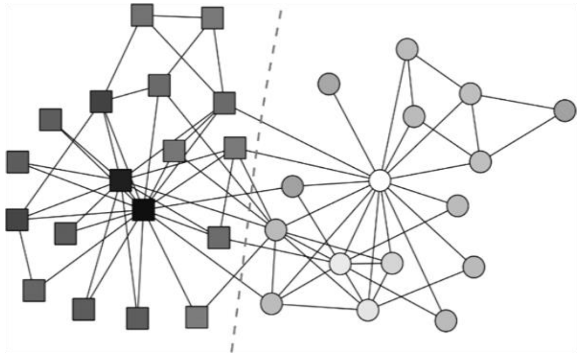
Watts-Strogatz (1998) Nature

Modularity

Moduls
Groups/subnetworks/moduls/communities emerge due to transitivity

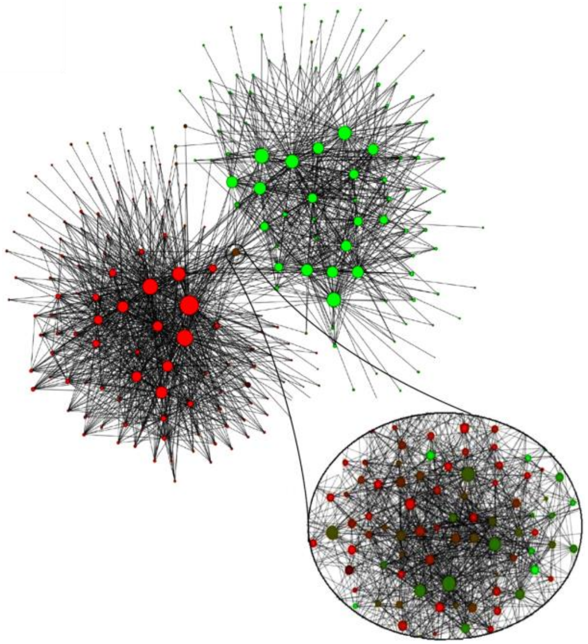


Density Hypothesis of Community detection:
Communities correspond to locally dense neighborhoods of a network

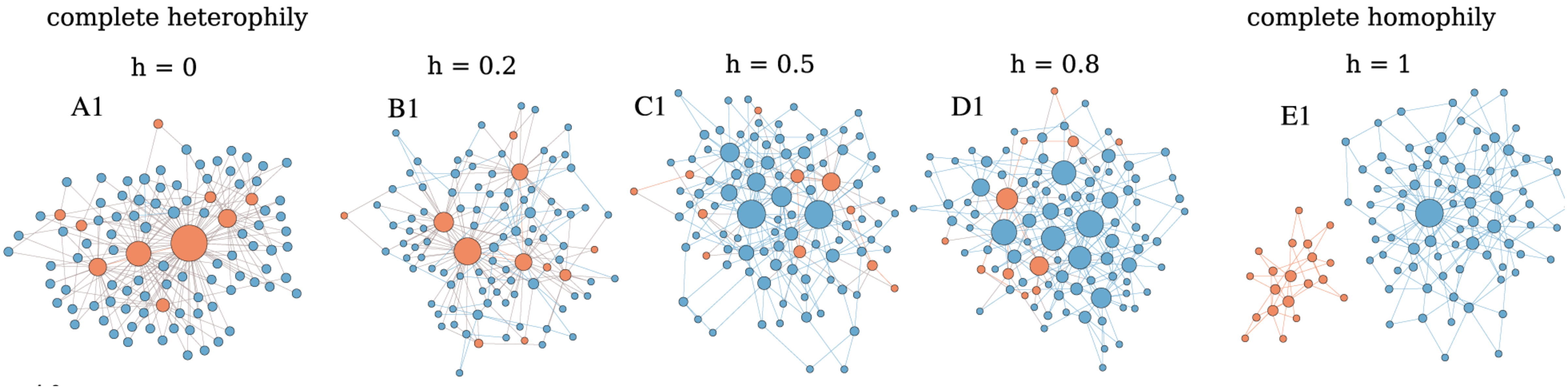


→ Karate Club:
Breakup of the club

→ Belgian Phone Data:
Language spoken



Homophily / assortativity



2. Economic relevance and geography of social and collaboration networks

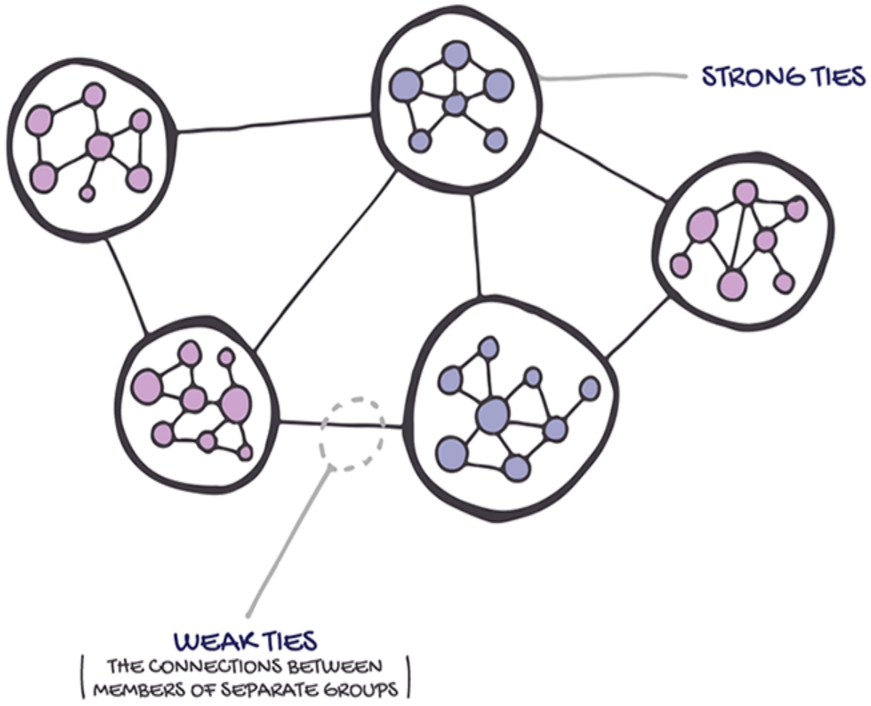
Weak ties and Brokers

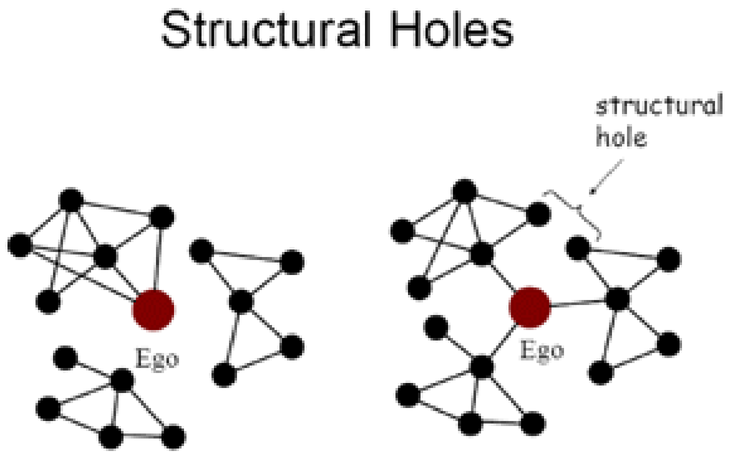
Weak ties (Granovetter, 1973):

- Valuable information comes from those contacts who are in occasional/not frequent relation with us.

Advantage of Brokers (Burt, 1992)

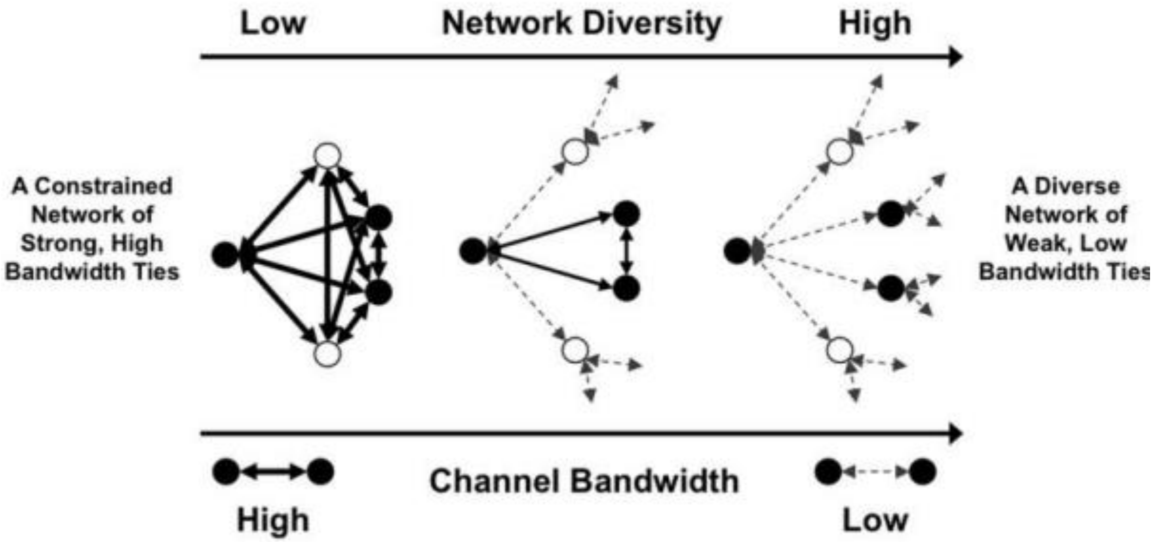
- Information is homogenous and redundant in dense clusters.
- In case information is not overlapping between two loosely knit clusters, there is a structural hole between these clusters.
- Brokers:
  - tertius gaudens -> control of flows
  - tertius iungens -> establish links

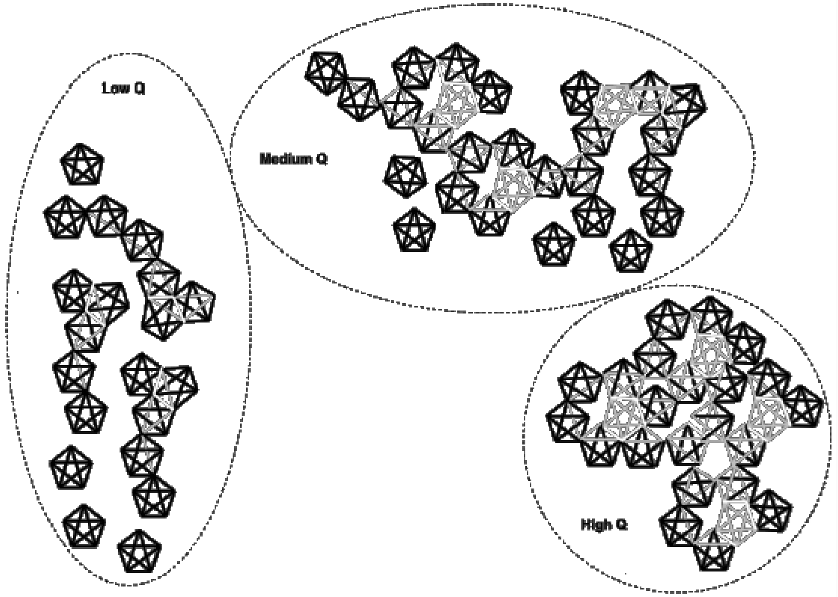




Benefits in small-world networks

- Cliques / strong ties help us to develop trust, and process information (Coleman, 1988)
- Bridges / weak ties provide us with diverse information (Granovetter, 1973; Burt, 1992)
- A combination of them are needed for success (Uzzi and Spiro, 2005)





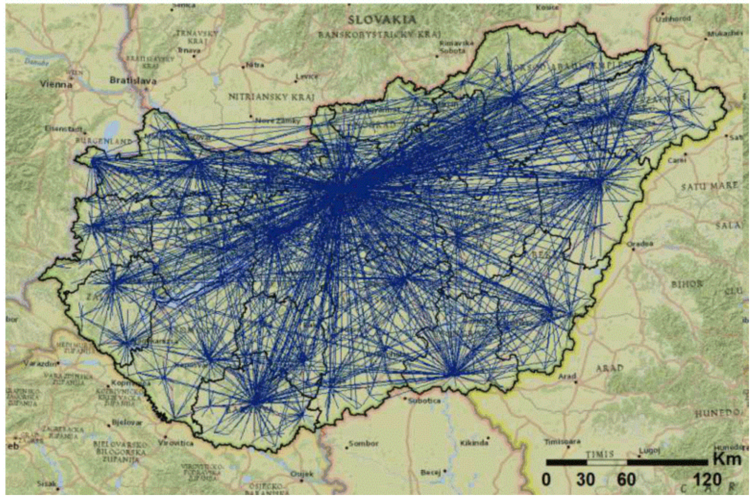
Aral, S. (2016) The Future of Weak Ties. *American Journal of Sociology*, 121, 6, 1931-1939.

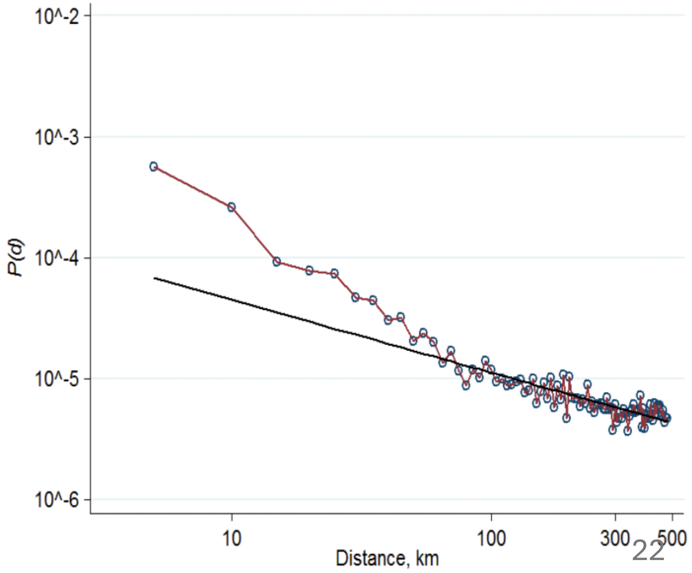
Distance effect

- Creation and maintenance come with costs
- Costs increase with distance
- Gravity models help us analyze the distance-cost relation

$$P = \Sigma_d L_{ij} / \Sigma_d N_i \times N_j$$

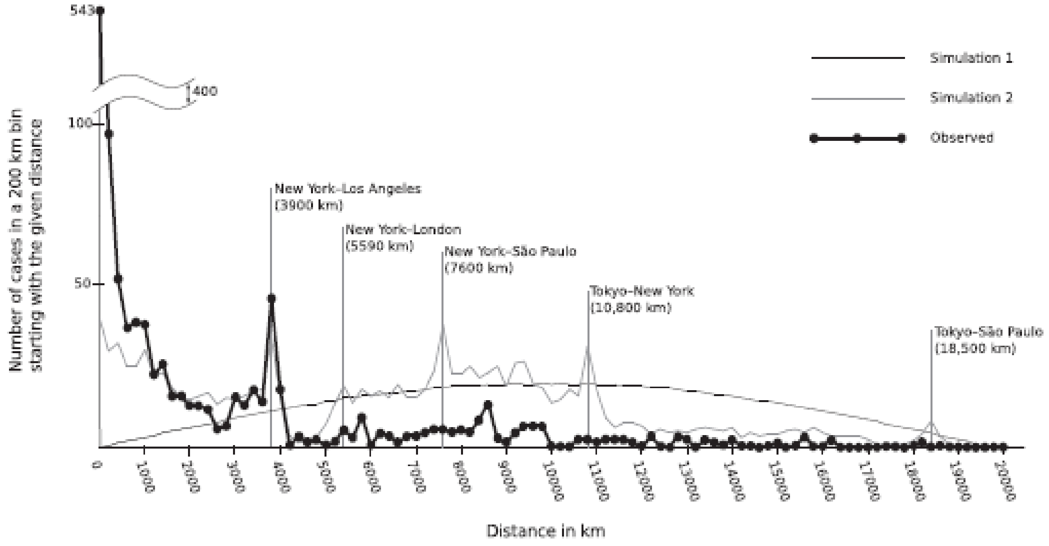
- The probability of triadic closure decreases with distance





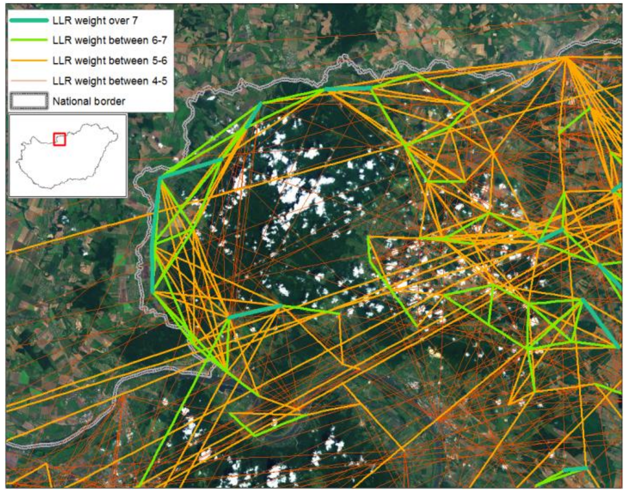
Liben-Nowell et al. (2005) PNAS; Lambiotte et al. (2008) Physica A; Lengyel et al (2015) PLOS ONE

