Agent-based Modeling: Principles and Applications

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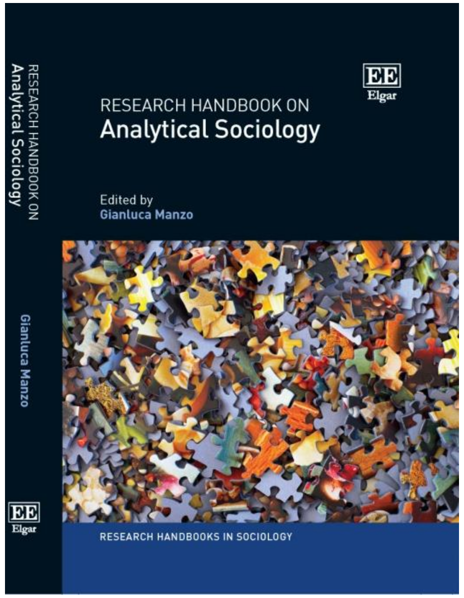
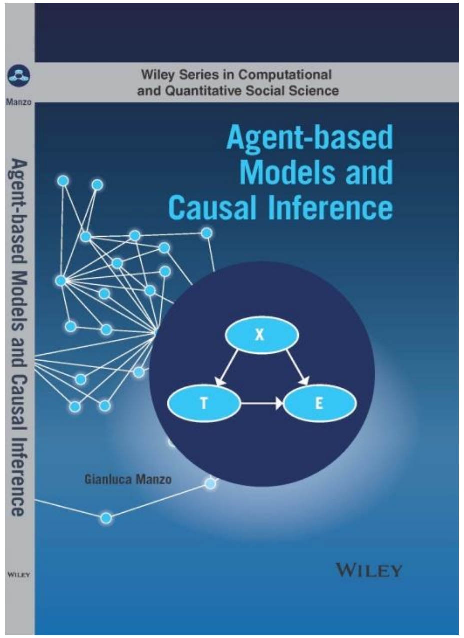
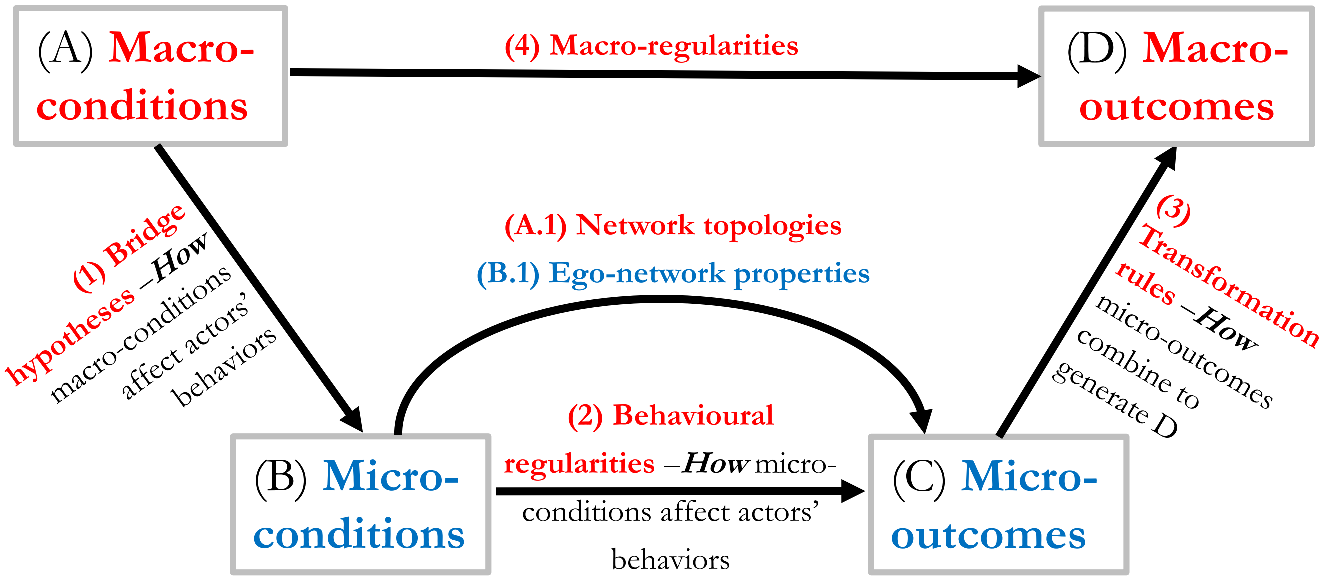
Paris-Saclay –June 16 2022

