Social Networks and Economic Geography

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Class 3: Networks, Social Capital, and Outcome

February 18 2025

Structure of the class

1. Small-world networks, social capital, and success in networks

2. Complementarity of social capital, detected from inventor mobility

3. Antidepressant use and spatial social capital

1. Small-world networks and social capital

Social Capital

- The ability to mobilize resources through social contacts.

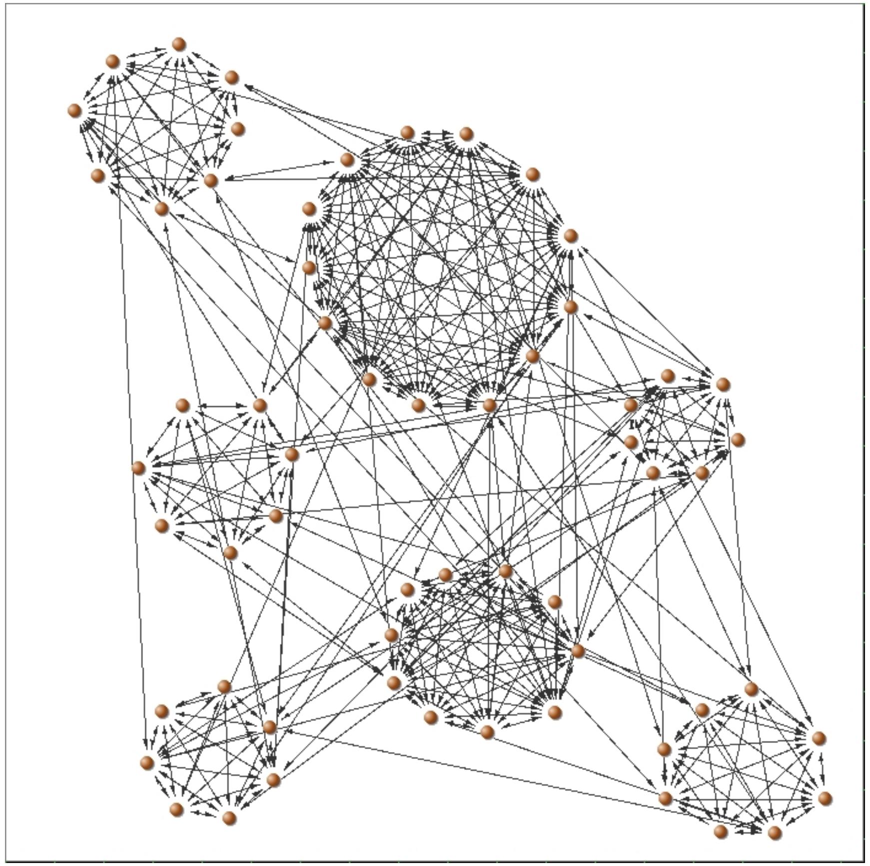
- The use of networks:
- Bonding social capital: strong ties, cliques etc.
- Bridging social capital: weak ties, bridges etc.

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

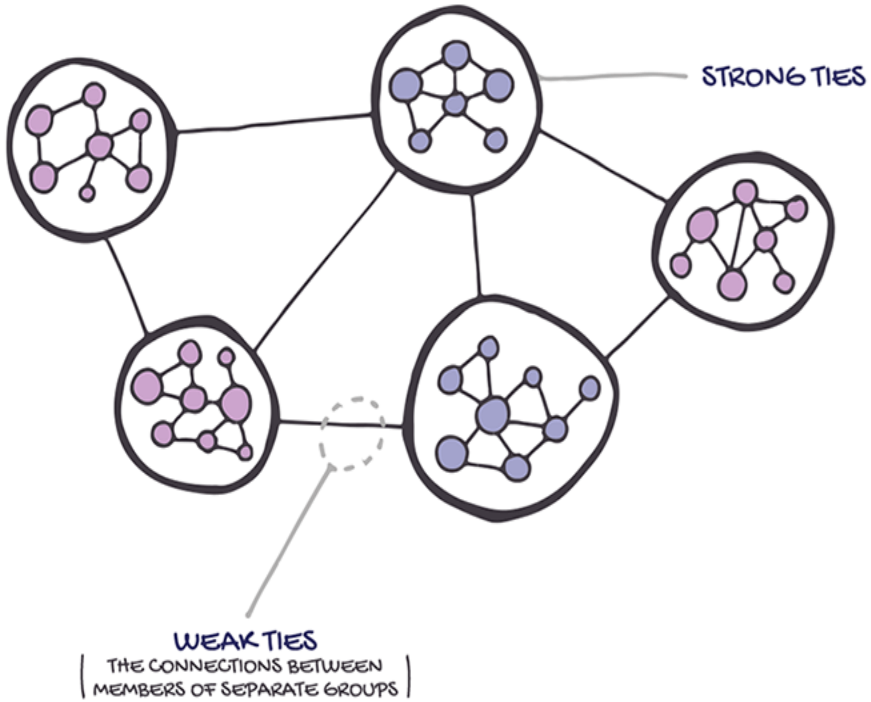
Weak ties and Brokers

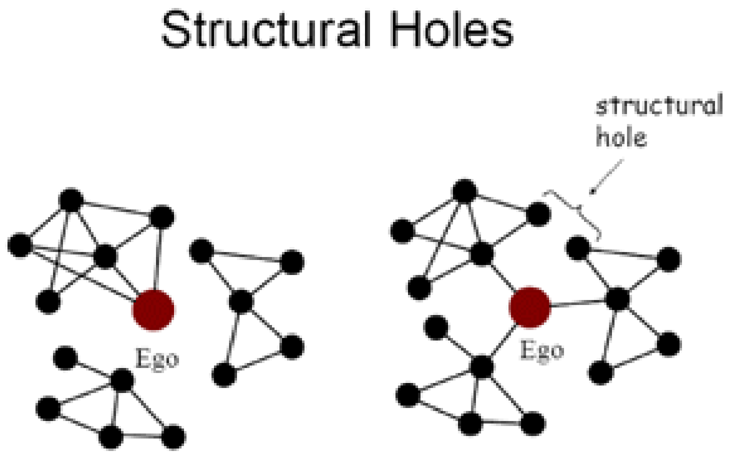
Weak ties (Granovetter, 1973):