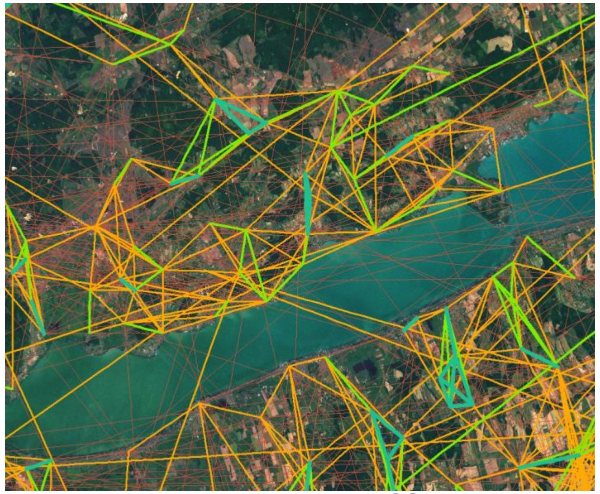
Spatial barriers



- Spatial mobility determines the geography of social networks

- Spatial barriers hinder mobility and influence network structure

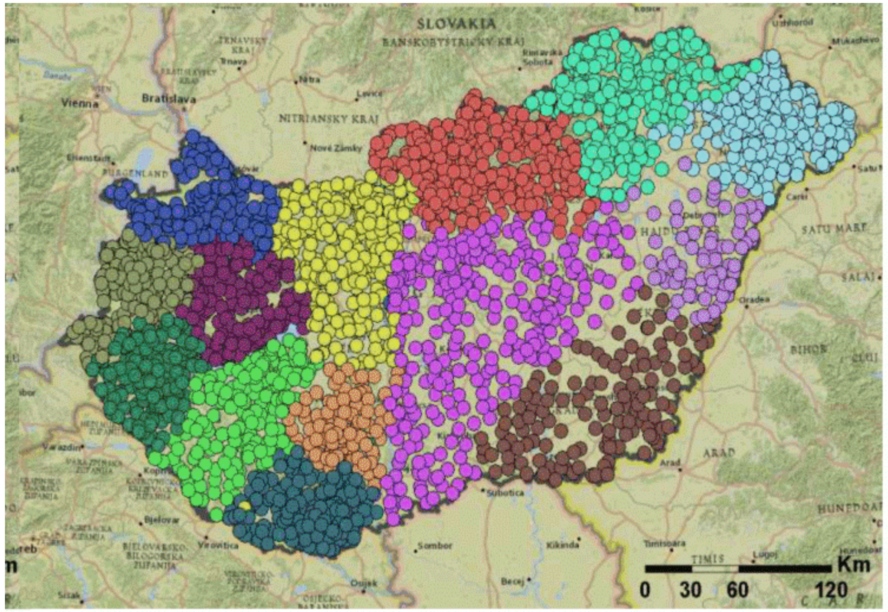


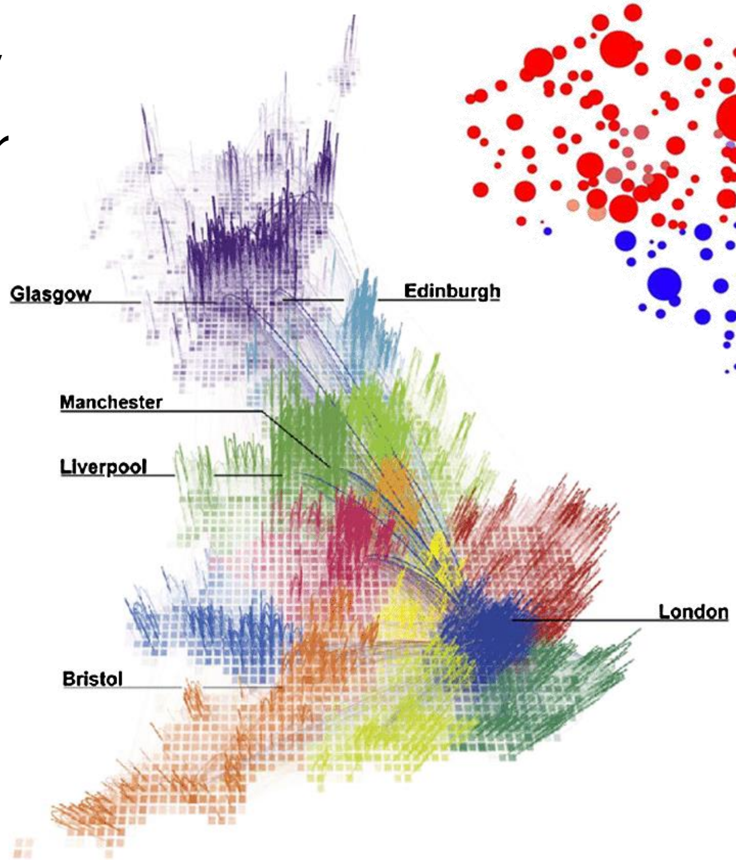


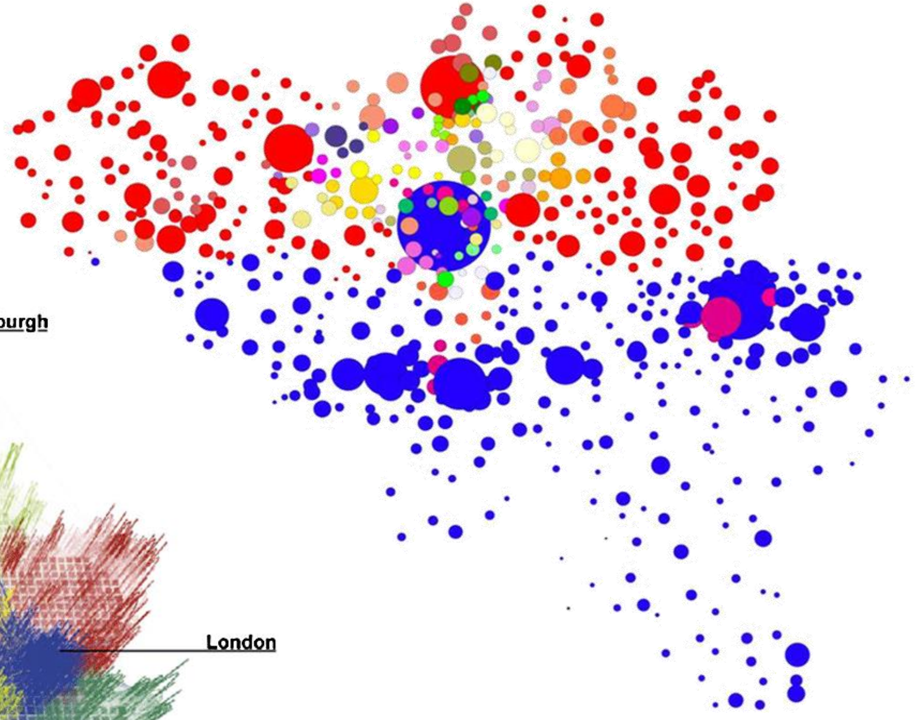
Thaktayev et al. (2012) Social Networks; Jakobi and Lengyel (2016) Springer

Spatial modules

- Social networks break down by administrative or cultural regior

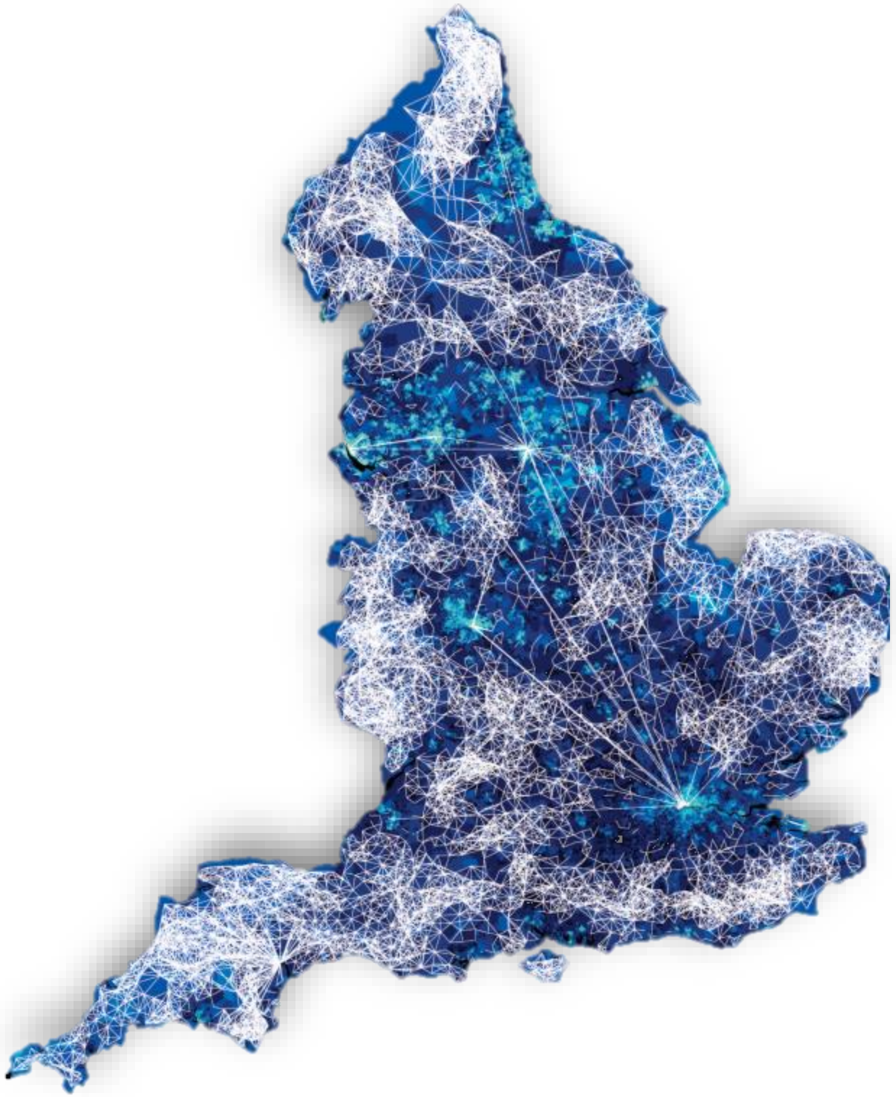


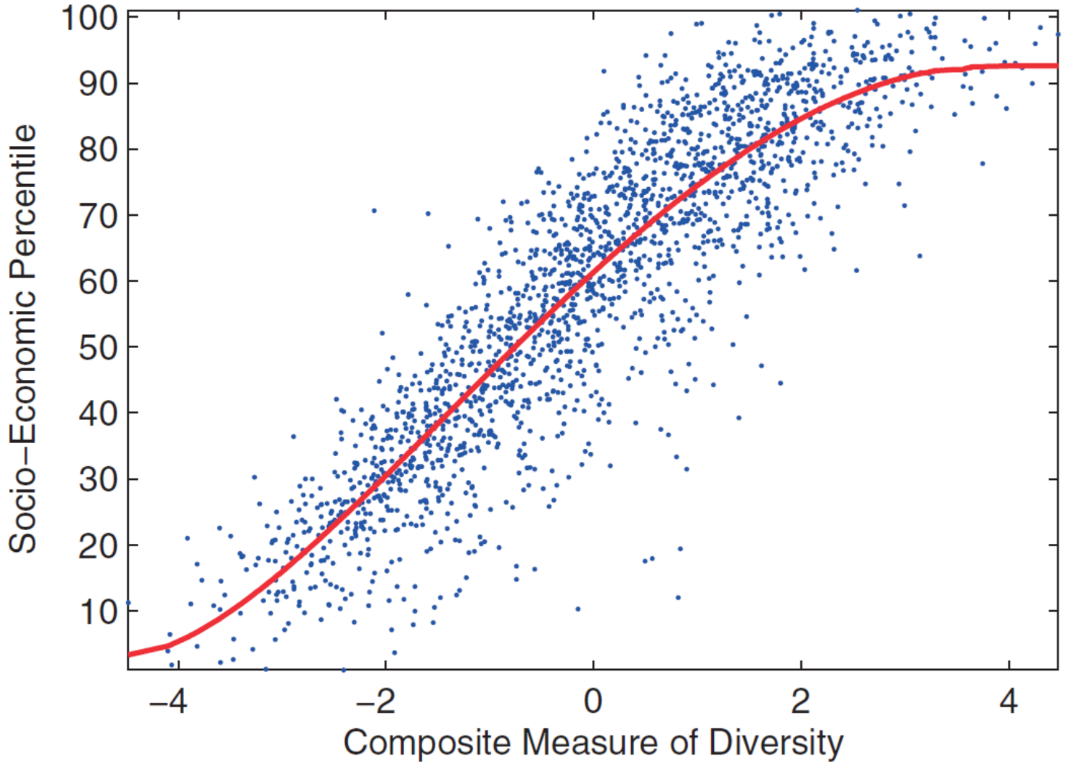




Expert et al. (2011) PNAS; Sobolevsky et al. (2013) PLoS ONE; Lengyel et al (2015) PLOS ONE

Social networks, geography and wealth

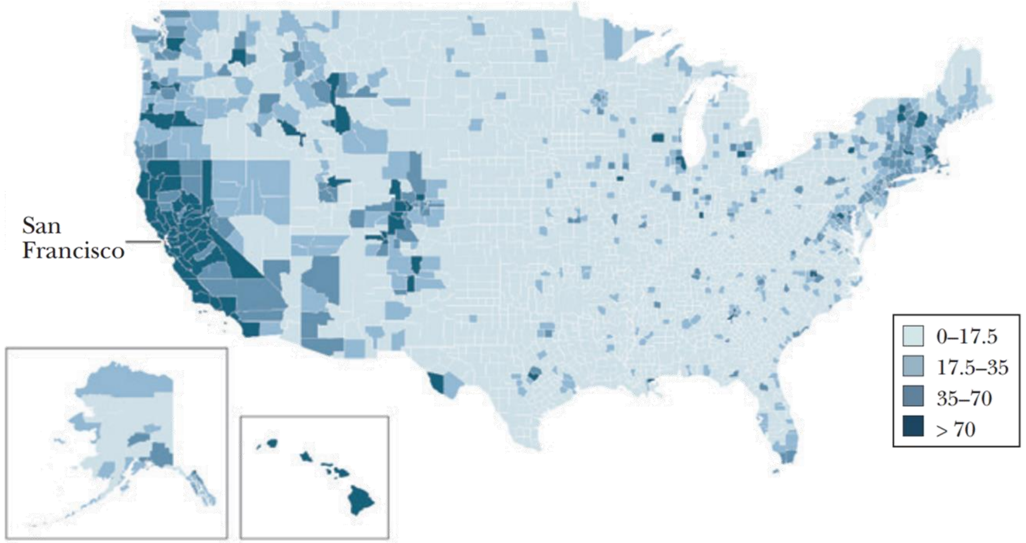




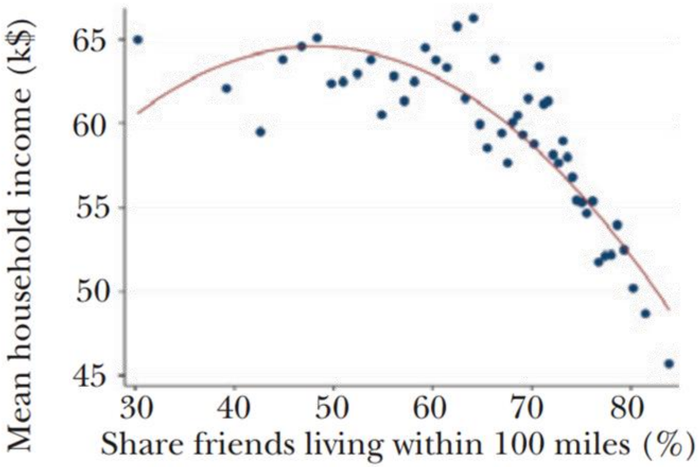
Eagle-Macy-Claxton (2010) Science

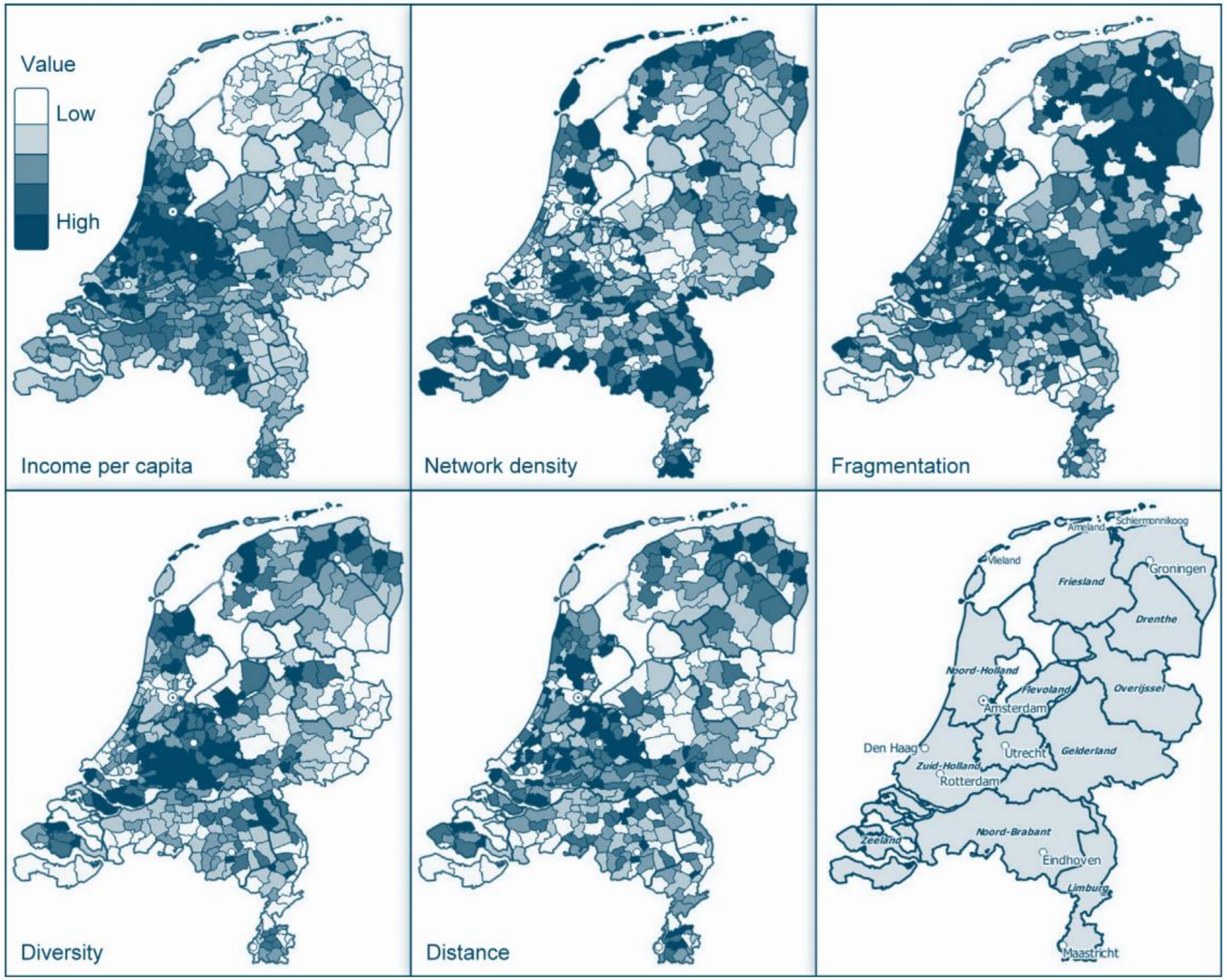
Aggregate social network structures correlate with regional average of individual income

A: Relative Probability of Friendship Link to San Francisco County, CA



A: Average Income





Bailey-Cao-Kuchler-Stroebel-Wong (2018) Journal of Economic Perspectives

Norbutas-Corten (2018) Social Networks

3. Data Lab

- Network data and visualization in Gephi
- Introduction to Igraph in R:
    - Network generation
    - Indicators
    - Community detection

4.1 Collaboration networks and innovation

Research Policy 52 (2023) 104886

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

Atypical combinations of technologies in regional co-inventor networks

Milad Abbasiharofteh [a,b,c,*], Dieter F. Kogler [d,e,f], Balázs Lengyel [g,h,i]