Overview





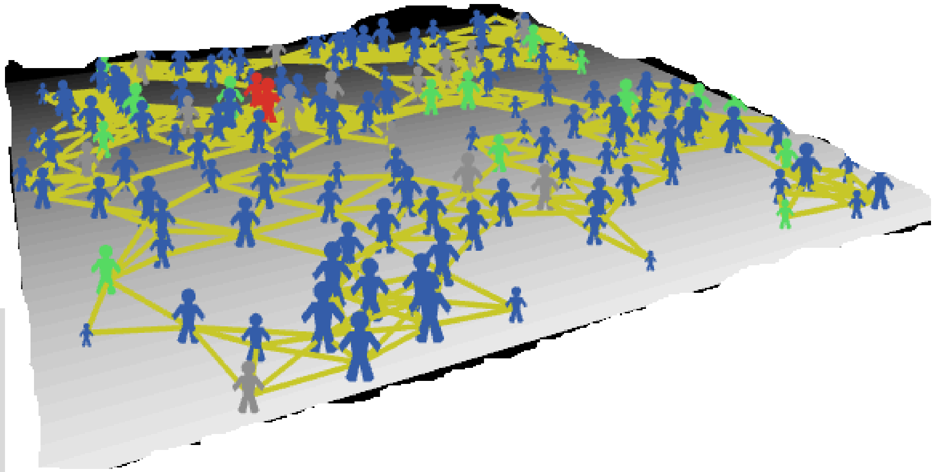
Theoretical Model-Building (Coleman diagram)



Adapted from Buskens, Corten & Raub (ch. 9: 156), In Gërxhani/de Graaf/Raub (eds.) *Handbook of Sociological Science* (EEP, 2022)

Formal Model-Building (Agent-Based Modeling)

1. Artificial agents
2. Heterogeneity
3. Micro-behaviours
4. Macro-structures
5. Spatial structures
6. Network structures
7. Loops



→ **Goals**
1. **Theoretical exploration**
2. **Virtual replica of real societies**

Macro-regularities	**Input** (calibration)	**Output** (validation)
1. Distributions of happiness (Manzo 2011)	—	Stilized facts (Tocqueville paradox)
2. Educational Inequalities between socio-economics groups (Manzo 2013)	Agent population and group sizes	Cross-sectional aggregate French data
3. Reputational hierarchies (Manzo & Baldassarri 2015)	—	Stilized facts (Winner-takes-it-all)
4. Diffusion of innovations across ethnic groups (Manzo et al. 2018)	Agent- & network-properties	Diffusion curves in India & Kenya
5. Virus propagation (Manzo & van der Rijt 2021)	Agent-, virus-, and network-properties	Stilized facts (Sigmoidal Infection Trajectories)

→ **Research Handbook on Analytical Sociology** (2021)
Ch. 19 (V. Spaiser): Digital Data & Methods
Ch. 24 (A. Flache & de Matos Fernandes): Agent-based computational models

→ **Handbook of Sociological Science** (EEP, 2022) by Gërxhani/de Graaf/Raub
Ch. 5 (A. Flache, M.Mäs & M. Keijzer): Computational approached in rigorous sociology: agent-based computational modeling and computational social sciences

1. Inter-generational Educational Mobility –The macro-regularties

EDUCATIONAL CHOICES AND SOCIAL INTERACTIONS: A FORMAL MODEL AND A COMPUTATIONAL TEST

Gianluca Manzo

ABSTRACT

In their authoritative literature review, Breen and Jonsson (2005) cl that 'one of the most significant trends in the study of inequalitie educational attainment in the past decade has been the resurgence rational-choice models focusing on educational decision making'. starting point of the present contribution is that these models have lar ignored the explanatory relevance of social interactions. To remedy shortcoming, this paper introduces a micro-founded formal model of macro-level structure of educational inequality, which frames educatic choices as the result of both subjective ability/benefit evaluations peer-group pressures. As acknowledged by Durlauf (2002, 2006) Akerlof (1997), however, while the social psychology and ethnogra literature provides abundant empirical evidence of the explanai relevance of social interactions, statistical evidence on their causal ef is still flawed by identification and selection bias problems. To assess relative explanatory contribution of the micro-level and network-bc mechanisms hypothesised, the paper opts for agent-based computatic