- 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

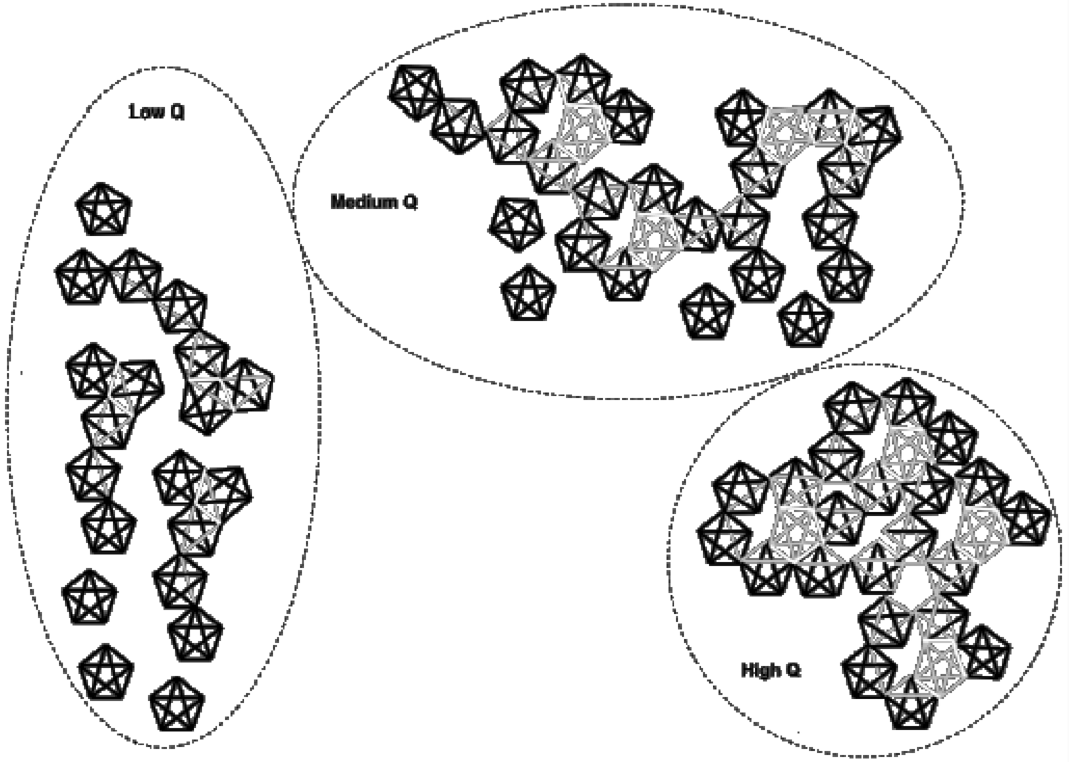




Optimal small worldliness: combination of diverse and cohesive networks

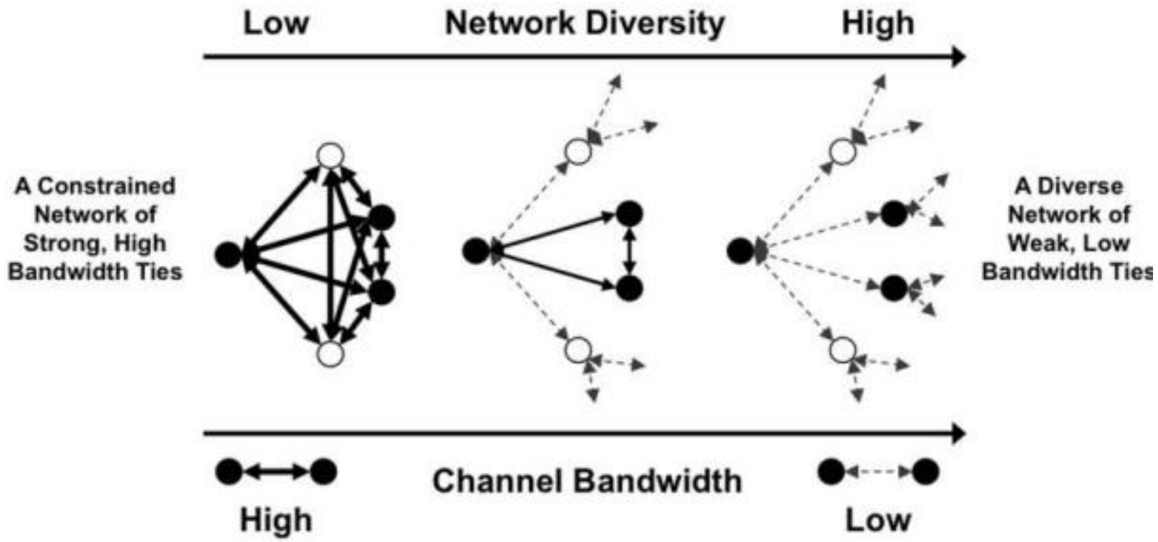
Uzzi and Spiro (2005) American Journal of Sociology

- Small-world Q: high transitivity and short paths
- Broadway musical example: high quality performance needs medium small-worldliness



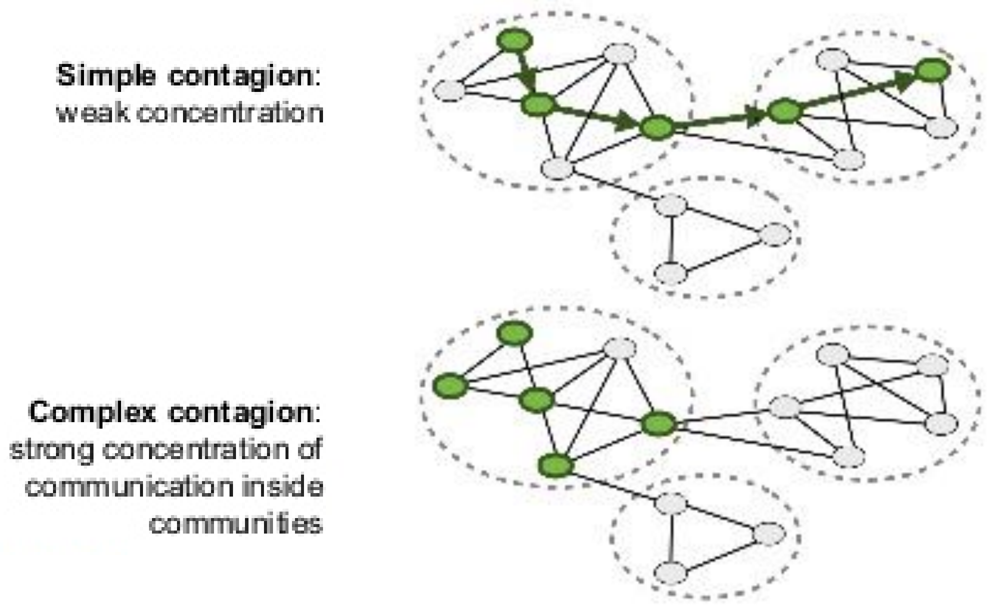
Benefits in small-world networks

- 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.

Tertius gaudens: brokers control the flows - role in network diffusion

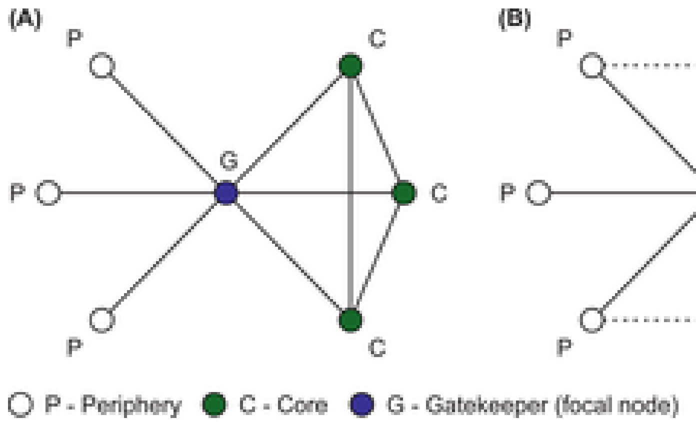


- Simple: contagion needs dyadic relation
- Complex: adoption is individual decision influenced by adoption of friends
- Virus diffusion is simple; Innovation diffusion is complex
- Small-world networks: clustering speeds up diffusion, the question are thresholds at bridges.

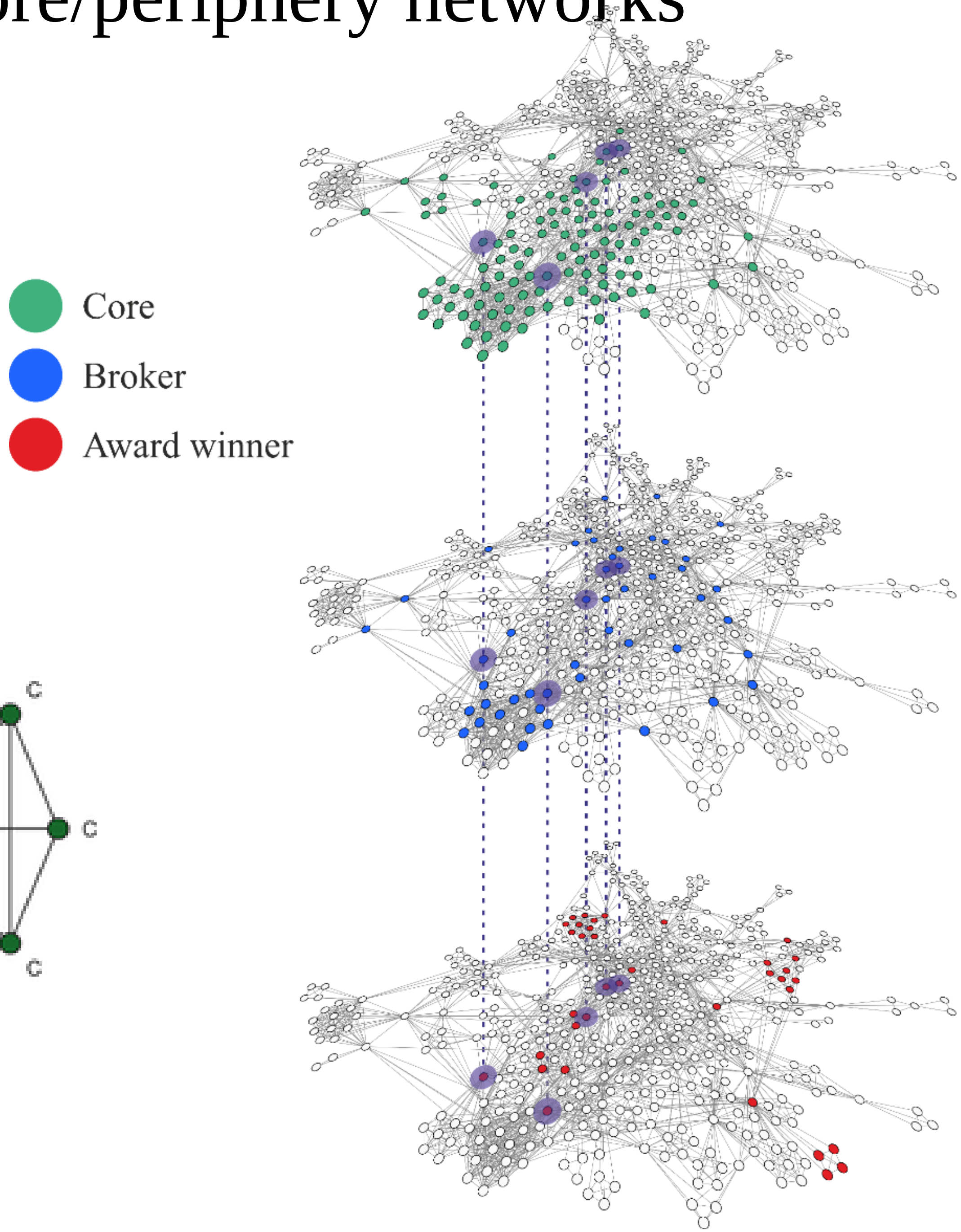
Tertius iungens: brokers and success in core/periphery networks