[a] Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, 9747 AD Groningen, the Netherlands
[b] Department of Human Geography and Spatial Planning, Utrecht University, 3584 CB Utrecht, the Netherlands
[c] Department of Structural Change, Leibniz Institute of Agricultural Development in Transition Economies, 06120 Halle, Germany
[d] Spatial Dynamics Lab, University College Dublin, D04 V1W8 Dublin, Ireland
[e] Insight Centre for Data Analytics, University College Dublin, D04 V1W8 Dublin, Ireland
[f] School of Architecture, Planning & Environmental Policy, University College Dublin, D04 V1W8 Dublin, Ireland
[g] Agglomeration and Social Networks Lendület Research Group, Centre for Economic- and Regional Studies, Eötvös Loránd Research Network, 1097 Budapest, Hungary
[h] Laboratory for Networks, Technology and Innovation, Corvinus Institute for Advanced Studies, Corvinus University of Budapest, 1093 Budapest, Hungary
[i] Institute of Data Analytics and Information Systems, Corvinus University of Budapest, 1093 Budapest, Hungary

Organization Science

Vol. 18, No. 6, November–December 2007, pp. 938–954
ISSN 1047-7039 | EISSN 1526-5455 | 07 | 1806 | 0938

informs

DOI 10.1287/orsc.1070.0289

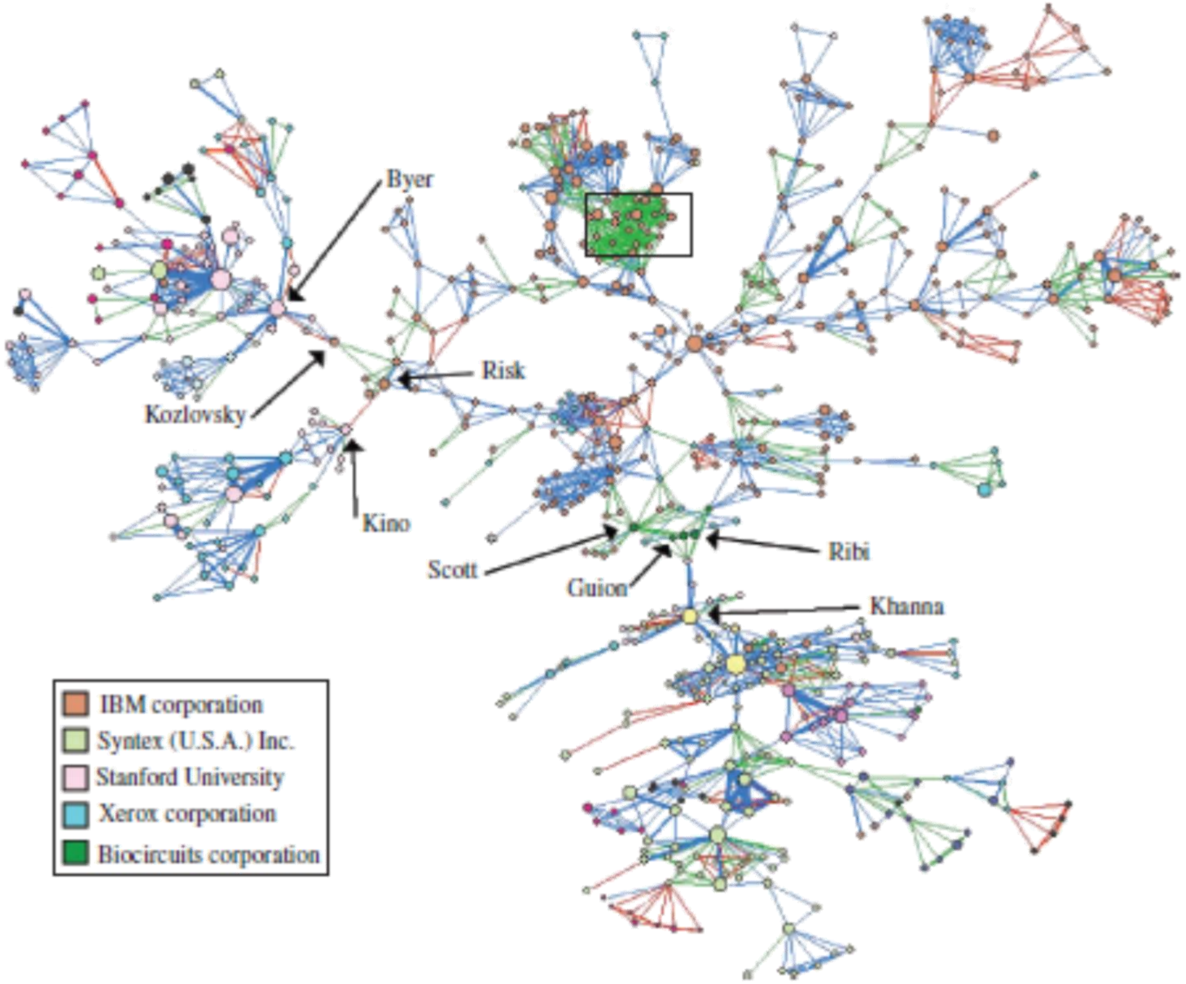
Small Worlds and Regional Innovation

Lee Fleming
Harvard Business School, Morgan Hall 485, Boston, Massachusetts 02163, lfleming@hbs.edu

Charles King III
Greylock McKinnon Associates, One Memorial Drive, Suite 1410, Cambridge, Massachusetts 02142, and
Pleiades Consulting Group, Inc., P.O. Box 711, Lincoln, Massachusetts 01773, cking@gma-us.com

Adam I. Juda
Google, Inc., 76 Ninth Avenue, 4th Floor, New York, New York 10011, juda@goggle.com

Short access in the co-inventor network speeds up information flow and induces the combination of knowlegde.



Network structure of inventor collaboration and innovative output in regions

Co-invention networks and inventive productivity in US cities

Stefano Breschi[a,1], Camilla Lenzi[b,*]

Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects

José Lobo[a,*], Deborah Strumsky[b]

How do inventor networks affect urban invention?

Laurent Bergé[a], Nicolas Carayol[b,*], Pascale Roux[b]

[a] CREA, Université du Luxembourg, Campus Limpertsberg, BRA 4.09, 162A Avenue de la Faïencerie, L-1511, Luxembourg
[b] Université de Bordeaux, GREThA, UMR CNRS 5113, Avenure Leon Duguit, F-33608, Pessac, France

Co-inventor networks and knowledge production in specialized and diversified cities

Frank van der Wouden | David L. Rigby

The role of knowledge: diversity vs specialization

Radical novelty needs diverse knowledge (Florida et al. 2017, Glaeser et al. 1992).

Specialization can also facilitate innovation (Beaudry and Schiffauerova, 2009; Lobo and Strumsky, 2008) when critical masses of experts specialized in distinct pieces of knowledge (Castaldi et al., 2015) are connected through knowledge transfer mechanisms (Berkes and Gaetani, 2020).

Boston biotechnology example (Cooke 2002, Powell et al. 1996): distinct local critical masses in engineering and biology connected by social ties.

The role of knowledge: network dynamics

Similar specialization in knowledge increases link probability.

- Local collaboration networks can become too cohesive and locked-in into technologies – Grabher (1993), Boschma & Frenken (2010), Giuliani (2013), Balland et al. (2016)

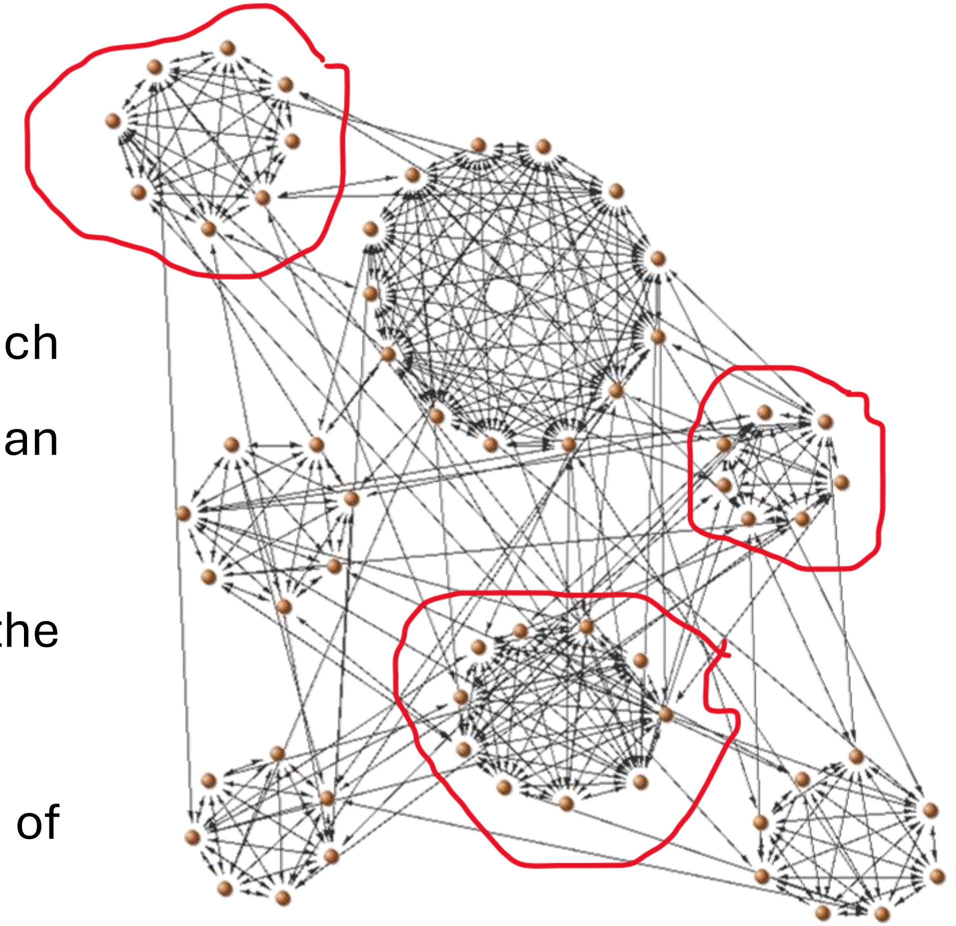
Inter-regional links can introduce novelty

- Inter-regional links combined with dense local networks
  - – theory: Bathelt et al. (2004), Glückler (2007);
  - – empirical evidence: Breschi and Lenzi (2016), Eriksson and Lengyel (2019); Kogler et al. (2023)
- Local variation – Juhász and Lengyel (2018)

Problem: the impact of knowledge and network dynamics are difficult to disentangle.

Solution: network communities

Network communities: cohesive segments of networks that are loosely connected to other communities.

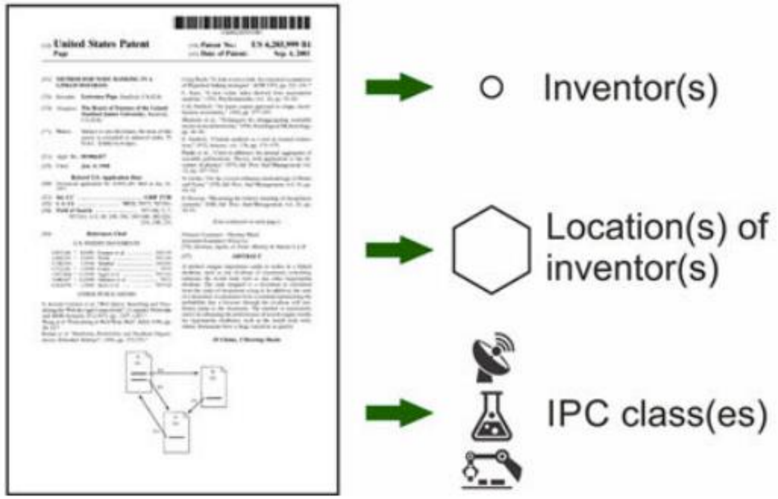


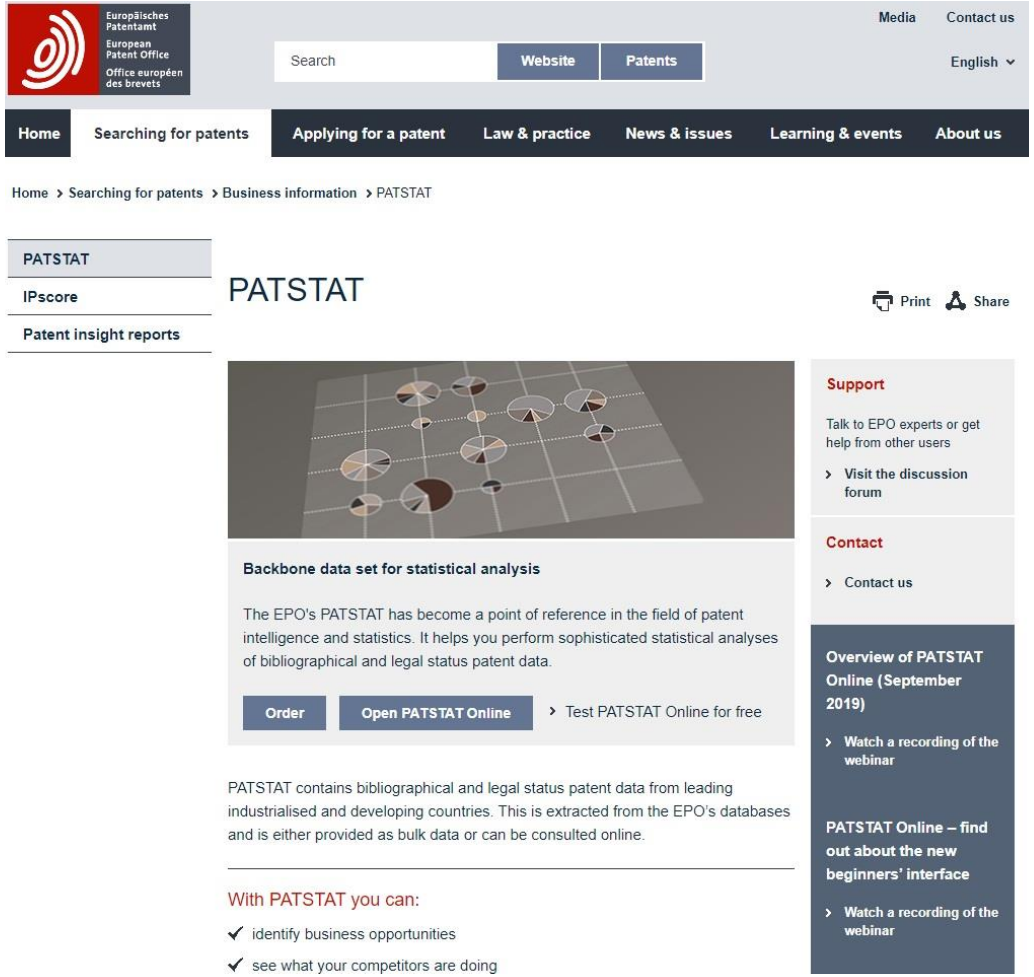
Advantages:

- Small-world networks can be decomposed to communities such that bridges are inter-community ties (Girwan and Newman 2002)
- Community detection only considers the structure of the network (Fortunato 2010) – Triadic Closure effect
- One can measure the technological specialization of communities – Technological Proximity effect

Data from European Patents

- The European Patent Office (EPO) PATSTAT database
- Creating co-inventor network in seven non-overlapping 5-year time-windows for each NUTS2 region





Tóth et al. (2021) European Planning Studies

Atypical patents as radical innovation

SHARE

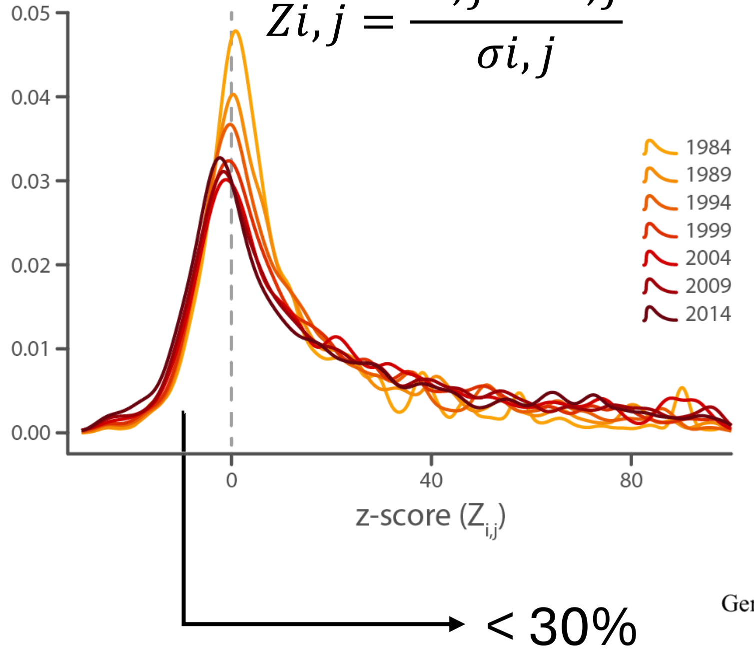
REPORT

Atypical Combinations and Scientific Impact

Brian Uzzi[1,2], Satyam Mukherjee[1,2], Michael Stringer[2,3], Ben Jones[1,4,*]
+ See all authors and affiliations

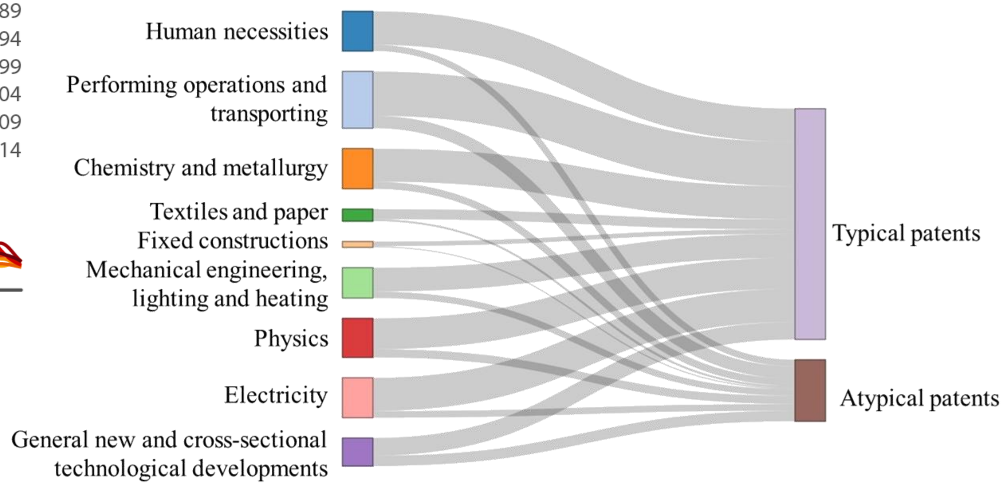
Science 25 Oct 2013:
Vol. 342, Issue 6157, pp. 468-472
DOI: 10.1126/science.1240474

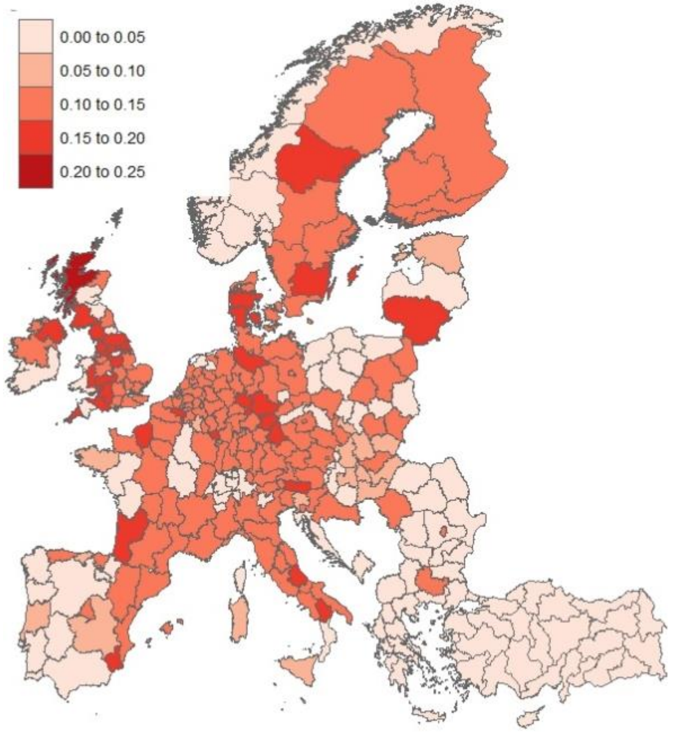
$$Zi,j = \frac{oi,j - ei,j}{\sigma i,j}$$



Negative values represent atypical combination of classes

Atypical patents concentrate in cities (Mewes 2019).