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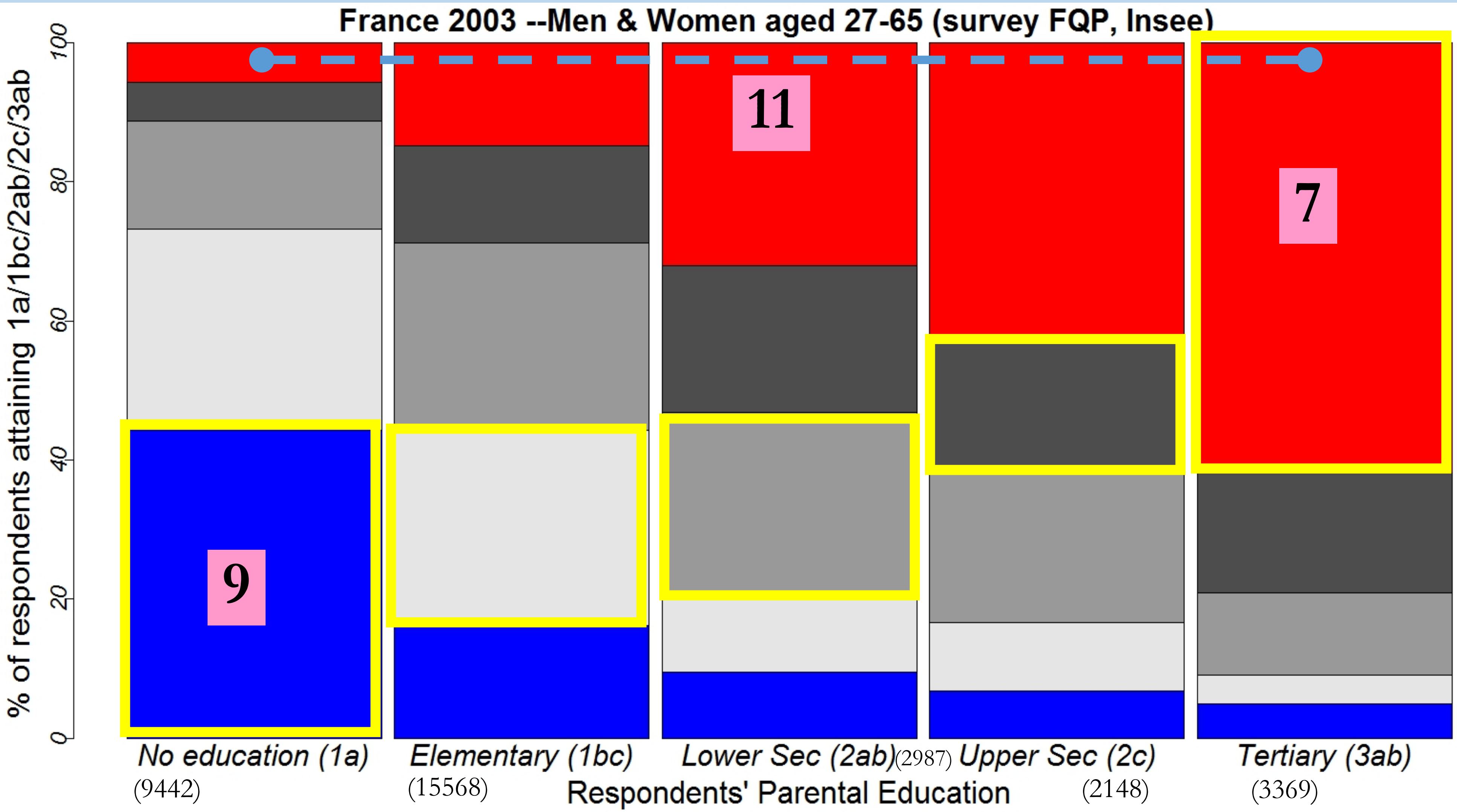
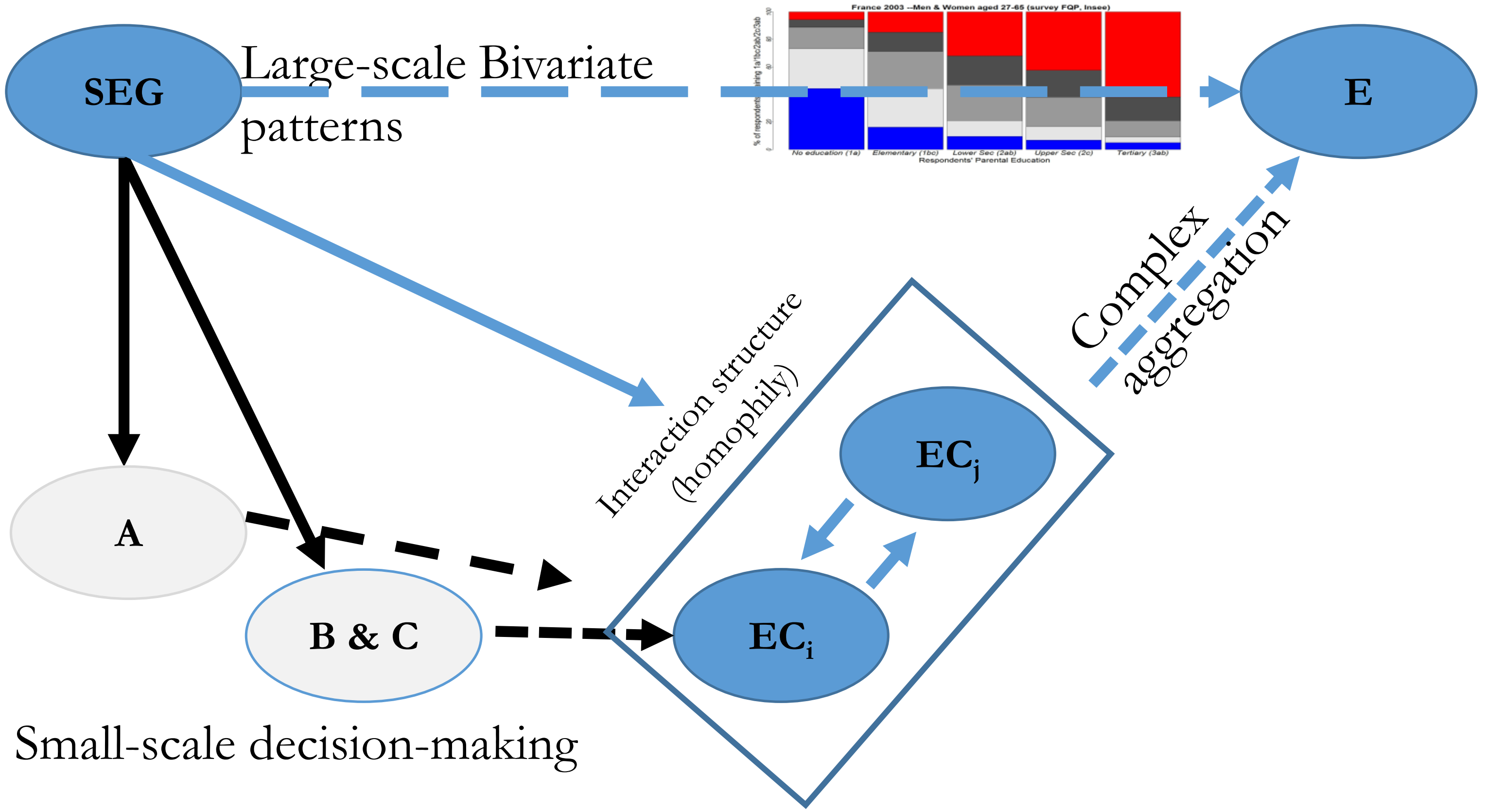