Core and Broker individuals are more successful than Peripheral and Non-Broker individuals

Gatekeeping between core and periphery adds to the probability of individual success



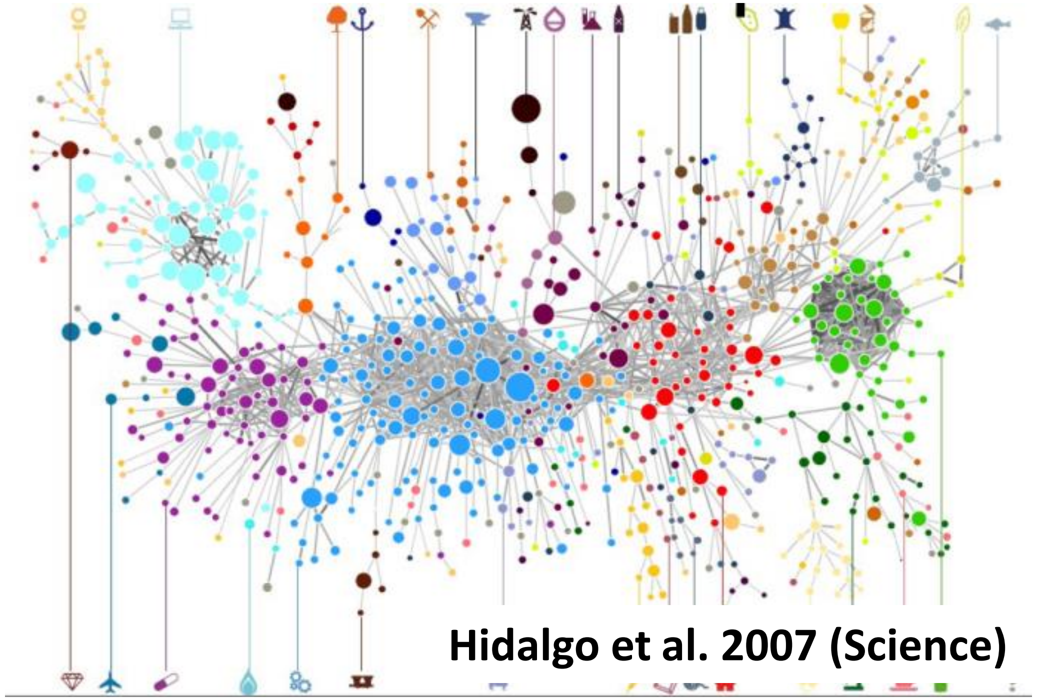
Juhász et al. (2020) PLoS ONE



2. Complementarity of social capital, detected from mobility

Economic progress and urban success

- Social interaction: population density
- Learning in the city: industry structure
- Related knowledge is easie to learn but contains less novelty



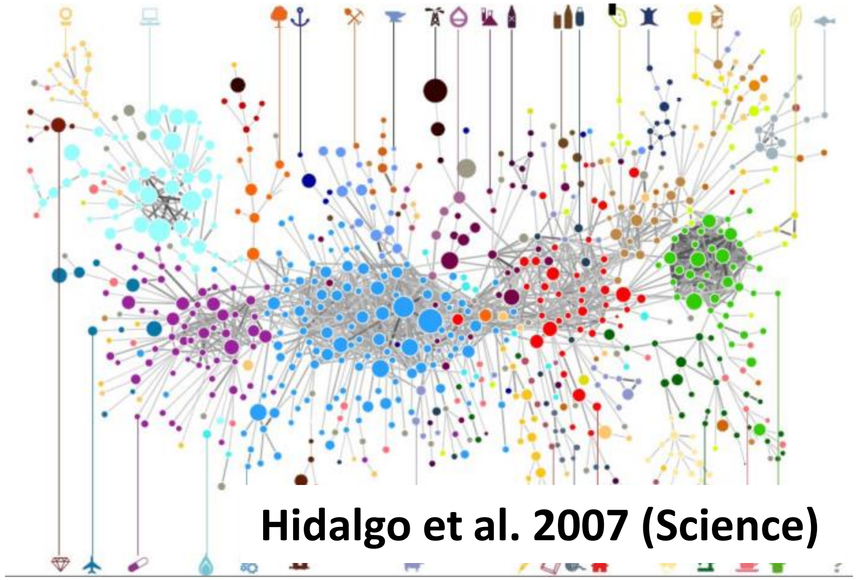
Hidalgo et al. 2007 (Science)

Human mobility and labor mobility

González et al. (Nature 2008)

- Labor mobility: PEOPLE CHANGE JOBS
- Direct effect
  - New employee brings new knowledge to the firm
- Indirect effect
  - Previous colleagues tend to communicate or even work together
- Urban success (Silicon Valley vs Route 128)

How does interaction between firms and industries induce economic success of cities?



Hidalgo et al. 2007 (Science)

Direct effect in the firm:
How does the knowledge of mobile employees induce firm performance?

Csáfordi, Zs., Lőrincz, L., Lengyel, B., Kiss, K.M. (2020) Productivity spillovers through labor flows: The effect of the productivity gap, foreign-owned firms, and technological relatedness. *The Journal of Technology Transfer*

Data:
Hungarian firms, 2003-2010
Company: revenues, costs, industry, size
Employees: education, wage, gender, age

Total factor productivity: all revenues over all cost

$$A_{j,t+1} = \alpha A_{j,t} + \beta_1 \cdot prodgap_{j,t} + \beta_2 \cdot HC_{j,t} + \beta_3 \cdot HC_{j,t+1} + \gamma \boldsymbol{X}_{j,t} + \delta \boldsymbol{D} + \varepsilon_{j,t}$$

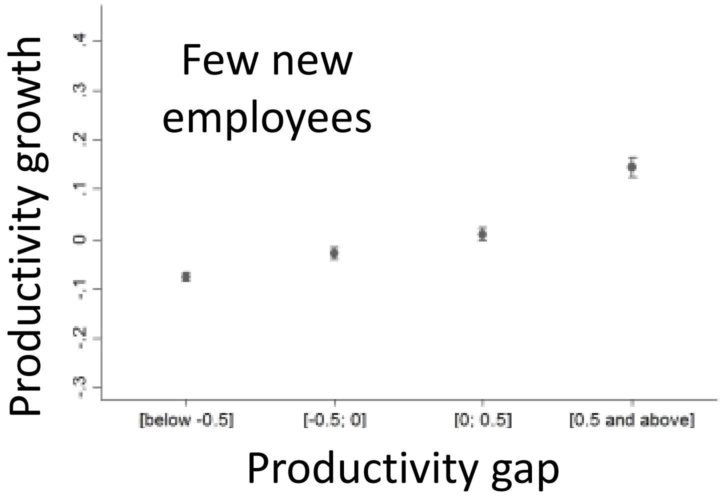
$$prodgap_{j,t} = \frac{\sum_{i=1}^{H_{j,t+1}} (A_{i,t} - A_{j,t})}{H_{j,t+1}} \cdot \frac{H_{j,t+1}}{N_{j,t+1}}$$