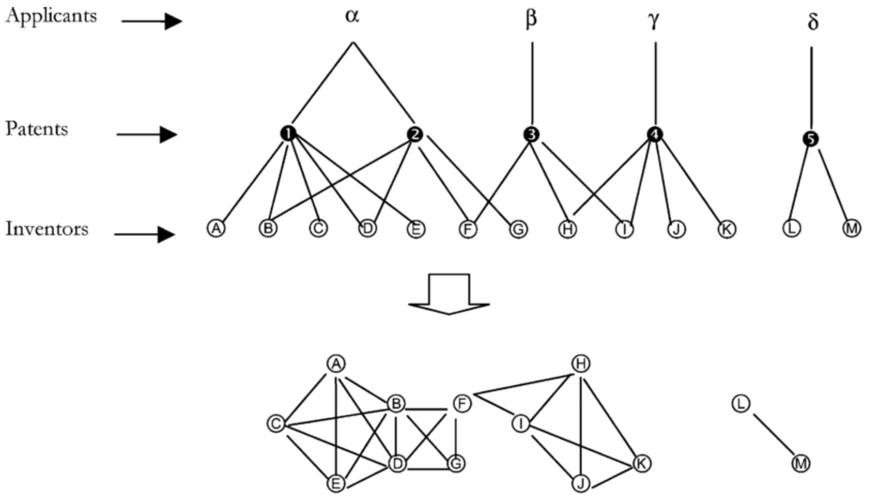


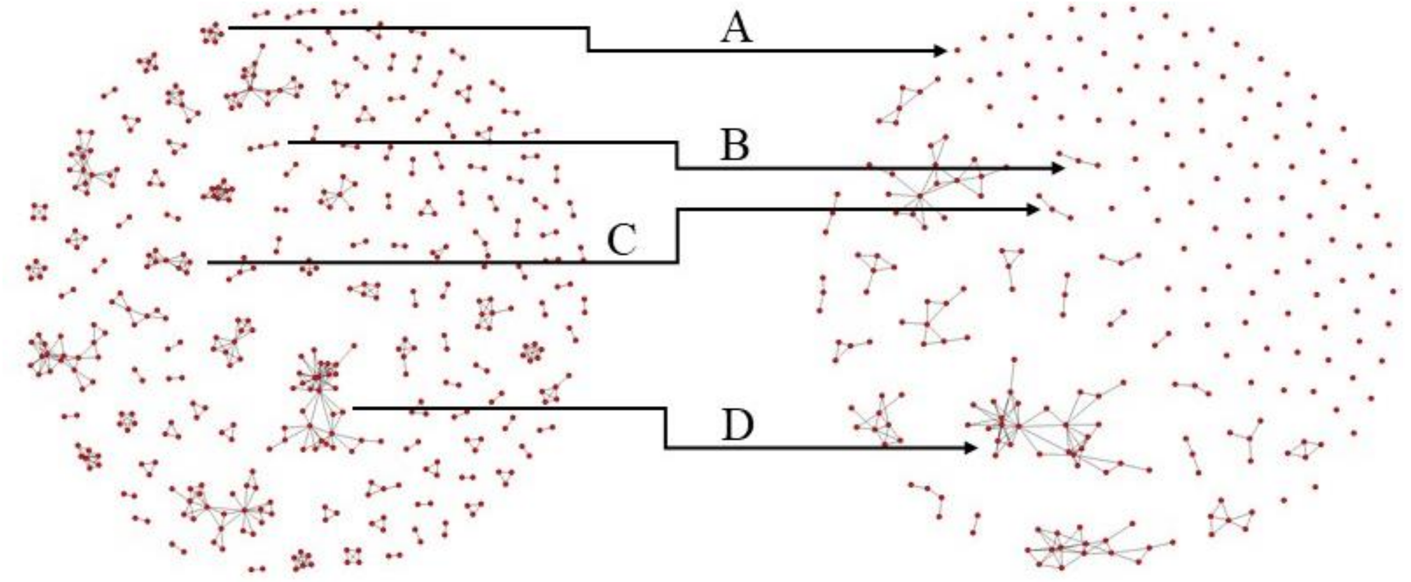


Dependent variable: share of atypical patents in EU regions, to avoid the effect of scale.

Network generation: networks of places

We handle structurally equivalent inventors as one node in the network.





Breschi et al. (2021) Research Policy

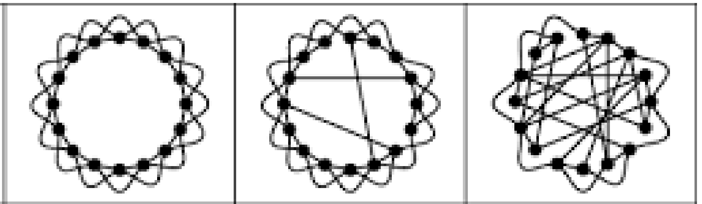
Lucena-Piquero and Vicente (2019) Research Policy

Network variables 1: small-worldness

Small-worldness (Neal, 2018)

1. Average path length / compared to a random network
2. Clustering / compared to lattice

Small worldness ranges from 0 to 1.



Network	Lattice, Ordered	Small World	Random, Disordered
Clustering Coefficient	High	High	Low
Mean Path Length	Long	Short	Short

$$\omega = \frac{L_r}{L} - \frac{C}{C_l}$$

$$SMALLWORLDNESS = 1 - |\omega|$$

Small-worldness

Small-world networks =

short access to diverse knowedge (Fleming et al. 2007)

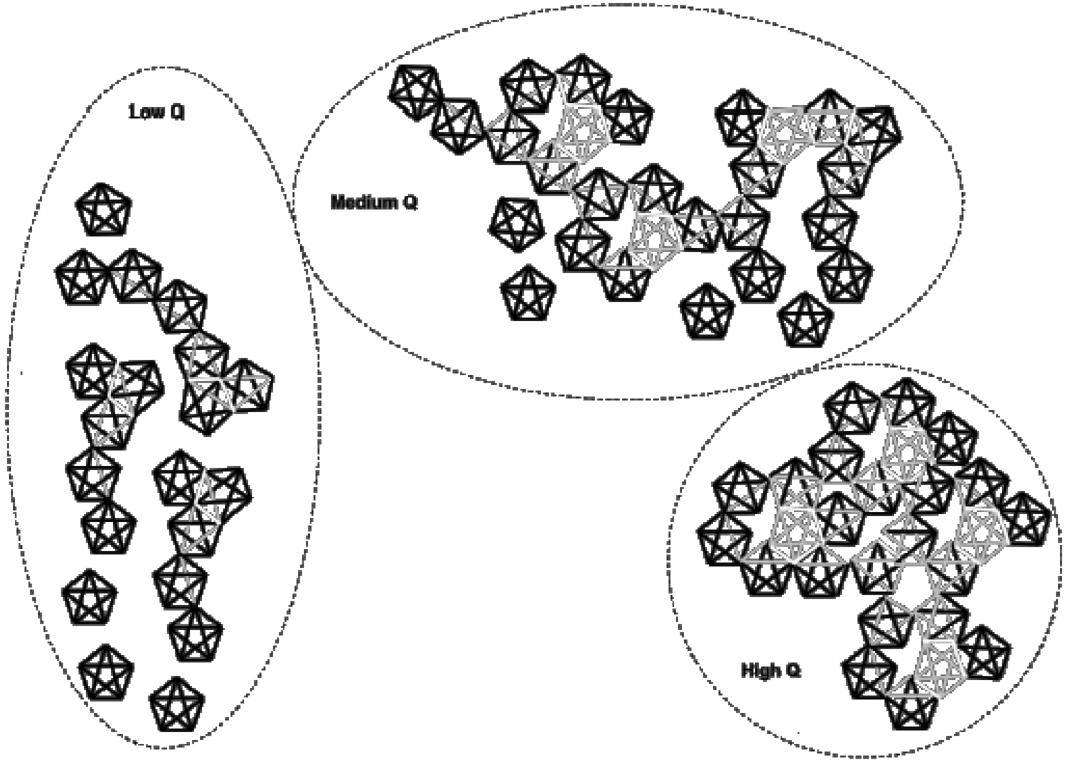
high absorptive capacity of strongly-knit cliques (Aral 2016)

Medium small-worldness is ideal for creative outcomes (Uzzi and Spiro 2005)

- Access is short but there is enough variety in the network.
- Absoprtive capacity is present

H1a: *The small-worldness of co-inventor networks is positively related to the proportion of atypical patents in the region.*

H1b: *The quadratic term of small-worldness of co-inventor networks is negatively related to the proportion of atypical patents in the region.*

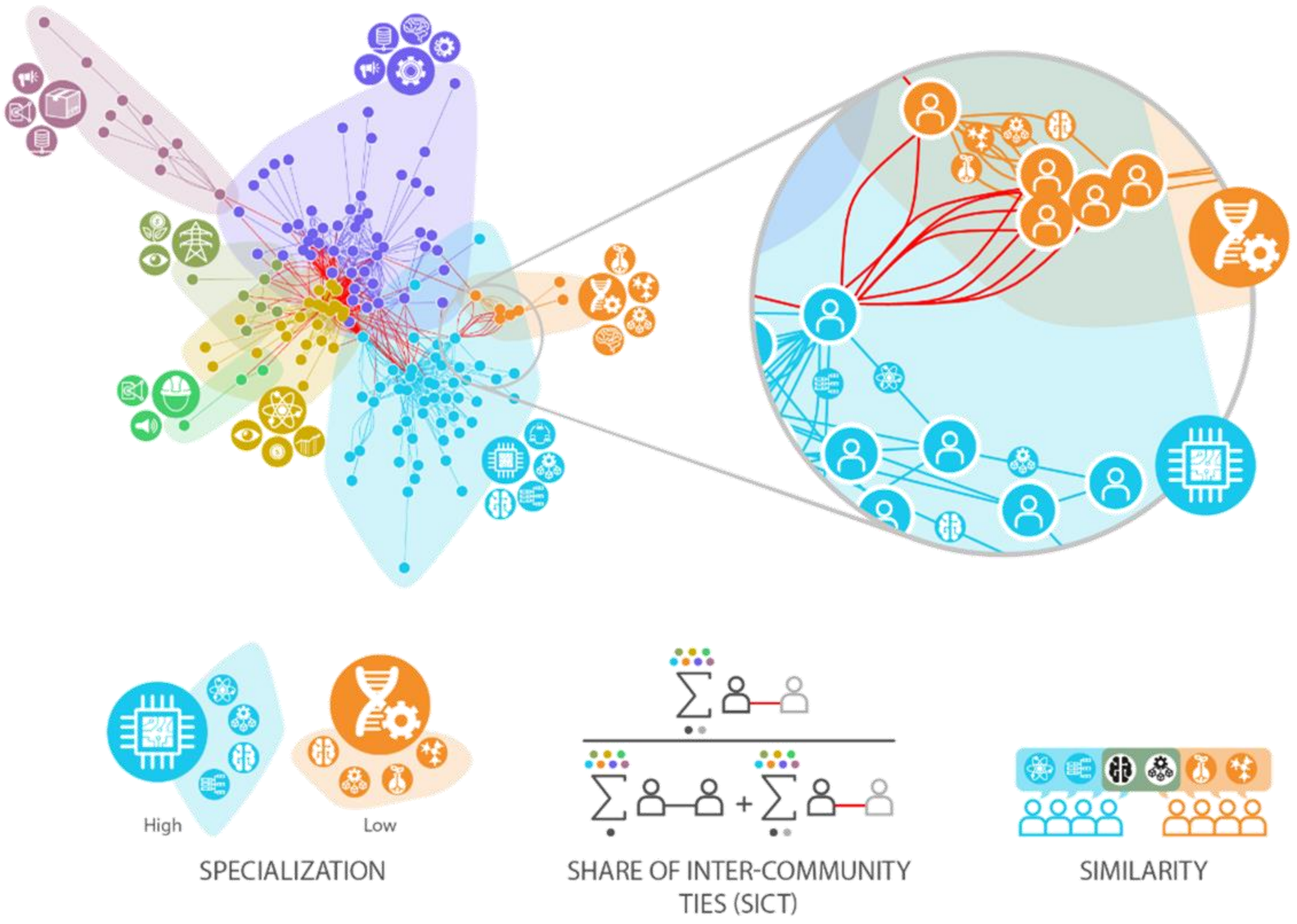


Network variables 2

Network communities are detected by the Louvain method

Regional-level indicators

1. Specialization: median level of technology HHI in network communities (not correlated with community and inventor numbers)
2. SICT: share of inter-community ties compared to randomly rewired networks
3. Similarity: median level of technology correlations (Spearman) across connected communities



Specialized inventor communities and their linkages in regions

Specialized inventor communities increase the scale and scope of knowledge in the domain (Kemeny and Storper 2015, De Noni and Belussi 2021) that can support the combination with distinct knowledge (Ter Wal et al 206, Tóth and Lengyel 2021).

> ***H2:*** *The median level of technological specialization of co-inventor communities in the region is positively related to the proportion of atypical patents in the region.*

Connections between specialized communities foster the combination of distinct knowledge (Powell et al. 1996, Glückler 2007).

> ***H3:*** *The proportion of inter-community ties of co-inventor networks is positively related to the proportion of atypical patents in the region.*

Distinct specializations across linked communities

Radically new knowledge can be generated by combining distinct knowledge pieces (Fontana et al. 2020, Uzzi et al. 2013, Wagner et al, 2019, Wang et al. 2017).

H4: *Technological similarity across bridged inventor communities is negatively related to the proportion of atypical patents in the region.*

Results

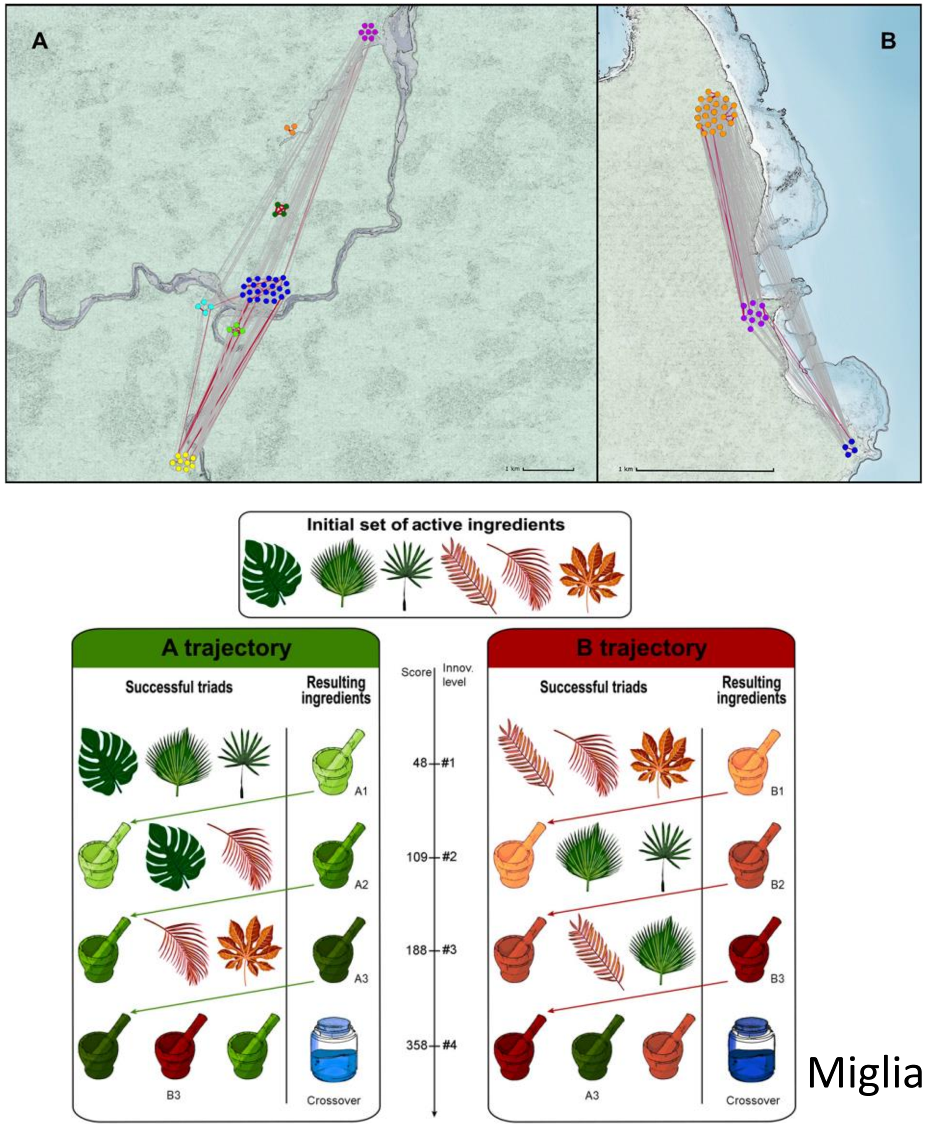
$$Y_{r,t} = \alpha + \beta_1 SMALLWORLDNESS_{r,t-1} + \beta_2 SPECIALIZATION_{r,t-1} + \beta_3 SICT_{r,t-1} + \beta_4\, SIMILARITY_{r,t-1} + \beta_5 N_{r,t-1} + \beta_6 Z_{r,t-1} + \varphi_t + \mu_r + \varepsilon_{r,t}$$

Controls:

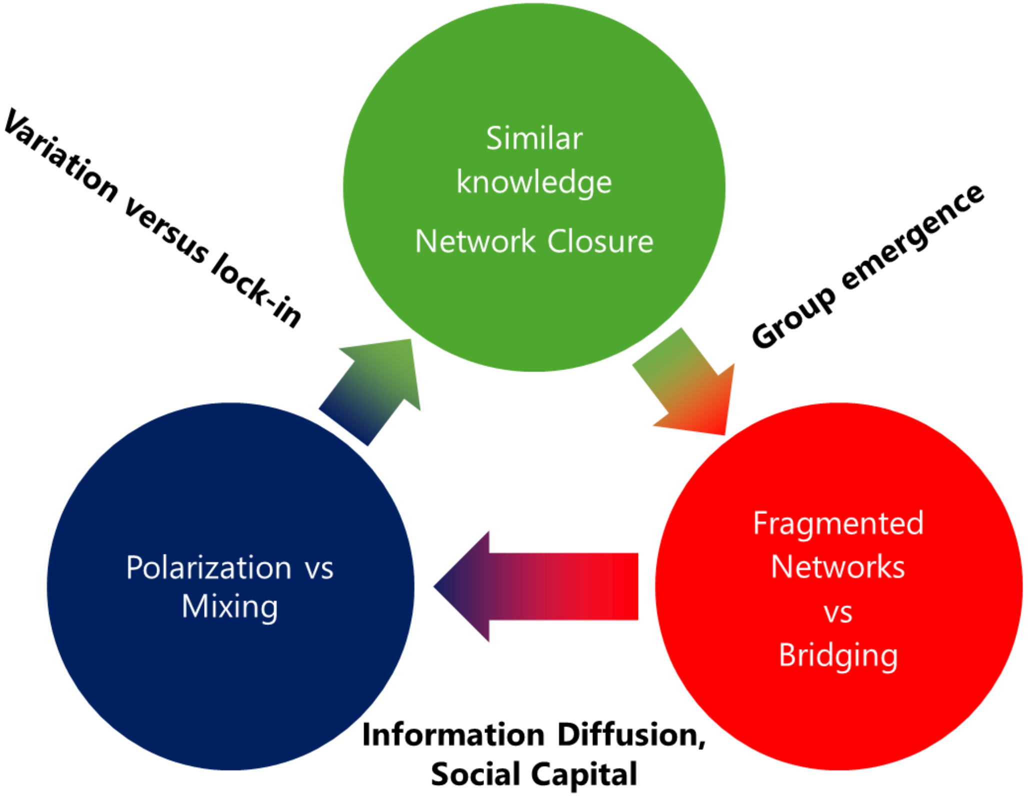
1. Average Related Density (van de Wouden and Rigby 2019)
2. Complexity (Hidalgo and Hausmann 2009)
3. Density (Bergé et al., 2018; Breschi and Lenzi, 2016)
4. Isolate (Lobo and Strumsky 2008)
5. Community
6. Population
7. Interregional ties

	Dependent variable: share of atypical patents
SMALLWORLDNESS	0.0115***
	(0.0039)
SPECIALIZATION	0.0405**
	(0.0188)
SICT	0.1041**
	(0.0523)
SIMILARITY	-0.0342***
	(0.0105)
Region FE	YES
Time FE	YES
N	1,526
R^2	0.4118

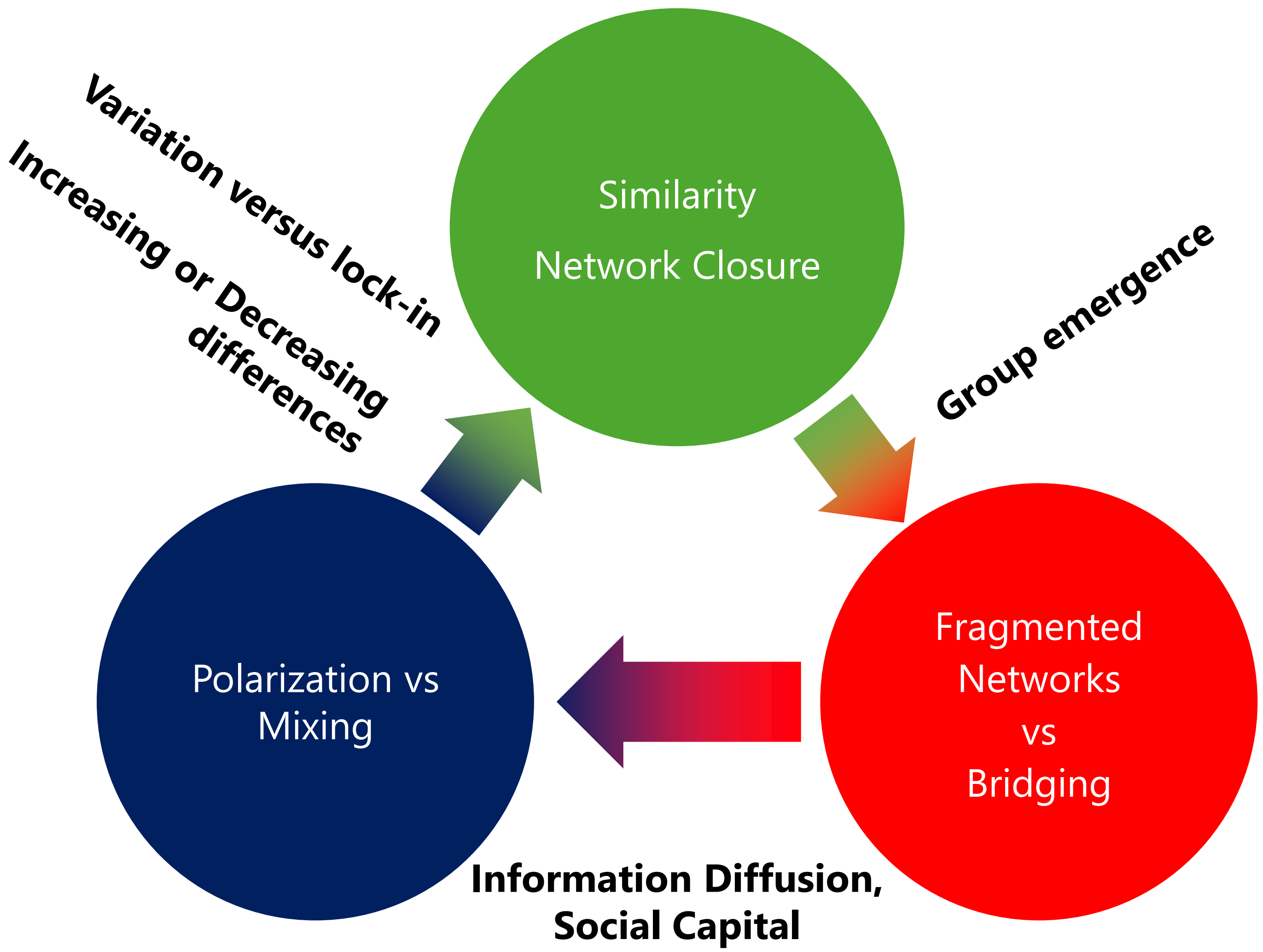
Network dynamics of specialization and radical combination

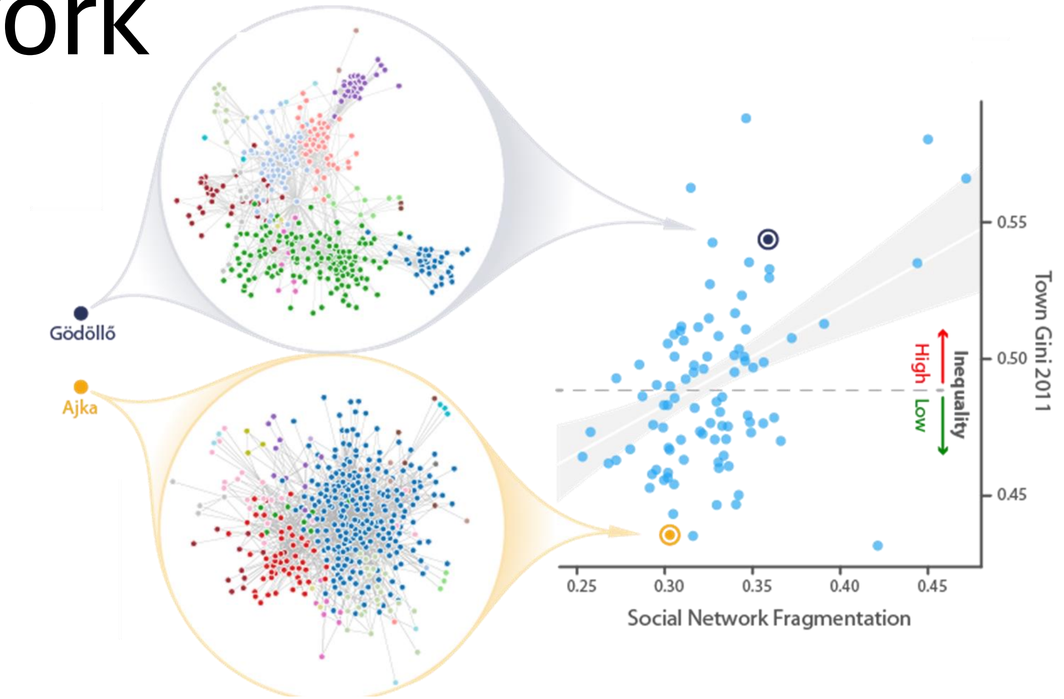


Migliano et al. (2020, Science Advances)



A Network Dynamics Framework





nature COMMUNICATIONS

ARTICLE

https://doi.org/10.1038/s41467-021-21465-0 OPEN

Check for updates

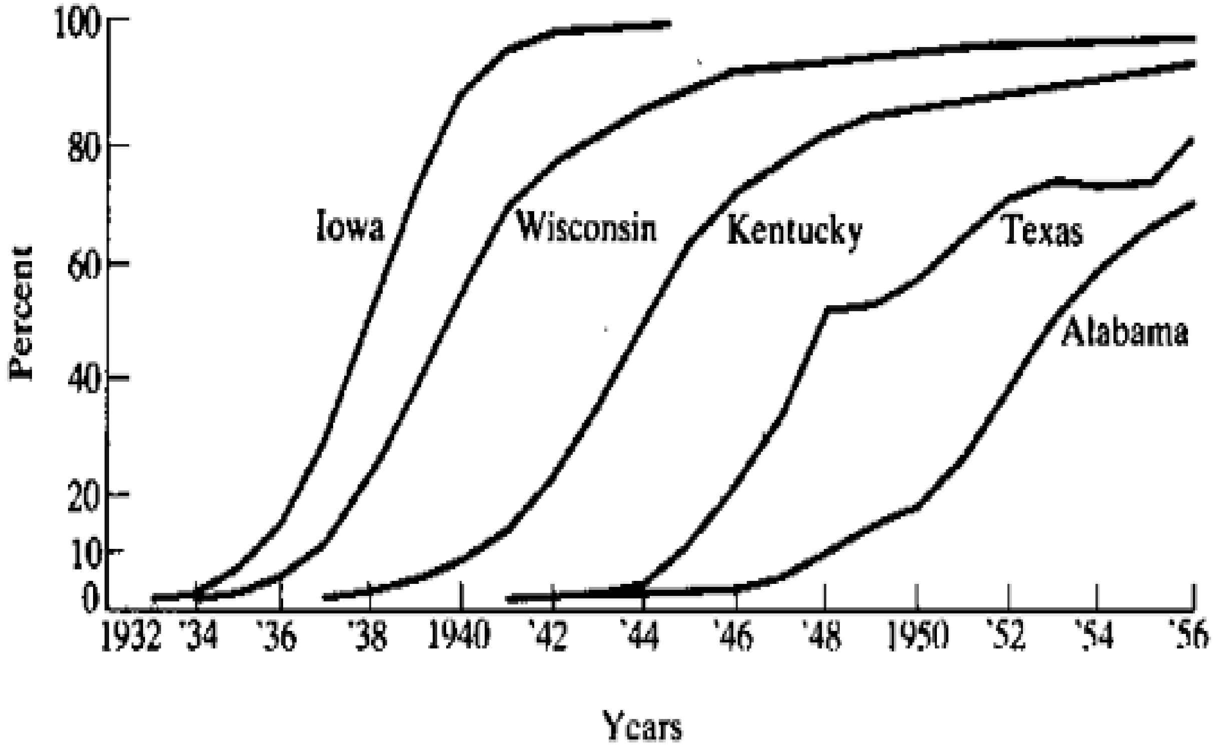
Inequality is rising where social network segregation interacts with urban topology

Gergő Tóth[1,2,13], Johannes Wachs[3,4,13], Riccardo Di Clemente[5,6], Ákos Jakobi[7,8], Bence Ságvári[1,9,10], János Kertész[11] & Balázs Lengyel[1,10,12]✉

4.2 Diffusion of innovation – extra material

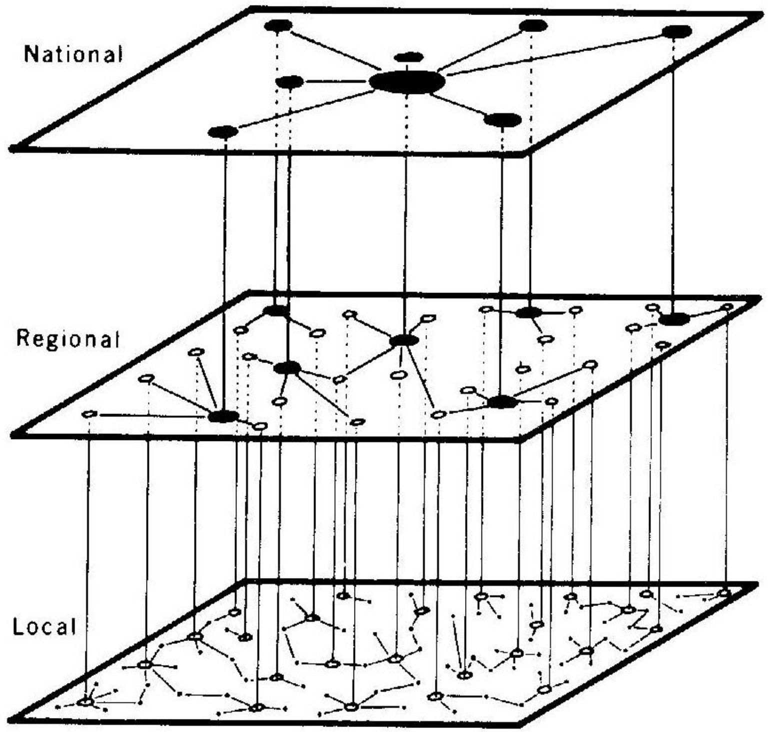
Spatial diffusion

Innovation gets quicker to proximate places.

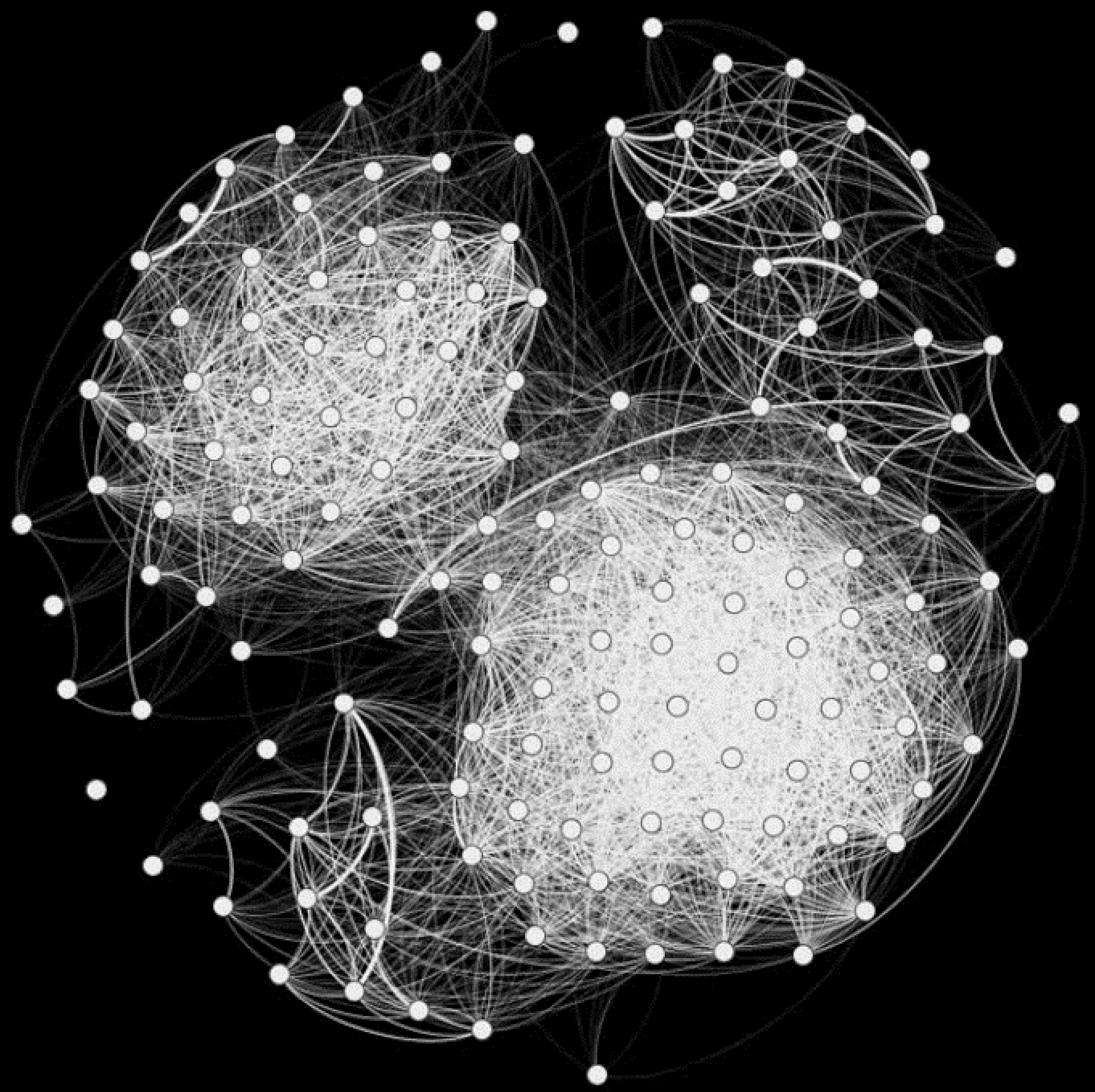


Griliches (1957, Econometrica)

Innovation spreads from big to medium cities and then to small towns.