IP	UMP	**HLGR(3a)**	AGOR	LGGOR(1a)	**HGGOR(3a)**
35.26	49.07	**10.87**	1.68	8.98	**6.90**

1. Inter-generational Educational Mobility –The Theoretical Model



"Individual choices (…) are influenced by **prior choices by members of ego's social network**, and **intergroup inequality** (…) is **amplified** to the extent that ego's social network is **homophilous** with respect to socioeconomic status"

DiMaggio & Garip (2011:116)

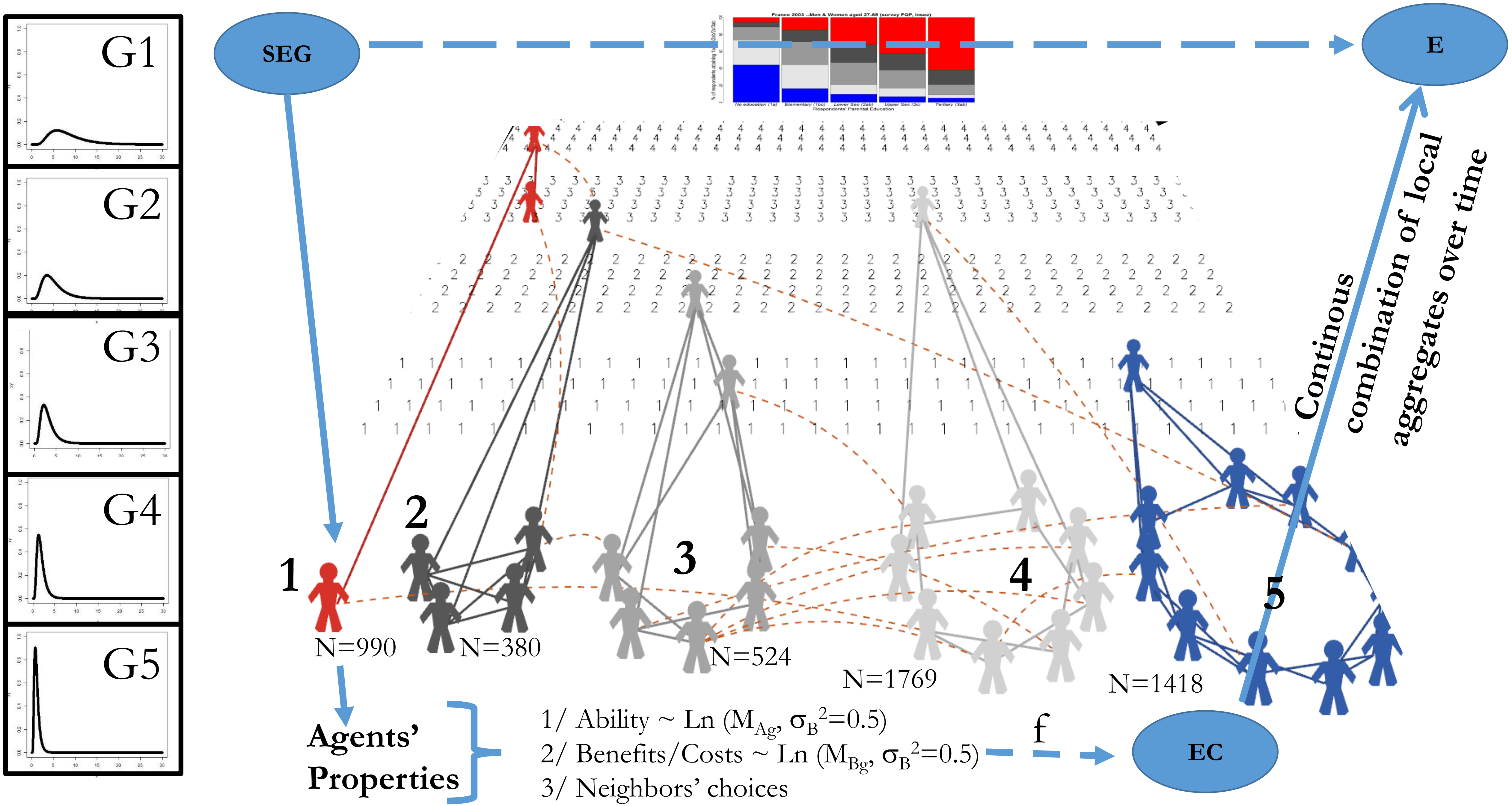
Educational traps: interactions triggers virtuous/vicious loops of mutually reinforcing behaviours (see Durlauf's concept of « poverty traps »)

Hypotheses come from, and combine:

A. (Sociology) Jackson, M. (ed.) (2013), *Determined to Succeed? Performance, Choice and Education,* Stanford, Stanford University Press.