Labor moves from company *i* to *j*

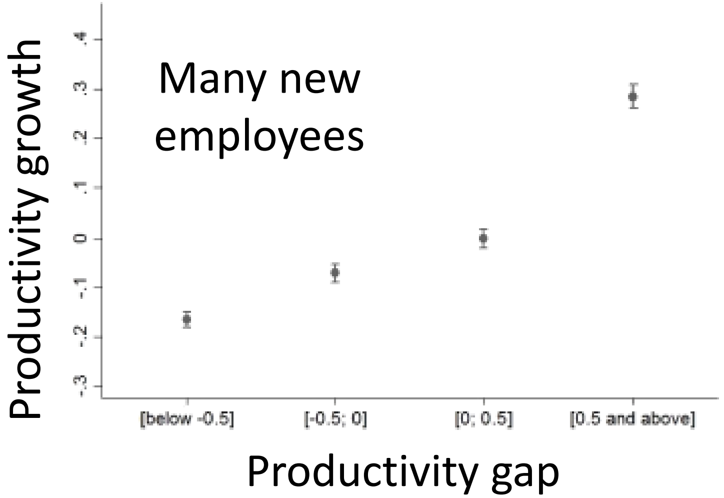
$A_{i,t}$ and $A_{j,t}$ are TFP of company *i* and *j*

$H_{j,t+1}$ is the number of moving employees

$N_{j,t+1}$ is company size



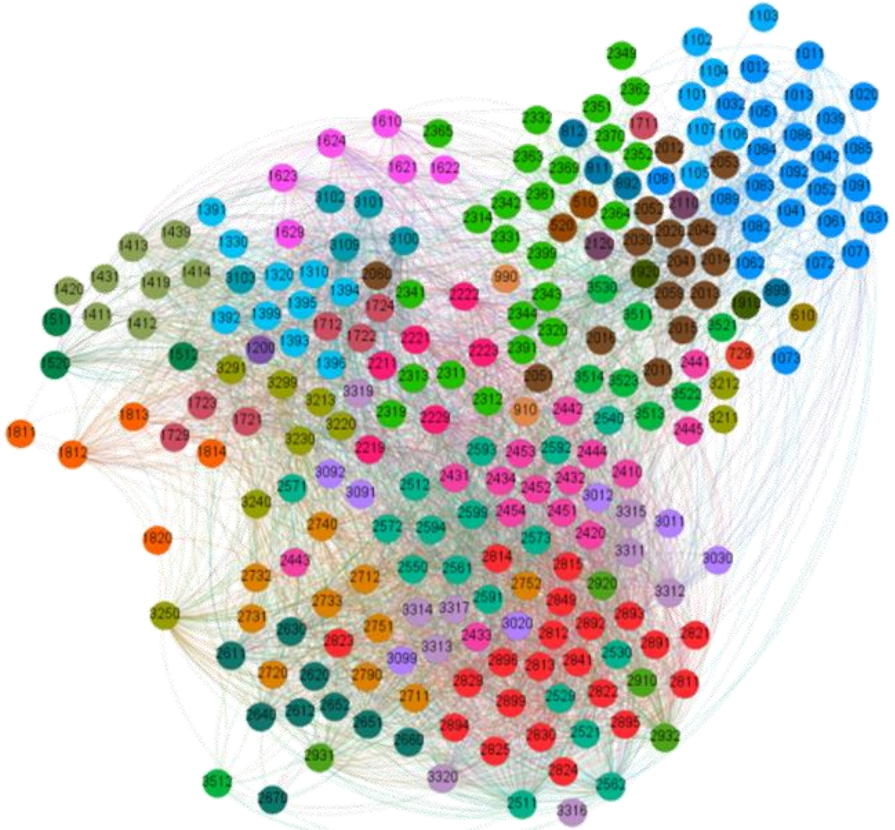
The larger the productivity gap between sending and receiving companies the bigger effect on receiving company.



Employees bring their skills to the new firm.

New knowledge boosts firm productivity

Relatedness from production:
Industries *p* and *q* are related if products classified by *p* are likely to be co-produced by products classified by *q* (Neffke et al. 2011)



	TFP
Lagged productivity	0.669***
	(0.017)
Productivity gap	0.269***
	(0.077)
Human capital	0.174***
	(0.036)
Share of related inflows	0.213*
	(0.090)
Share of same industry inflows	0.051
	(0.078)
Observations	10,857
R-squared	0.695

Related but new skills matter more
Employees coming from firms that produces similar but not identical products induce productivity of the receiving firm.

Complementarity of weak and strong ties

Tóth, G., Lengyel, B. (2021) The Journal of Technology Transfer

Inventor mobility
Data: European patents in ICT, 1977-2010
Observations: author a patent for SOURCE FIRM , then later for DESTINATION FIRM
Dependent variable: Citations to the patents of the DESTINATION FIRM
Explanatory variables: 1. Ego network of mobile inventors, 2. Collaboration networks in the DESTINATION FIRM

$$Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t-3} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + D_t + \varepsilon_{B,t}$$

Pooled OLS with year FE, clustered standard errors

X – inventor characteristics
Z – qualities of DESTINATION FIRM
W – qualities of SOURCE FIRM
T – treatment dummy
D – year fixed effect

$$(1) \qquad Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t-3} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + D_t + \varepsilon_{B,t}$$

$$(2) \qquad Y_{B,t+v} = \alpha + \beta_1 \cdot X_{i,t} + \beta_2 \cdot Z_{B,t} + \beta_3 \cdot W_{i,A,B,t} + \beta_4 \cdot T_{B,t} + D_t + \varepsilon_{B,t}$$

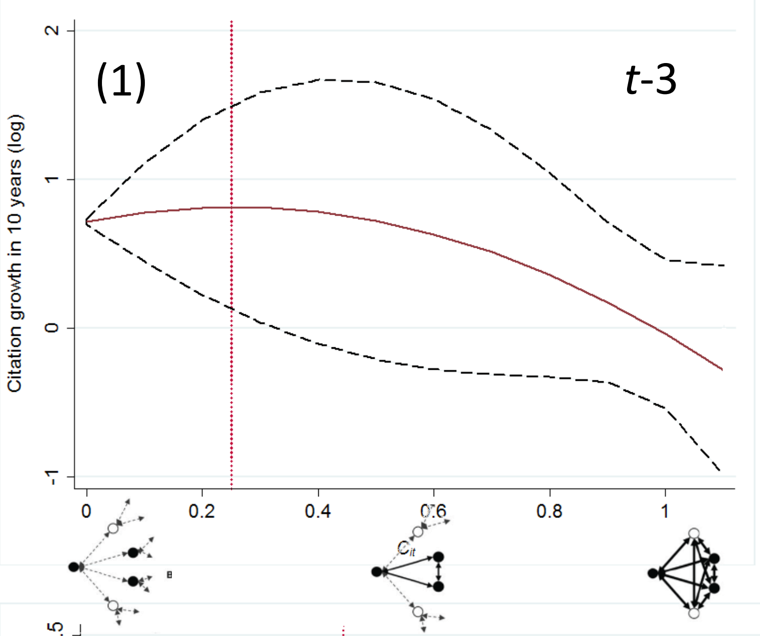
Pooled OLS with year FE, clustered standard errors

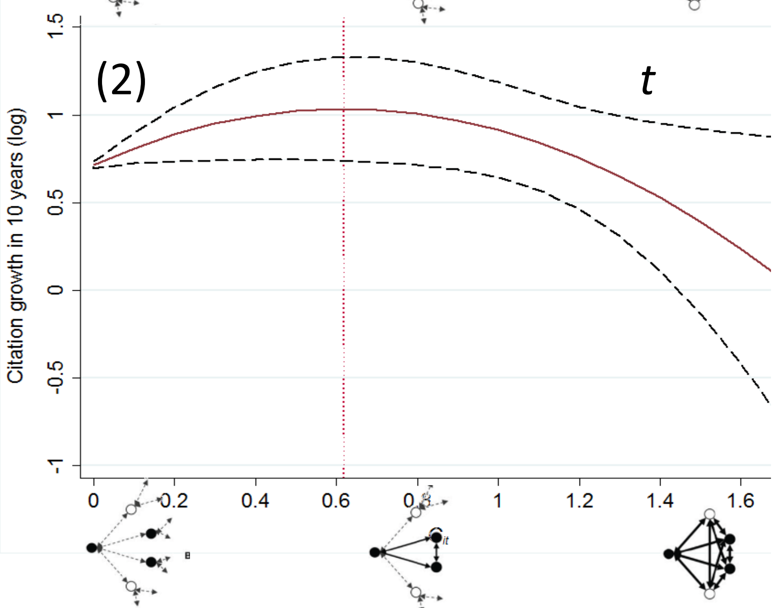
X – inventor characteristics
Z – qualities of DESTINATION FIRM
W – qualities of SOURCE FIRM
T – treatment dummy
D – year fixed effect

MARGINAL EFFECT OF EGO NETWORK COHESION

(1) Mobile inventors with non-cohesive networks before the event of mobility induce citation (3 years before patent application).