Haegerstrand (1953, Chicago UP)



Aplin et al. (2015) Nature

Threshold models of adoption

Shelling: segregation in cities

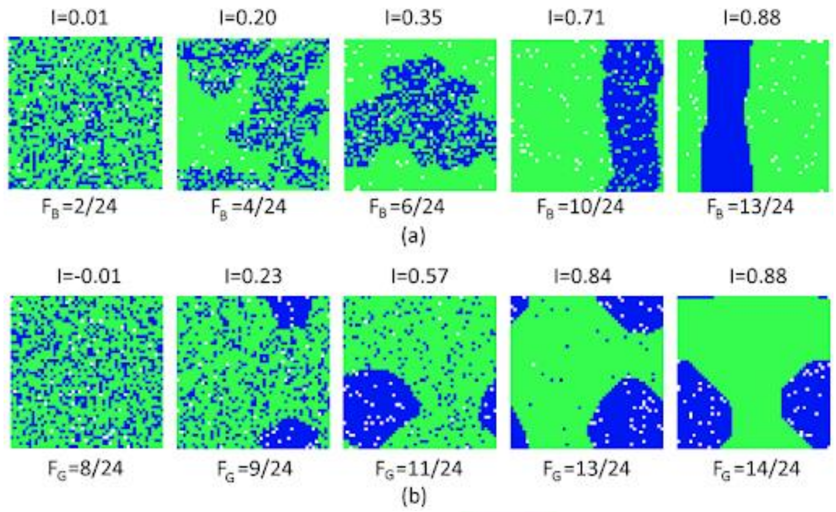
- Individual threshold in terms of ratio of tolerated different neighbors is heterogenous
- Low threshold individuals move away first that increases the probability of movement of high threshold individuals

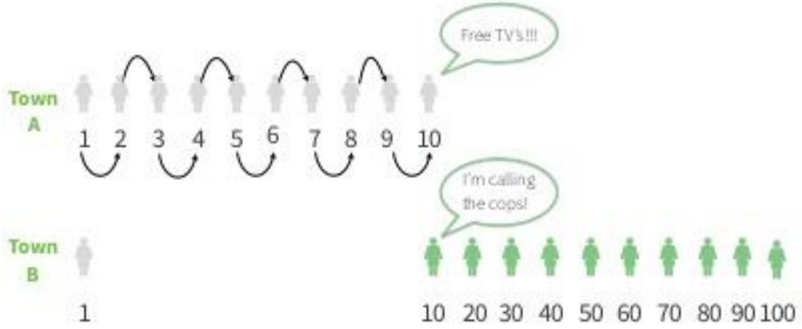
Granovetter: behavior in a protest

- Individual threshold: how many individuals is needed to start the activity before the individual will decide to start

Watts: cascading behavior in networks

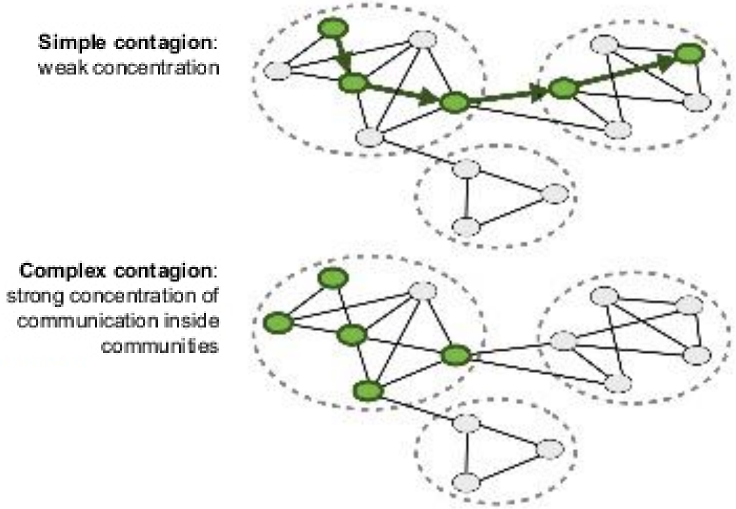
- A behavior will diffuse only if the network structure follows the threshold sequence
- Innovators are connected to Early Adopters

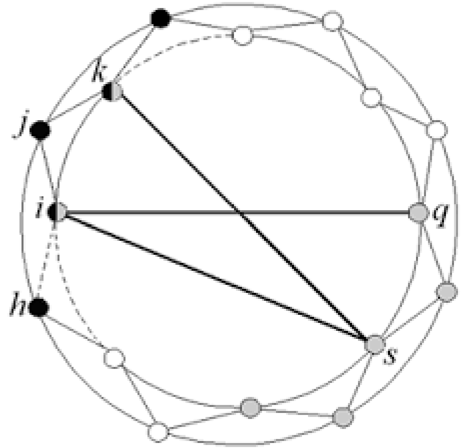


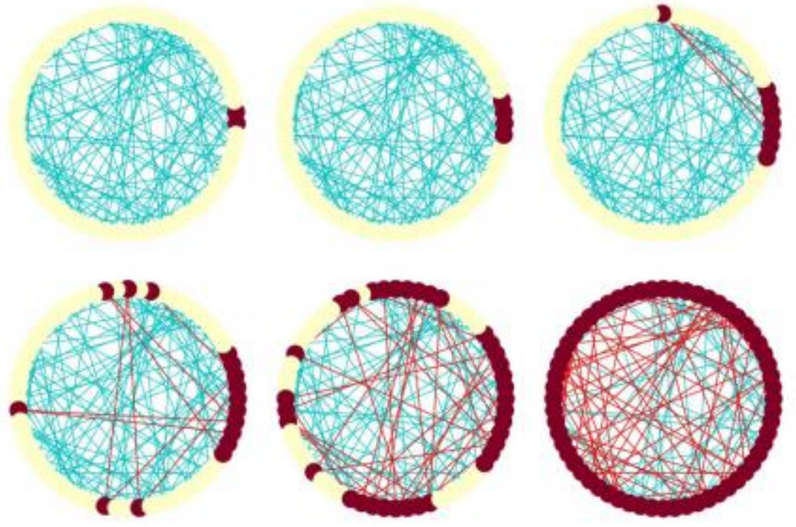


Simple vs. complex contagion

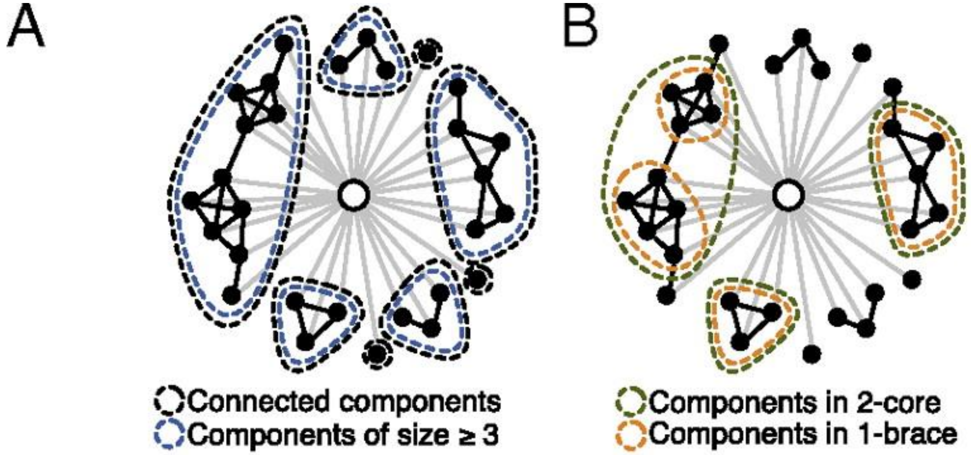
- Simple: infection depends on dyadic probability
- Complex: adoption is a process of convincing-decision and depends on fraction/number of adopting friends
- Innovation diffuses through complex contagion.
- Small-world networks: high clustering speeds diffusion up, bridges slow it down.

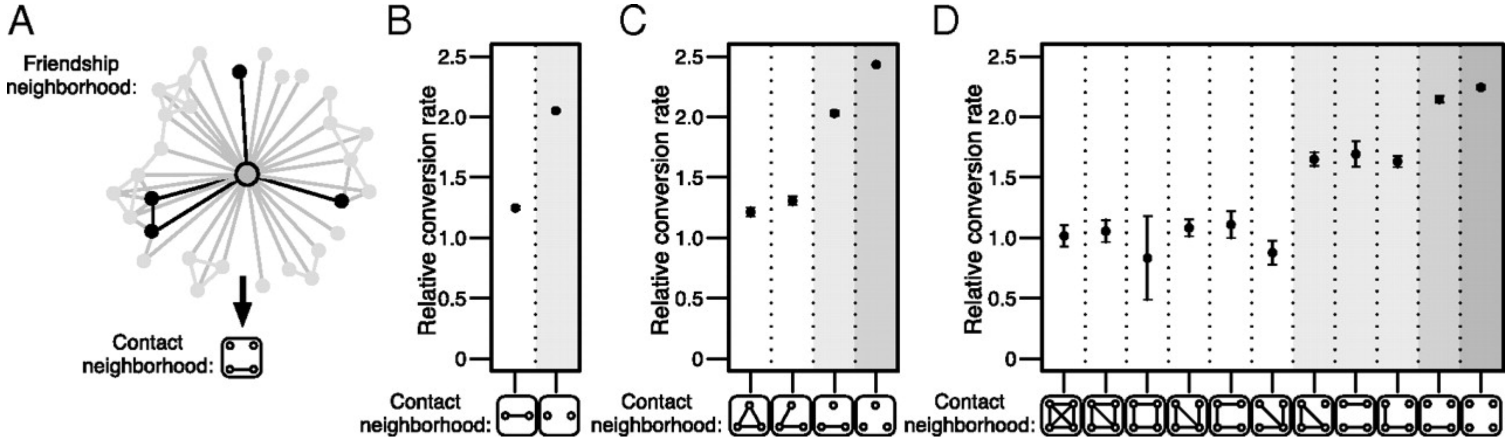


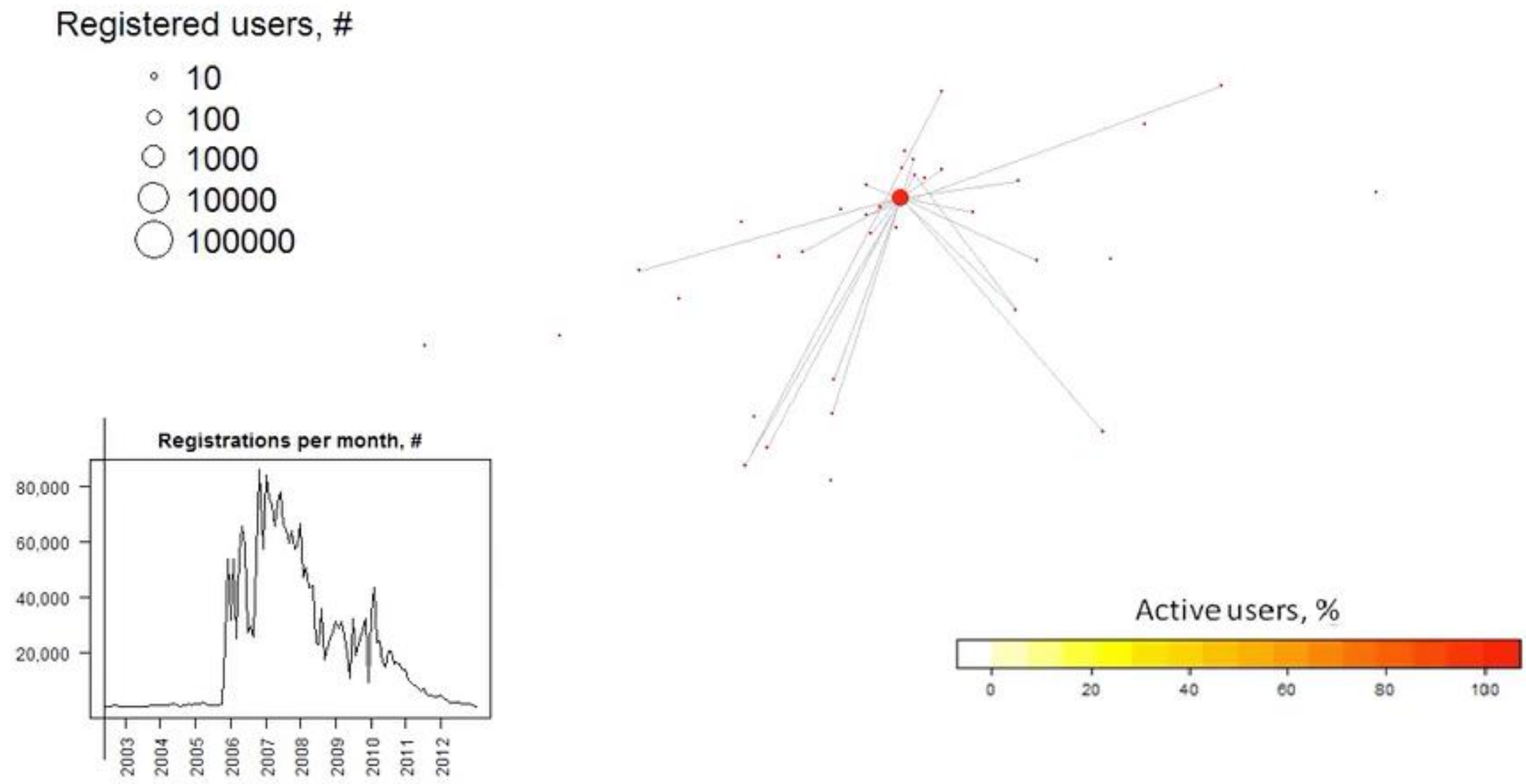




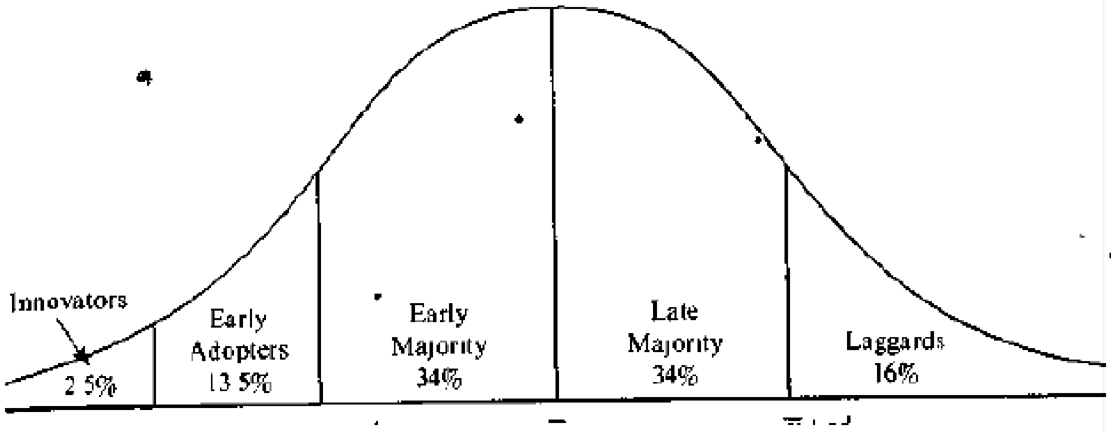
Role of communities: adoption probability increases after adoption in diverse communities

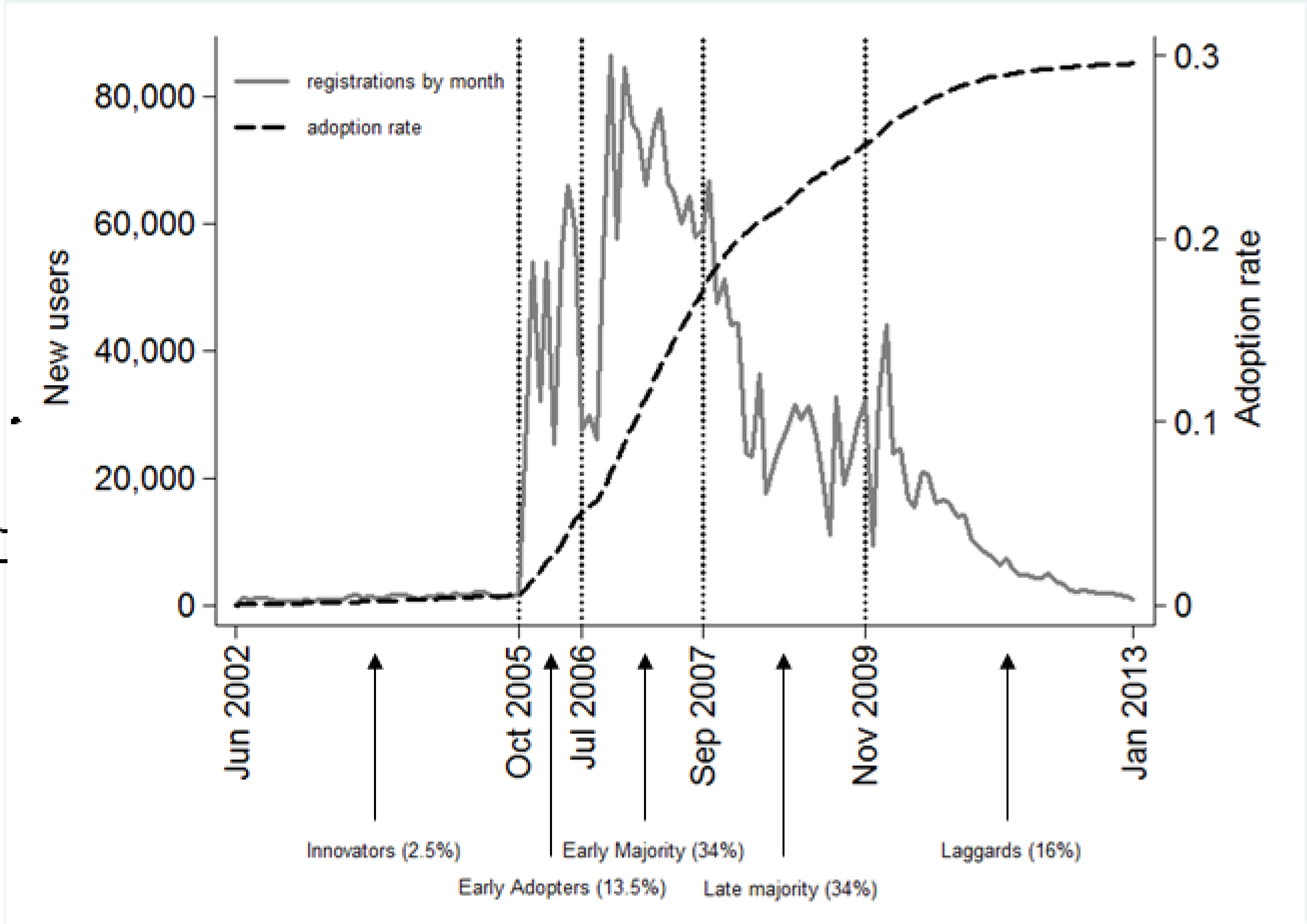





Registered users, #
10
100
1000
10000
100000
Registrations per month, #
80,000
60,000
40,000
20,000
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
Active users, %
0
20
40
60
80
100