B. (Economics) Akerlof, G. "Social Decisions and Social Distance", *Econometrica*, 1997, 65, 5, pp. 1006-1007

1. Inter-generational Educational Mobility –The Agent-based model



1. Inter-generational Educational Mobility – The Agents' Behaviour

Choice Probability:

$$\Pr_{ig}(L = 1 \mid L - 1 = 1) = \frac{\exp(\mathrm{P}_{\mathrm{igL}} - c)}{1 + \exp(\mathrm{P}_{\mathrm{igL}} - c)}$$

No utility maximisation

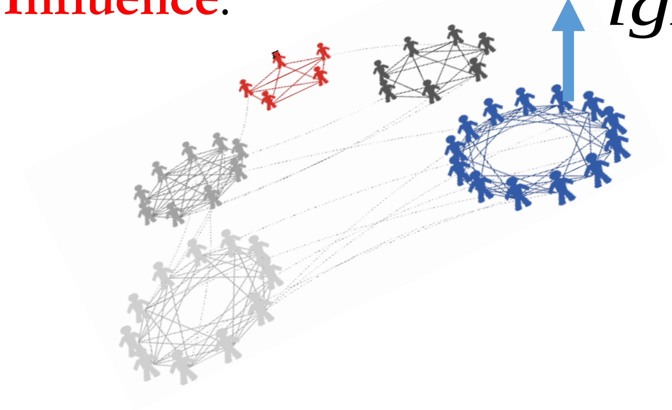
Preference Strength:

$$P_{igL} = A_{ig} + \phi(\mathrm{A}) * B_{ig} + SI_{igL}$$

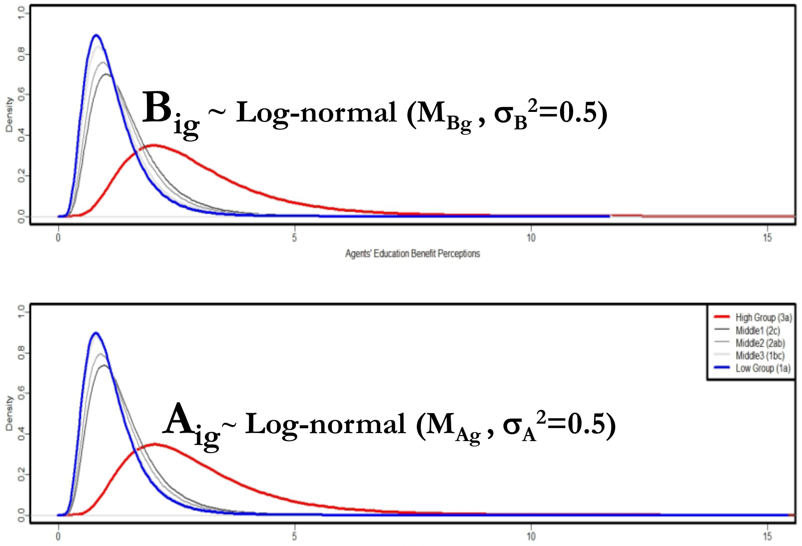
Heuristic-driven behaviour

Network-based **Influence**:

$$SI_{igL} = \frac{N_i(L=1)_{t-1}}{N_i}$$



Heterogeneity



1. Inter-generational Educational Mobility – The Artificial, small-world-like, network

Variant of Strogatz/Watts SW Net

Fixed network degree (**K**)