(2) An optimal network structure emerges during working on the patent.
- The ego-network of mobile inventors becomes more cohesive.





Complementarity of weak and strong ties

Interactions between:
Firm network variables such as TRANS and APL
Inventor IMPACT (citations)
Inventor BROKERAGE (1-constraint)

(1)
High impact inventors have larger effect if work in networks with high triadic closure.

(2)
The effect of broker inventors is higher if there are short paths in the firm network.

(3)
The company needs a cohesive environment to exploit high impact and diverse new external knowledge.

	CUMULATIVE CITATIONS		
	(1)	(2)	(3)
IMPACT× TRANS	2.923***		4.116***
	(0.852)		(1.130)
IMPACT× APL	-0.009		-0.097
	(0.058)		(0.078)
BROKERAGE × TRANS		0.363	1.440**
		(0.957)	(0.626)
BROKERAGE× APL		-0.107**	-0.157***
		(0.047)	(0.032)
BROKERAGE	0.844***	1.011***	0.980***
	(0.246)	(0.256)	(0.242)
IMPACT	-0.051**	-0.009	-0.045**
	(0.021)	(0.045)	(0.021)
TRANS	0.362***	-0.001	-1.077*
	(0.031)	(0.957)	(0.626)
APL	-0.017***	0.090*	0.139***
	(0.005)	(0.047)	(0.032)
Constant	-0.338	-0.504	-0.473
	(0.325)	(0.332)	(0.321)
adj. R-sq	0.279	0.279	0.279
N	95788	95788	95788

3. Antidepressant use and spatial social capital

Balázs Lengyel[1,2,], Gergő Tóth[1,3], Nicholas A. Christakis[4], Anikó Bíró[1]
[1] HUN-REN KRTK, Budapest, Hungary
[2] Corvinus University of Budapest, Budapest, Hungary
[3] Umeå University, Umeå, Sweden
[4] Yale University, New Haven CT, US

Literature

The **theory of social capital** (R. D. Putnam 2000; J. S. Coleman 1988) has been widely used to understand **mental health inequalities** (K. McKenzie, et al. 2002; S. Henderson & H. Whiteford 2003). Accordingly social support became part of health policy interventions fighting mental disorders (A. M. Almedom 2005).

The **structural form of social capital**, can reduce stress, anxiety, and depression (J. N. Rosenquist 2011; Z. I. Santini, et al. 2020). The help of emotional support gained from **cohesive networks** where individuals can source bonding social capital (N. Lin 2017).

Much fewer argue for the importance of bridging social capital, despite the pivotal role of **weak ties** and **diverse networks** in providing economic opportunities (N. Eagle, et al. 2010, R. Chetty, et al. 2022) that subsequently influence health outcomes (R. M. Thomson, et al. 2022).

Previous empirical work mostly used **small-scale surveys** to collect social connections that could not map the full horizon of weak ties (M. S. Granovetter 1973; R. I. Dunbar 1998). These data limitations made mental health outcomes of bonding and bridging social capital difficult to compare for preceding research.

State of the art

Design

- 32 years of survey data of Framingham Heart Study (Boston MA)
- 12067 people assessed
- Depressive symptoms

Results

- Depression scores correlated with peers' scores
- 3-degrees of separation
- Female friends are more influential

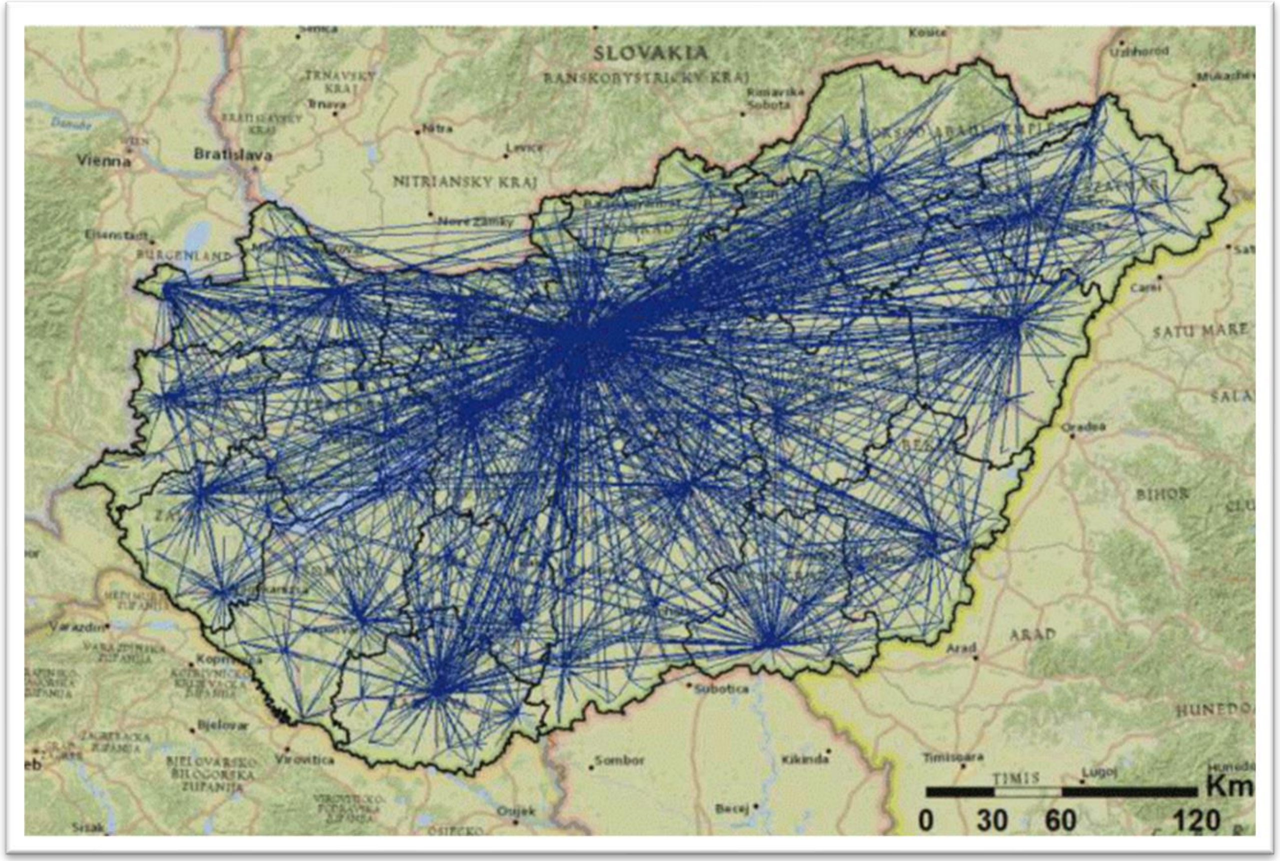
Limitations

- Not a real network structure: the network is based on the closest people coming from a survey
- Clear selection bias: all the participants are people treated with CVD problems and their family members/friends
  - Social status
  - Geographically bounded
- No objective evaluation: depression scores are based on a questionnaire
- Endogeneity: causality is vaguely discussed

Rosenquist, J. N., et al. (2011). Social network determinants of depression. *Molecular psychiatry*, 16(3), 273-281.

Scaling up: large data

Rosenquist, J. N., et al. (2011). Social network determinants of depression. *Molecular psychiatry*, 16(3), 273-281.