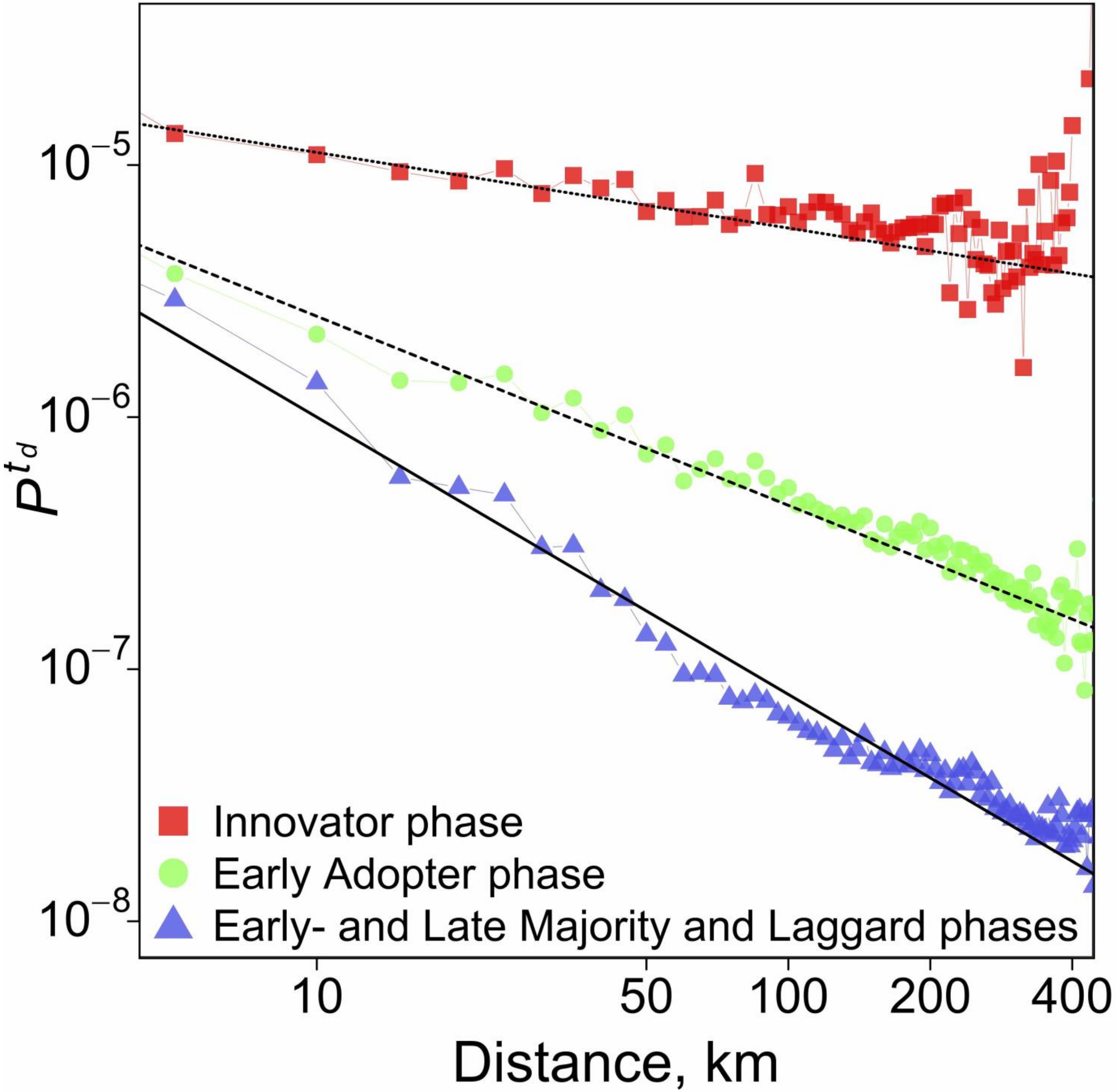
The iWiW life cycle by Rogers categories





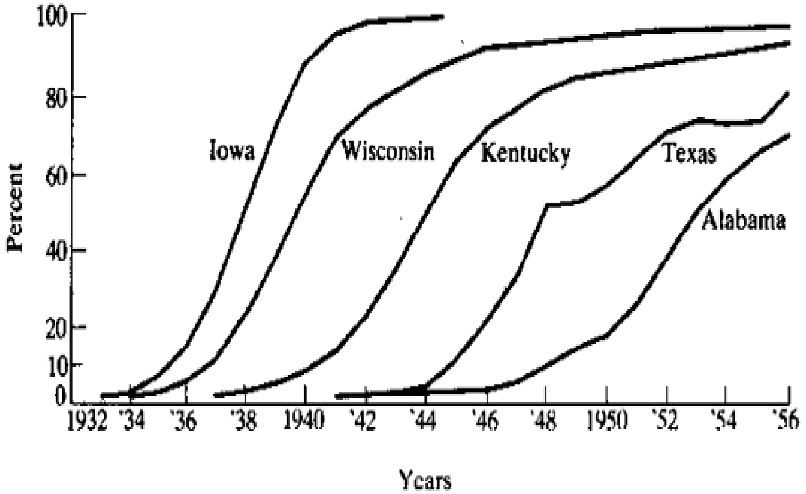
Forrás: Rogers (The Free Press, 1962),

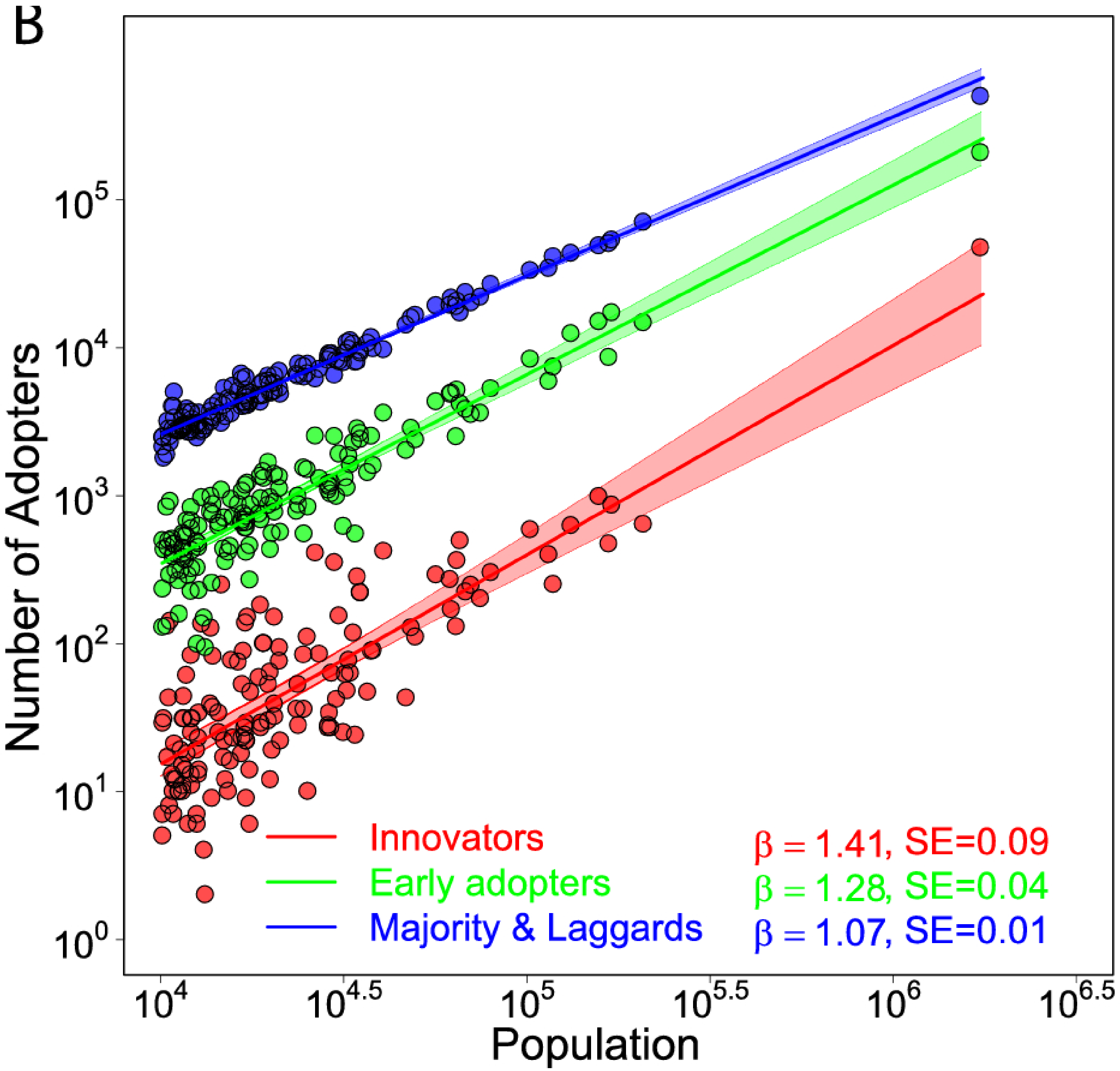
The role of distance



Distance only slightly decreases the probability of invitaiton in early phases

Diffusion becomes local in later phases.

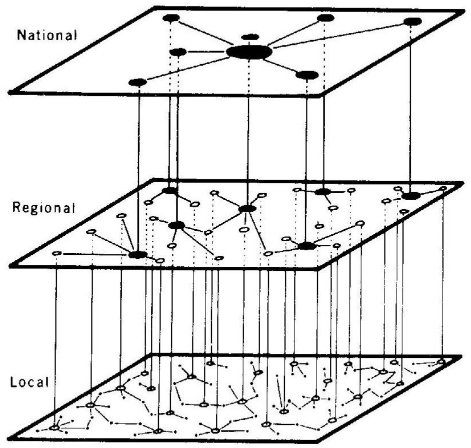




The role of size

Innovators and Early Adopters concentrate in cities.

Majority and Laggards are proportional to town size.



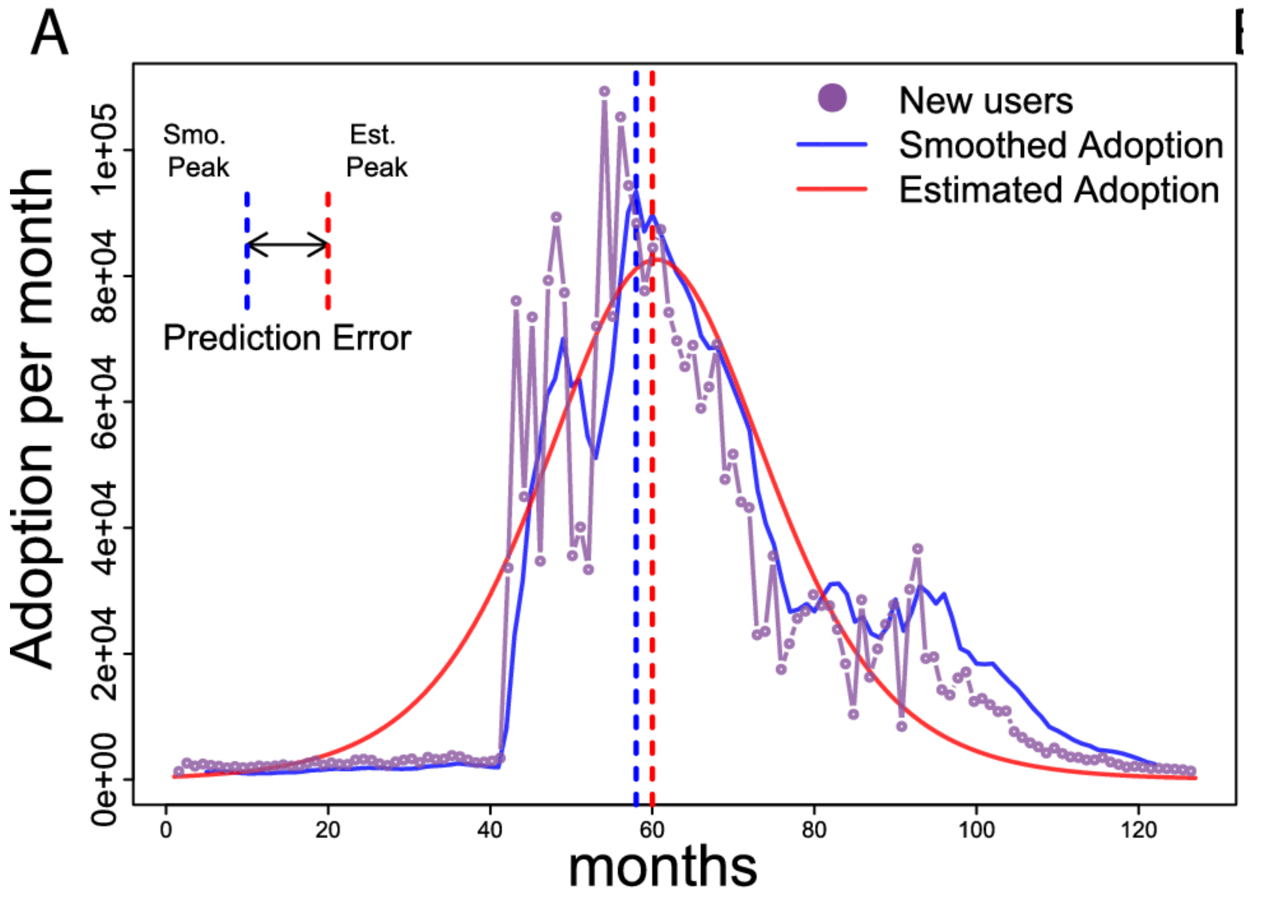
Adoption Rate

(Bass Curve)

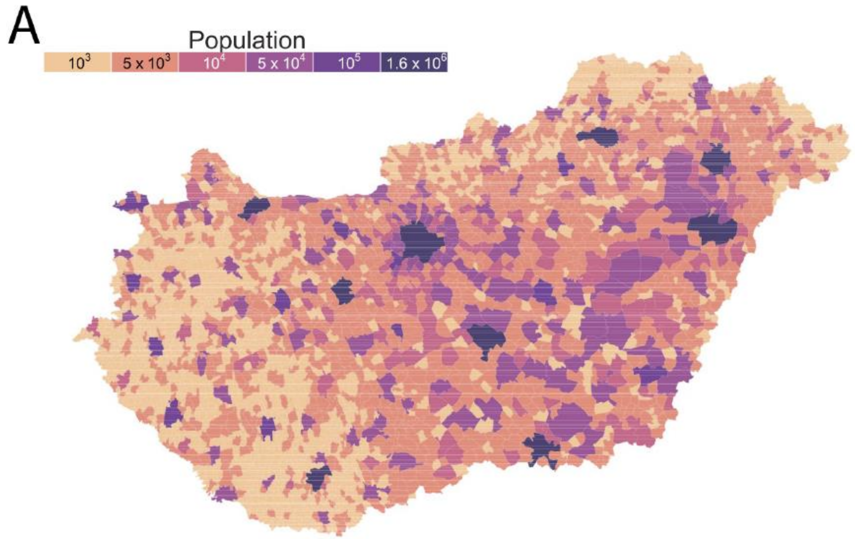
$$\frac{dy_a(t)}{dt} = (p_a + q_a y_a(t))(1 - y_a(t))$$

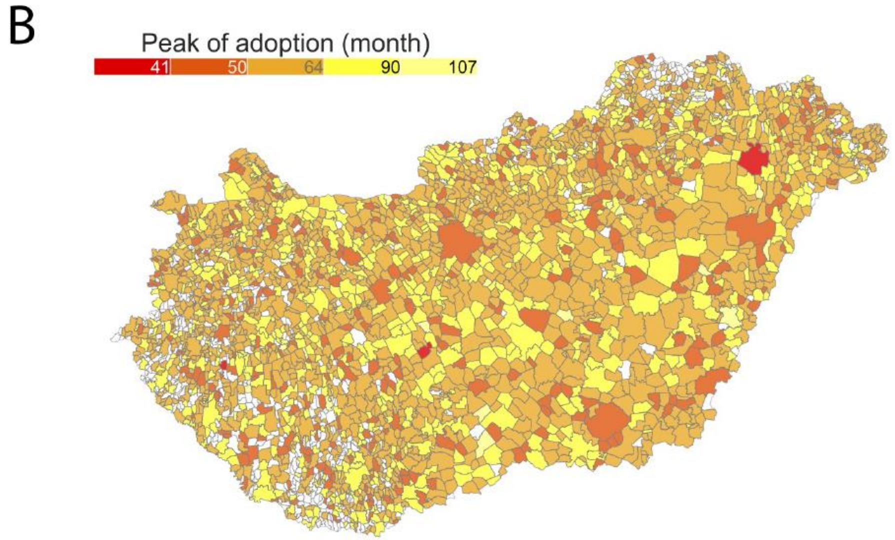
$$y_a(t) = m\frac{1 - e^{-(p_a+q_a)t}}{1 + \frac{q_a}{p_a}e^{-(p_a+q_a)t}},$$

# of adopters	Innovation Par.
$y_a(t)$	p_a
t	q_a
Time (months)	Imitation Par.

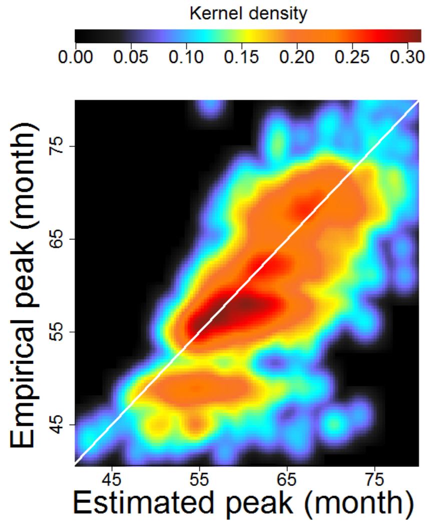


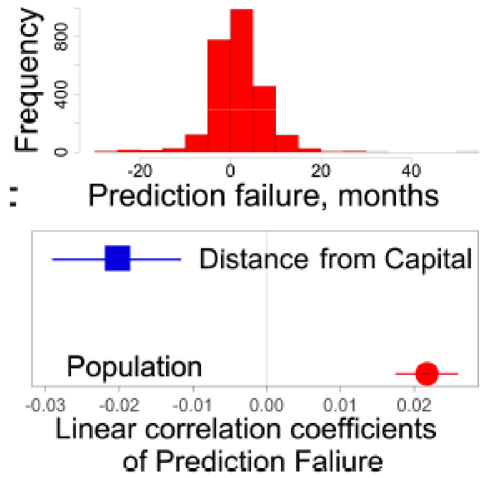
Local adoption peaks and prediction errors





$$T^{i}_{peak-t} = \frac{\ln p^{i}_{a} + \ln q^{i}_{a}}{p^{i}_{a} + q^{i}_{a}}$$

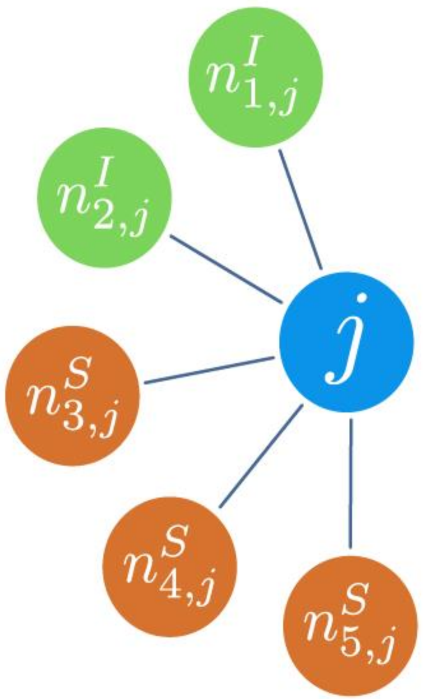




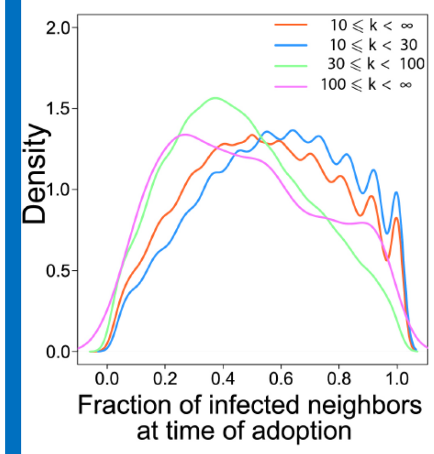
Agent-based model of diffusion in the network

- We fix the network.
- Inactives are not removed.