Lengyel, B., et al. (2015). Geographies of an online social network. *PloS one*, *10*(9), e0137248.

Data 1: online social network

iWiW - OSN

2.7 Million individuals in 2557 towns
pre-Facebook: no friend recommendations
Collection of offline connections on the online platform
Full life-cycle

- Location (self-reported settlement)
- Birthdate (the 1900 problem)
- Gender
- Date of registration and last login
- ID of friends
- ID of inviters

A specific kind of social network:

- Very broad definition of a tie
- Low cost for making and maintaining a tie
- No information about the kind or strength of a tie

Data 2: administrative data on drug prescriptions

Állami Egészségügyi Ellátó Központ

National Healthcare Service Centre

Administrative data on drug usages in 2011 (-2015)

- ATC (anatomical therapeutic chemical)
- N06A (antidepressants)

Total population of Hungary

- Gender
- Birthdate
- Settlement
- Etc.

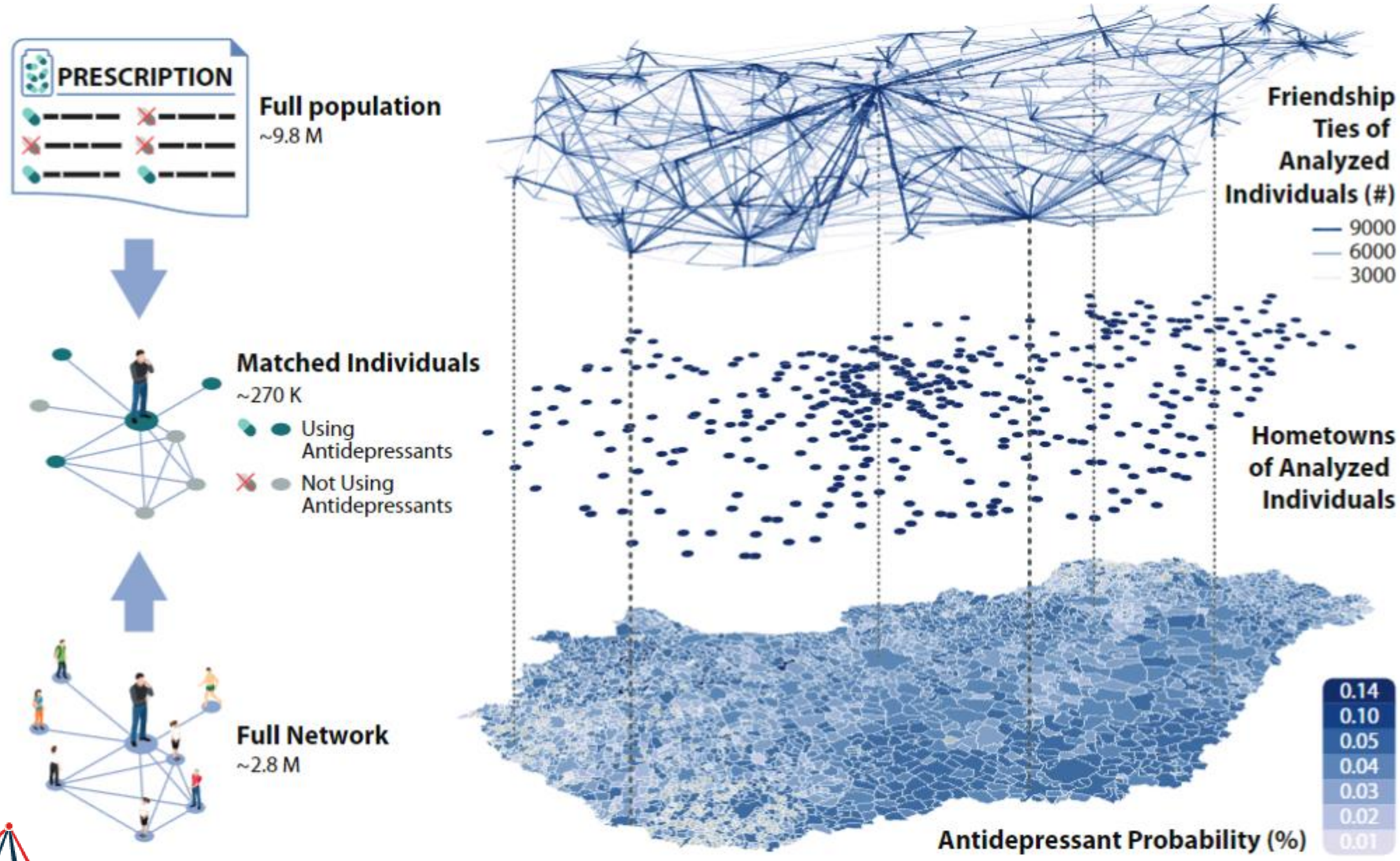
In 2011 – in total 407,546 people had the prescription for antidepressants.

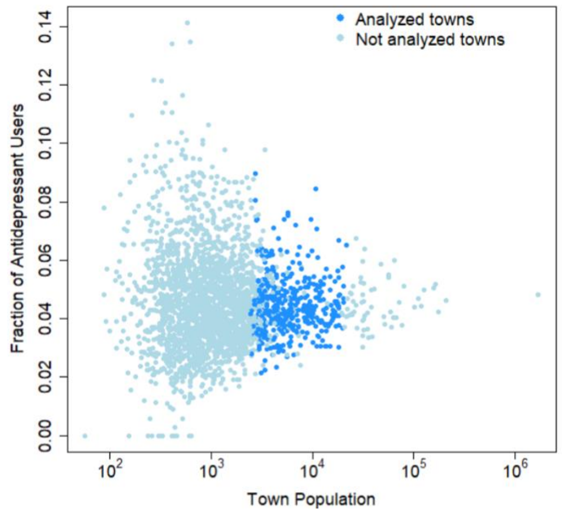
The most common diagnosis codes (ICD10) indicated on the antidepressant prescriptions: F32 – depressive episode (25%), F33 – recurrent depressive disorder (20%), F34 – persistent mood disorders (4%), F41 – other anxiety disorders (30%).

A binary variable: symptoms + treatment

Caveats:

- Inequality in treatment access
- False negatives and false positives
- Severity of symptoms





two-sided Mann-Whitney U test: *(p=0.971)*

- population
- income
- unemployment

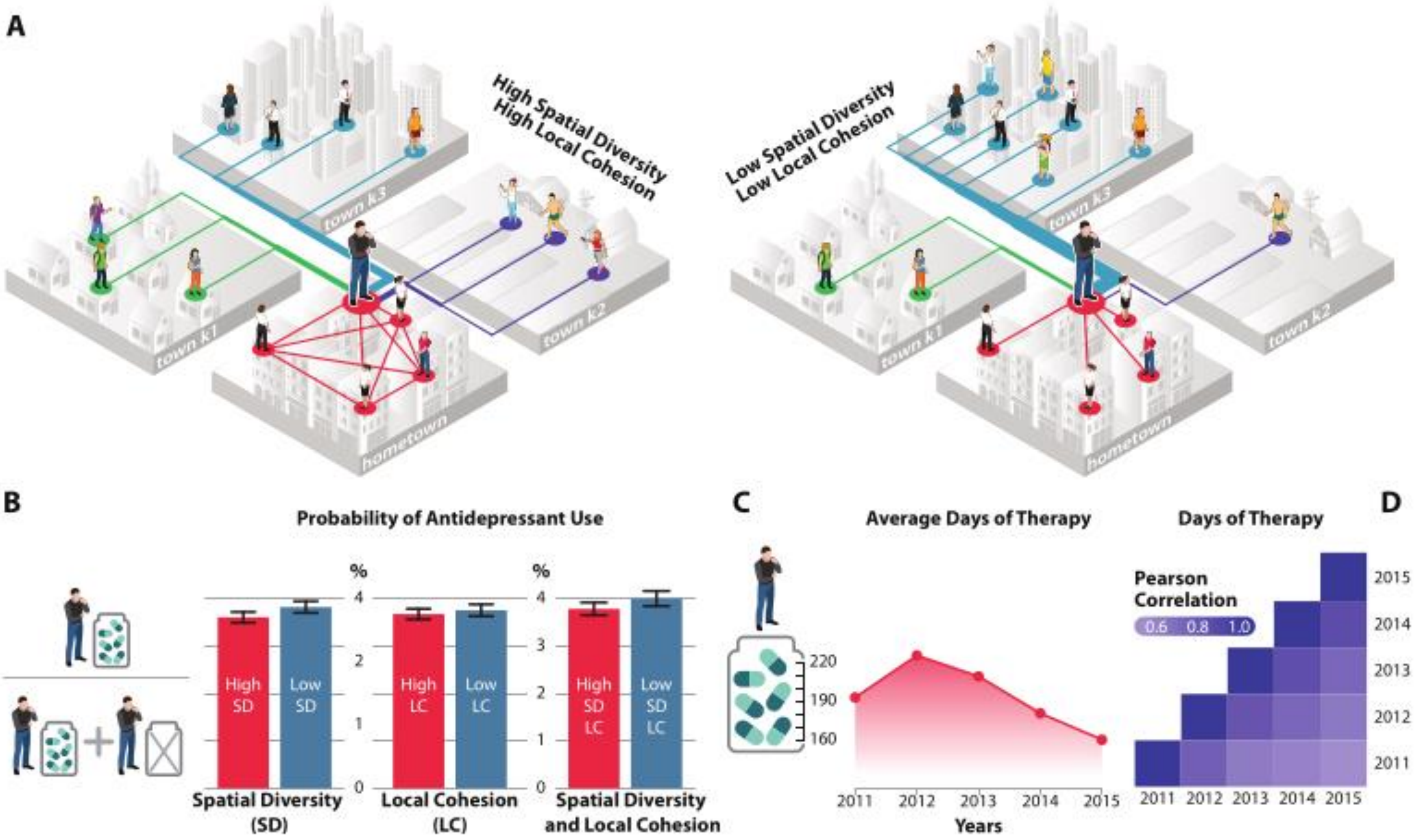
Permissions and ethical considerations

OSN data: Non-disclosure agreement with the data owner. Placed in KRTK Databank

Anti-depression prescription data: contract with AEEK / KRTK Databank

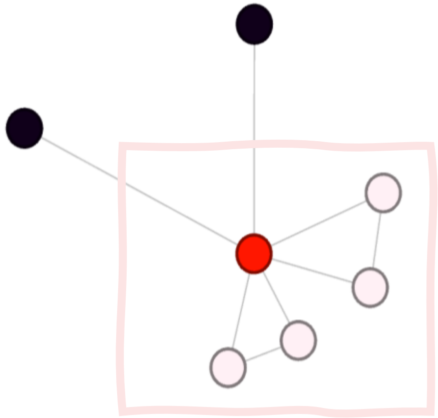
Matching: Ethical Committee of Medical Research Council

What is the relationship between (ego)network structure and anti-depression use in large-scale data?

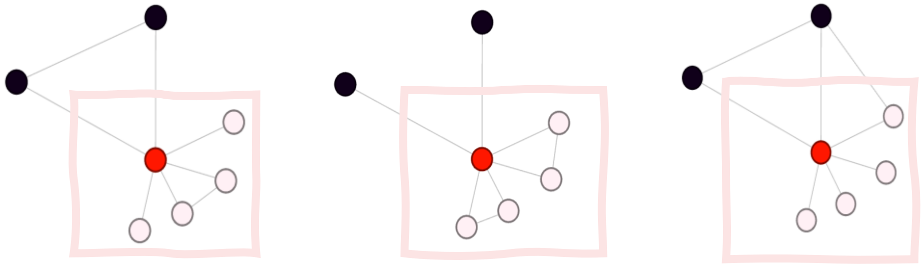


Local cohesion

Ego (i)   Ego's friends within hometown   Ego's friends outside hometown



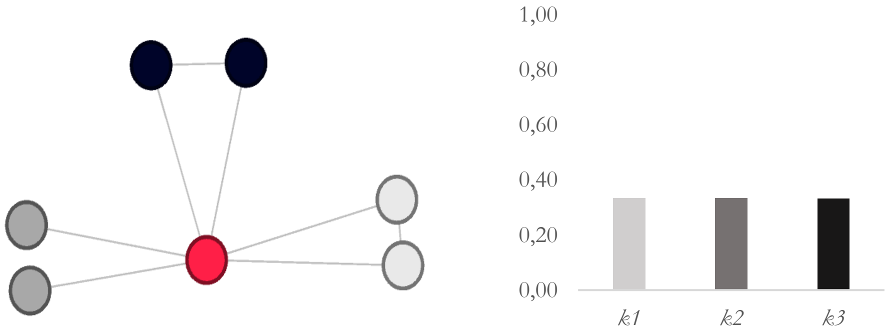
$$C_{ik} = \frac{2L_{ik}}{m_{ik}\,(m_{ik}-1)}$$

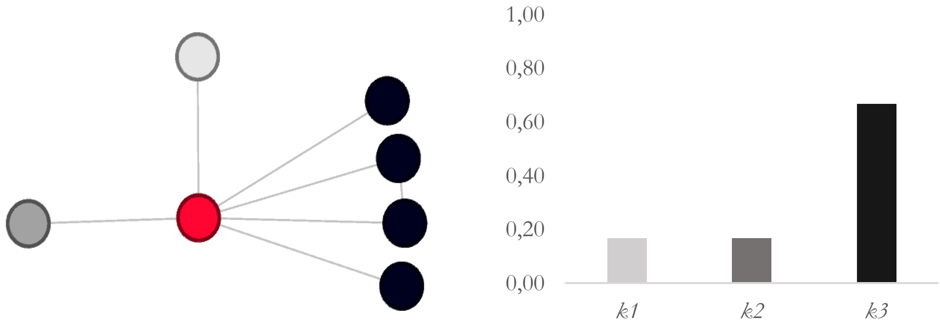


$$C_{ER} = \frac{2\langle L\rangle}{N(N-1)}$$

Spatial Diversity

Ego (i) in town k_0 · Ego's friend(s) in town k_1 · Ego's friend(s) in town k_2 · Ego's friend(s) in town k_3





High entropy (spatial diversity)

$$\frac{-\sum_{k=1}^{K} p_{ik} \times \log(p_{ik})}{\log(K)}$$

Low entropy (spatial concentration)

Estimation Strategy

normalized local cohesion (LC)

$$\bar{C_{ik}} = \frac{C_{ik}}{C_{ER}}$$

share of friends in 50km

friend using antidepressant

age

$$P\left(Y_i = 1\right) = \alpha + \beta_1 M_i + \beta_2 A_i + \beta_3 ln\left(d_i\right) + \beta_4 \bar{C_{ik}} + \beta_5 H_i^{'} + \beta_6 F_i^{50km} + \gamma_1 Y_{j \in G_i} + \beta \mathbf{X}_k + \epsilon_i$$

antidepressant usage
binary (0,1)

sex
(ref. woman)

degree
‘friends’