- 10% sample (300 K users)
- Sampling stratified by towns and network moduls



Innovation or Marketing parameter



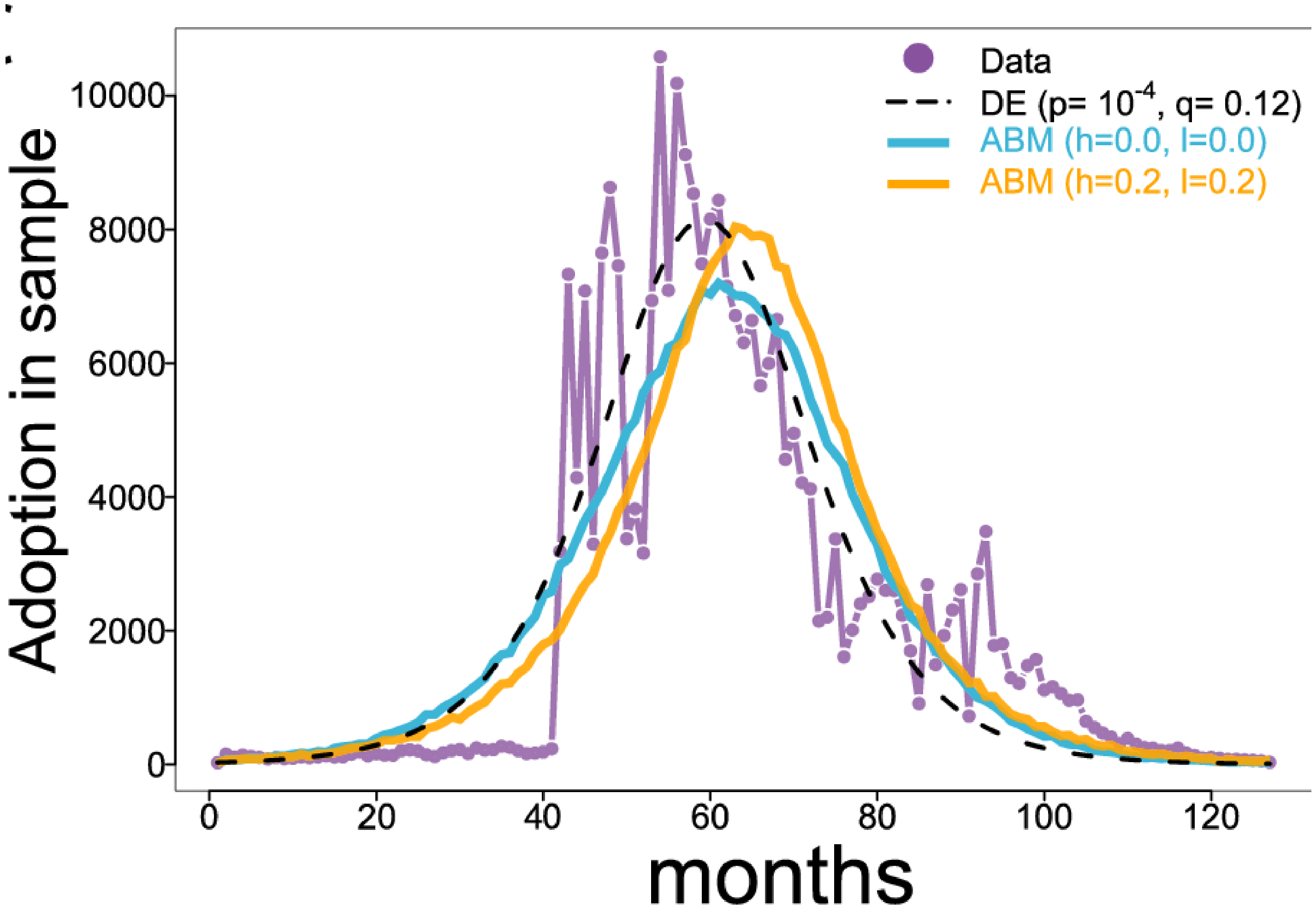
Network effect

$$\mathcal{N}_j(t) = \frac{\#n_j^I(t)}{\#n_j^I(t) + \#n_j^S(t)}$$

$$F_j(t+1) = \begin{cases} I & \text{if } U(0,1)_{jt} < \hat{p}^{\mathrm{ABM}} + T(\mathcal{N}_j(t), h, l) \times \mathcal{N}_j(t) \times \hat{q}^{\mathrm{ABM}} \\ S & \text{otherwise} \end{cases}$$

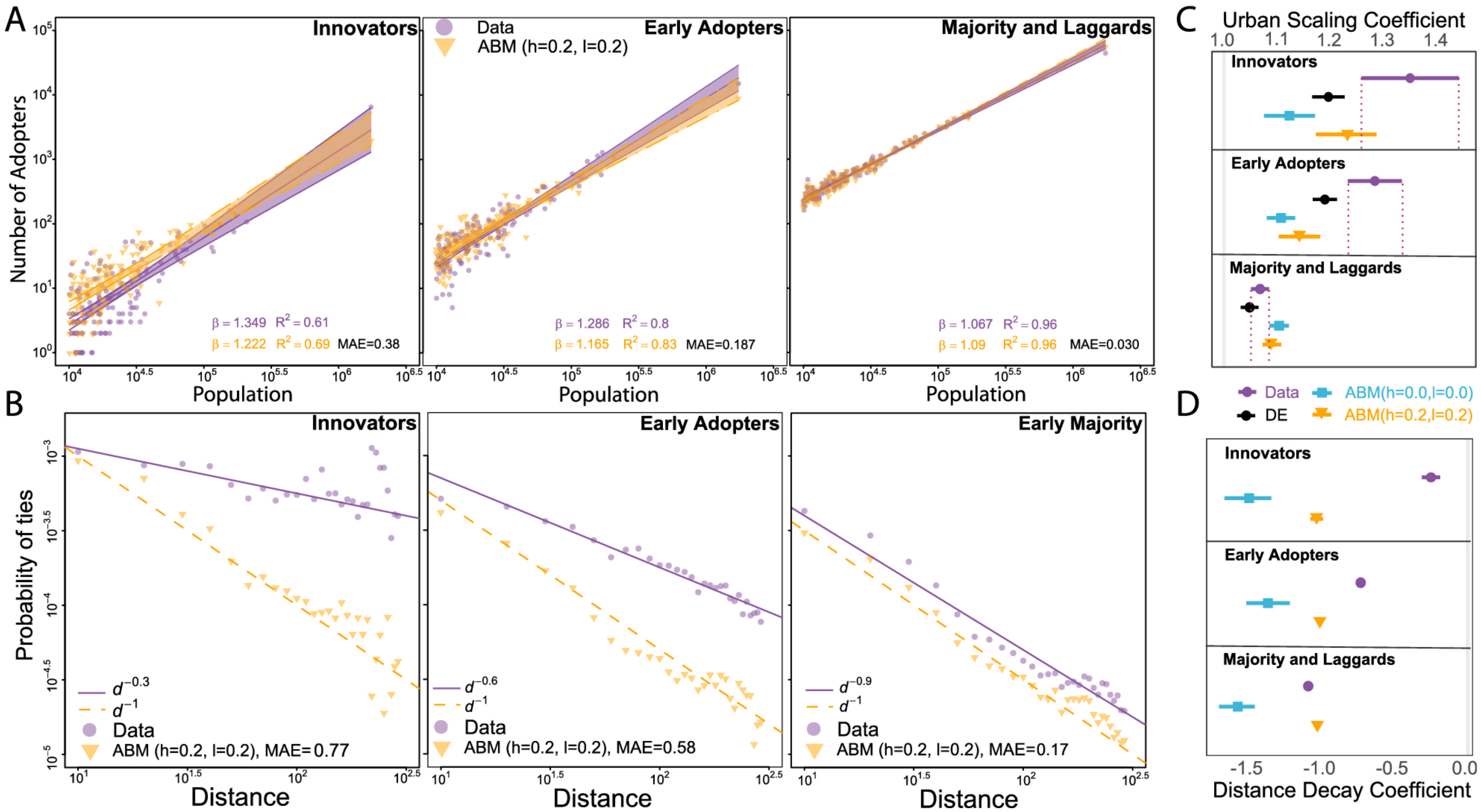
Imitation parameter

Results



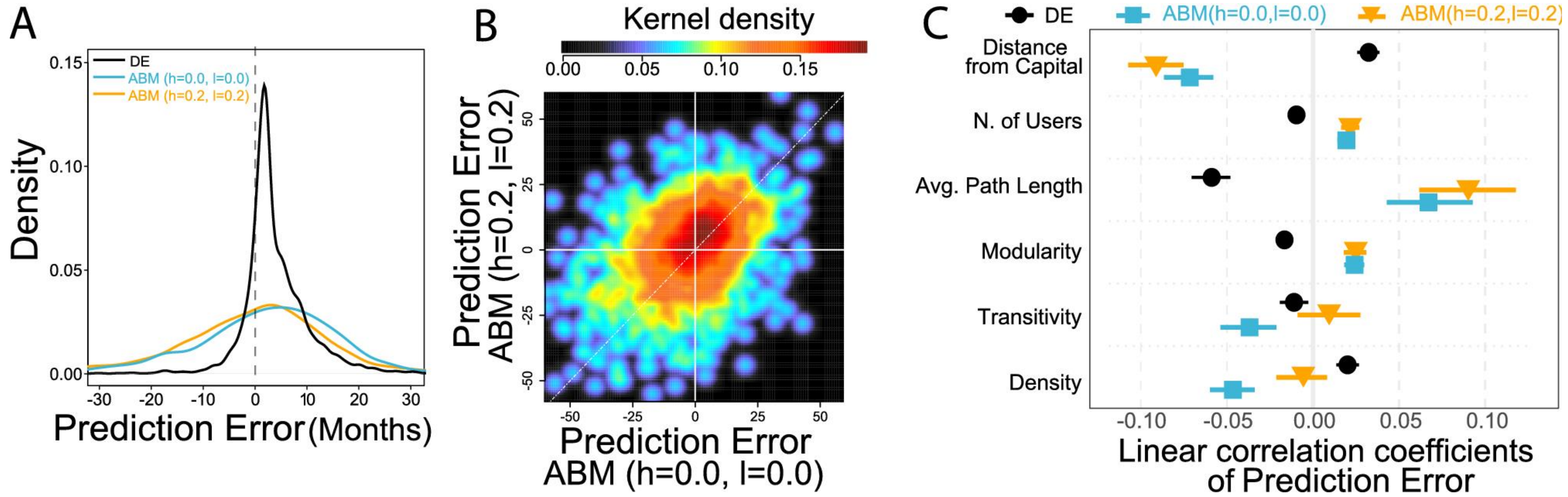
Data
DE (p= 10-4, q= 0.12)
ABM (h=0.0, l=0.0)
ABM (h=0.2, l=0.2)
Adoption in sample
10000
8000
6000
4000
2000
0
0
20
40
60
80
100
120
months

Results



A
Innovators
Early Adopters
Majority and Laggards
Data
ABM (h=0.2, l=0.2)
Number of Adopters
Population
β = 1.349 R² = 0.61
β = 1.222 R² = 0.69 MAE=0.38
β = 1.286 R² = 0.8
β = 1.165 R² = 0.83 MAE=0.187
β = 1.067 R² = 0.96
β = 1.09 R² = 0.96 MAE=0.030
B
Innovators
Early Adopters
Early Majority
Probability of ties
Distance
d^−0.3
d^−1
Data
ABM (h=0.2, l=0.2), MAE=0.77
d^−0.6
d^−1
Data
ABM (h=0.2, l=0.2), MAE=0.58
d^−0.9
d^−1
Data
ABM (h=0.2, l=0.2), MAE=0.17
C
Urban Scaling Coefficient
Innovators
Early Adopters
Majority and Laggards
D
Data
DE
ABM(h=0.0,l=0.0)
ABM(h=0.2,l=0.2)
Innovators
Early Adopters
Majority and Laggards
Distance Decay Coefficient

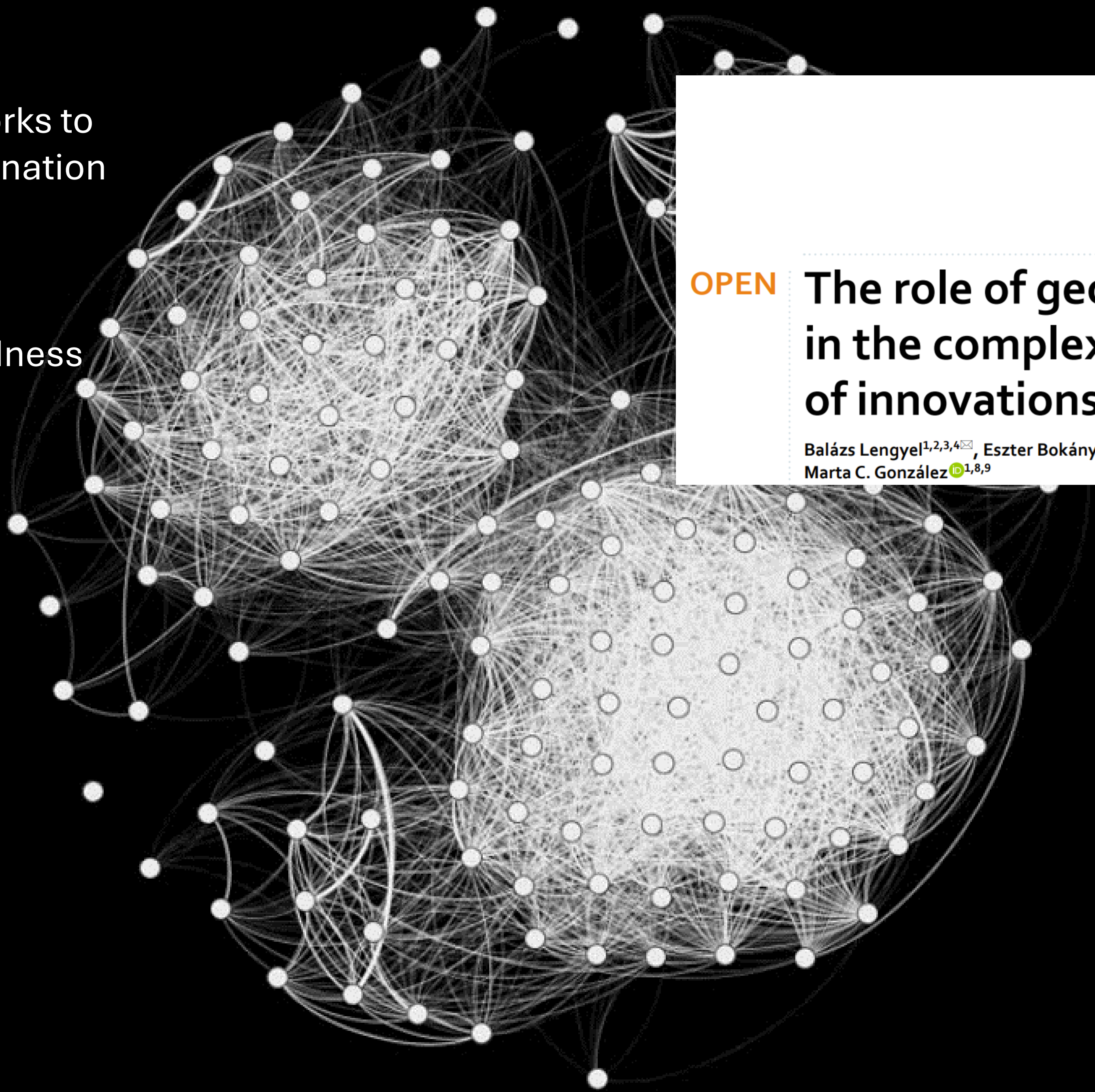
Results



A
DE
ABM (h=0.0, l=0.0)
ABM (h=0.2, l=0.2)
Density
Prediction Error (Months)
B
Kernel density
0.00 0.05 0.10 0.15
Prediction Error
ABM (h=0.2, l=0.2)
Prediction Error
ABM (h=0.0, l=0.0)
C
DE
ABM(h=0.0,l=0.0)
ABM(h=0.2,l=0.2)
Distance from Capital
N. of Users
Avg. Path Length
Modularity
Transitivity
Density
-0.10 -0.05 0.00 0.05 0.10
Linear correlation coefficients of Prediction Error

The role of diffusion in networks to understand knowldge combination

- diverse vs cohesive links,
- type of knowledge,
- organizations and firms,
- specialization and relatedness



SCIENTIFIC REPORTS
natureresearch

Check for updates

OPEN

The role of geography in the complex diffusion of innovations

Balázs Lengyel[1,2,3,4]✉, Eszter Bokányi[3,4], Riccardo Di Clemente[1,5,6], János Kertész[7] & Marta C. González[1,8,9]

Aplin et al. (2015) Nature


















Thank you!

anetilab.org

lengyel.balazs@krtk.hun-ren.hu

@blengyelb

HUN REN | KRTK Centre for Economic and Regional Studies

ANETILAB HUN-REN CERS • Corvinus University

CORVINUS UNIVERSITY of BUDAPEST

Openings

- **MC Postdoc opening**
  - **MARIE-CURIE POSTDOCTORAL FELLOWSHIPS TAILORED TO US**
  - **3 years, European salary in Budapest**
  - **Apply this spring!!!**

- Agglomeration, Networks and Innovation (2024-2029)
  - Organizations: GitHub collaboration, work from home,
  - Urban inequalities: Twitter, mobility data
  - Diffusion: scientific publications, patents
- Complex Links of Neighborhoods - Driving Urban Transition (2025-2027)
  - 15-min city: mobility, amenities, public transport, segregation, commuting