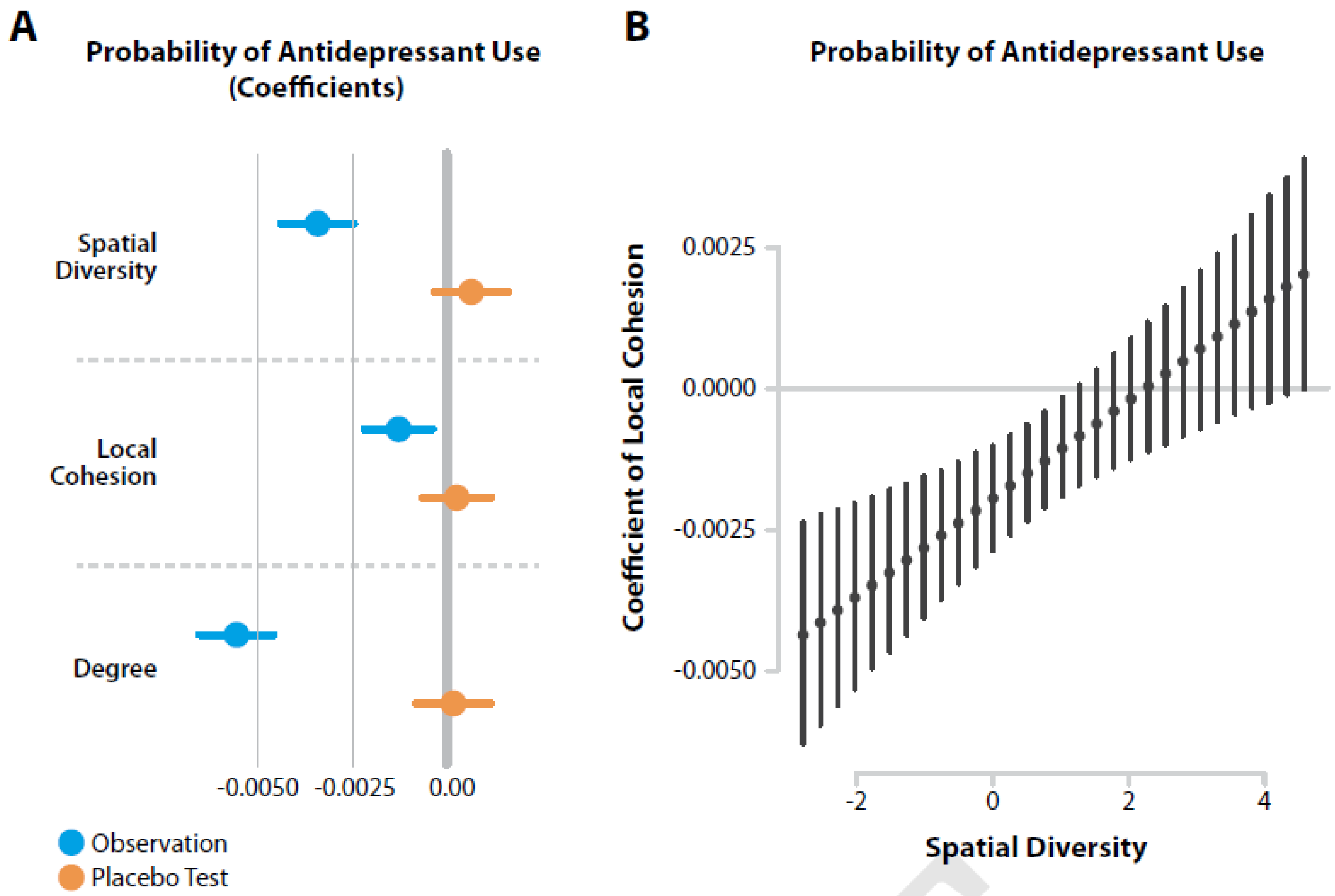
normalised Spatial Diversity (SD)

$$H_i^{'} = \frac{-\sum_{k=1}^{K} p_{ik} \times \log(p_{ik})}{\log(K)}$$

Town level control variables

- ln(Income per capita)
- Unemployment %
- Km to nearest border
- County FE

Probability of antidepressant use



Robustness

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Baseline	Strict Definition (ICD-10)	d$\geq$ 10	Friend	Psychiatry	Borders
SD_i	-0.0034***	-0.0034**	-0.0035***	-0.0033***	-0.0034***	-0.0034***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LC_i	-0.0012***	-0.0011**	-0.0016***	-0.0010**	-0.0012***	-0.0013***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\ln(d_i)$	-0.0055***	-0.0049***	-0.0056***	-0.0070***	-0.0055***	-0.0056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F_i^{50}	0.0006	0.0002	-0.0007	-0.0007	-0.0006	-0.0007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.0201***	-0.0208***	-0.0200***	-0.0199***	-0.0201***	-0.0201***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.0261***	0.0245***	0.0260***	0.0255***	0.0261***	0.0261***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment$_h$	0.0017***	0.0019**	0.0017**	0.0017**	0.0017**	0.0016**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income$_h$	-0.0014**	-0.0009	-0.0013**	-0.0011*	-0.0013**	-0.0016**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Friend takes Antidep.				0.0064***		
				(0.000)		
Distance to Psych					0.0000	
					(0.000)	
Km to any border						-0.0000**
						(0.000)
Constant	0.0517***	0.0488***	0.0519***	0.0476***	0.0515***	-0.0529***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.022	0.021	0.022	0.022	0.022	0.022
N	265719	265719	263894	265719	265719	265719

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Dynamics: days of therapy, 2011-2015

$$Z_{i,t} = \alpha + \beta_1 Z_{i,2011} + \beta_2 \hat{A}_h + \beta_3 LC_i + \beta_4 SD_i + \beta_5 ln\left(d_i\right) + \beta_6 F_i^r + \beta \mathbf{X}_i + \beta \mathbf{S}_h + \mathbf{D}_c + \epsilon_{i,t},$$

$\hat{A}_h$ is the predicted probability that the individual living in town *h* takes antidepressant.

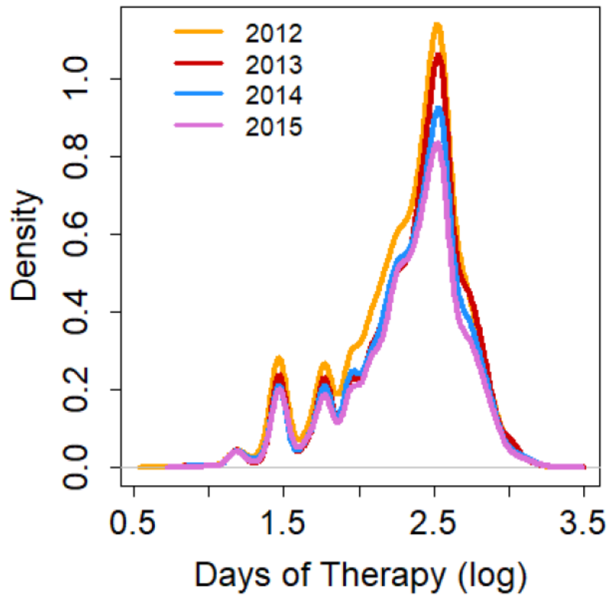


Table S8. Antidepressant use, distance to psychiatric centers and usage rate in the regio

	Dependent variable: Probability of Antidepressant Use		
	(1)	(2)	(3)
Distance to psychiatric centers (km)	0.0005		0.0002
	(0.001)		(0.001)
Antidepressant usage rate in the region (log)		0.892***	0.891***
		(0.054)	(0.054)
Constant	−3.272***	−0.417**	−0.426**
	(0.022)	(0.173)	(0.175)
Observations	277,344	277,344	277,344

Note: Standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

Spatial Diversity and dynamics of antidpressant use

Table 1. Days of Therapy for patients who took antidepressants in 2011, Ordinary Last Squares regression. Not reported variables are town-level income and unemployment, and friends within 50km. Standard errors in parentheses. ***,**,* denote significance at the 1, 5, 10 percent level.

	(1)	(2)	(3)	(4)
	$Z_{i,2013}$	$Z_{i,2013}$	$Z_{i,2013}$	$Z_{i,2015}$
$Z_{i,2011}$	1.393***	1.393***	1.393***	1.221***
	(0.020)	(0.020)	(0.020)	(0.022)
Male$_i$	−0.247***	−0.248***	−0.248***	−0.305***
	(0.050)	(0.050)	(0.050)	(0.053)
Age$_i$	0.334***	0.333***	0.334***	0.312***
	(0.027)	(0.027)	(0.027)	(0.029)
SD_i	−0.071**	−0.068**	−0.122***	−0.138***
	(0.031)	(0.031)	(0.041)	(0.044)
LC_i	−0.023	−0.022	−0.026	−0.021
	(0.027)	(0.027)	(0.027)	(0.029)
$ln(d_i)$	−0.057*	−0.055*	−0.054*	−0.039
	(0.030)	(0.030)	(0.030)	(0.032)
$\hat{A_h}$		9.021*	9.315*	15.087***
		(5.165)	(5.165)	(5.505)
SD_i × Male$_i$			0.010	0.085
			(0.053)	(0.056)
SD_i × Age$_i$			0.072***	0.066**
			(0.028)	(0.030)
Constant	−4.064***	−4.409***	−4.409***	−3.816***
	(0.176)	(0.265)	(0.265)	(0.282)
Observations	9,769	9,769	9,769	9,769
R^2	0.355	0.355	0.355	0.277
Adjusted R^2	0.353	0.353	0.353	0.274

Discussion

- The unprecedented scale of the data signals a previously unknown correlation between **spatial diversity** of social connections and **mental health**.

- Engagement in diverse communities creates opportunity to develop connections of various functions, reduces isolation and consequently, helps to maintain mental balance.

- Cohesion and diversity in social networks are often thought to **complement** each other to maximize economic advantage. However, we find that this might be not the case for mental health outcomes. Bridging social capital across distant groups can **substitute** local social bonding in helping individual mental well-being.

Thank you!

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