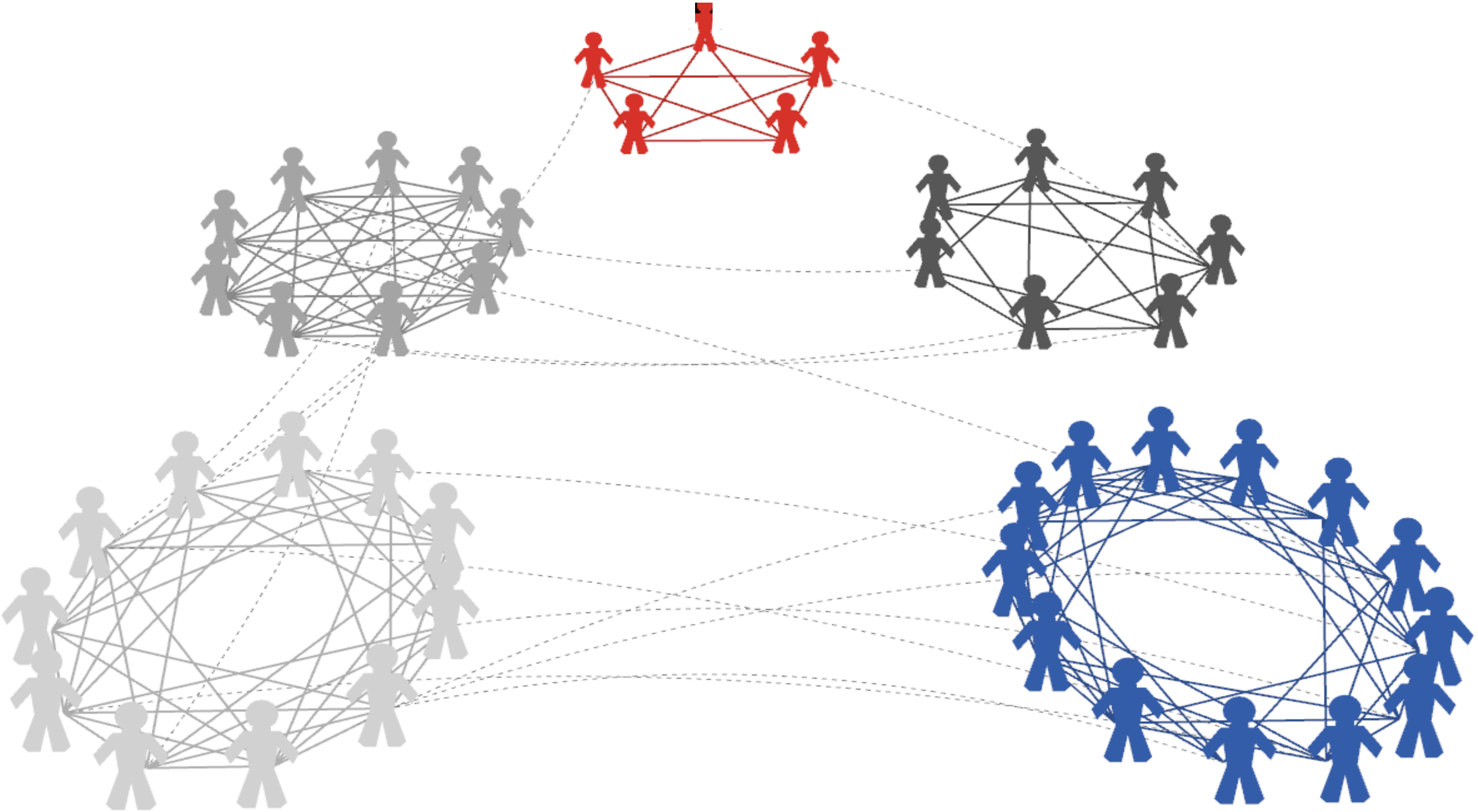
Out-group tie probability (**p**)

Out-group target $P_{T(d=1/2/3/4)}$

Homophily is represented as follows:

1. Most of the ties are **in-group ties** ("strong ties")

2. Most of the **out-group ties** connect agents belonging to groups that are **"socially" close**

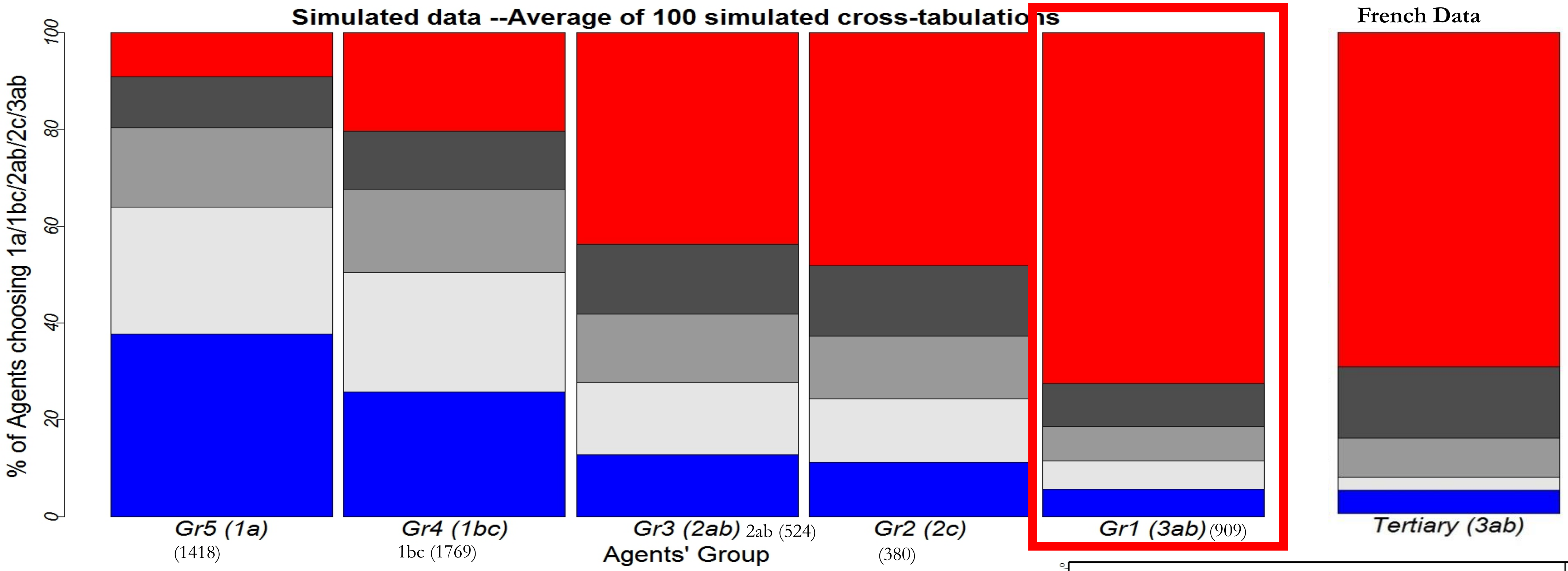


Example –

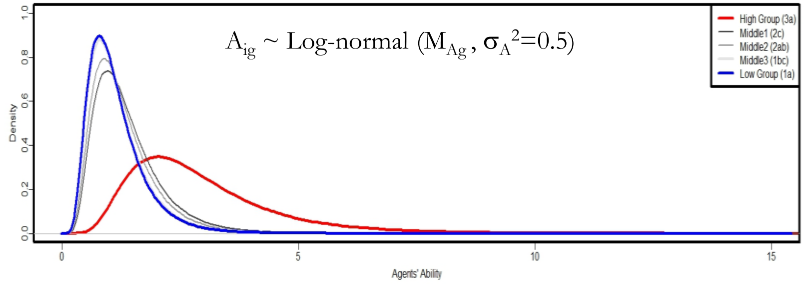
5000 Agents * **k=4**) / 2 → 10000 ties

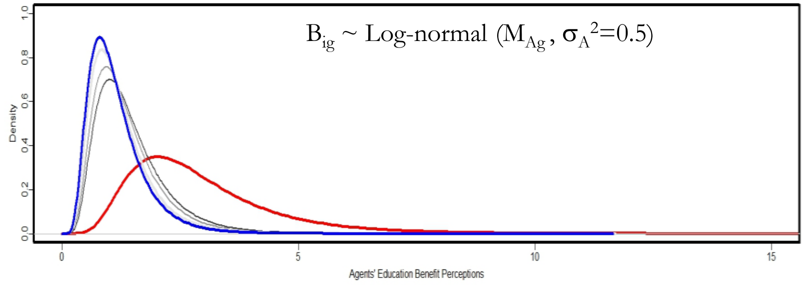
10000 * **p=0.1** 1000 → short-range inter-group ties

1. Inter-generational Educational Mobility – Result 3 (when the network is included)

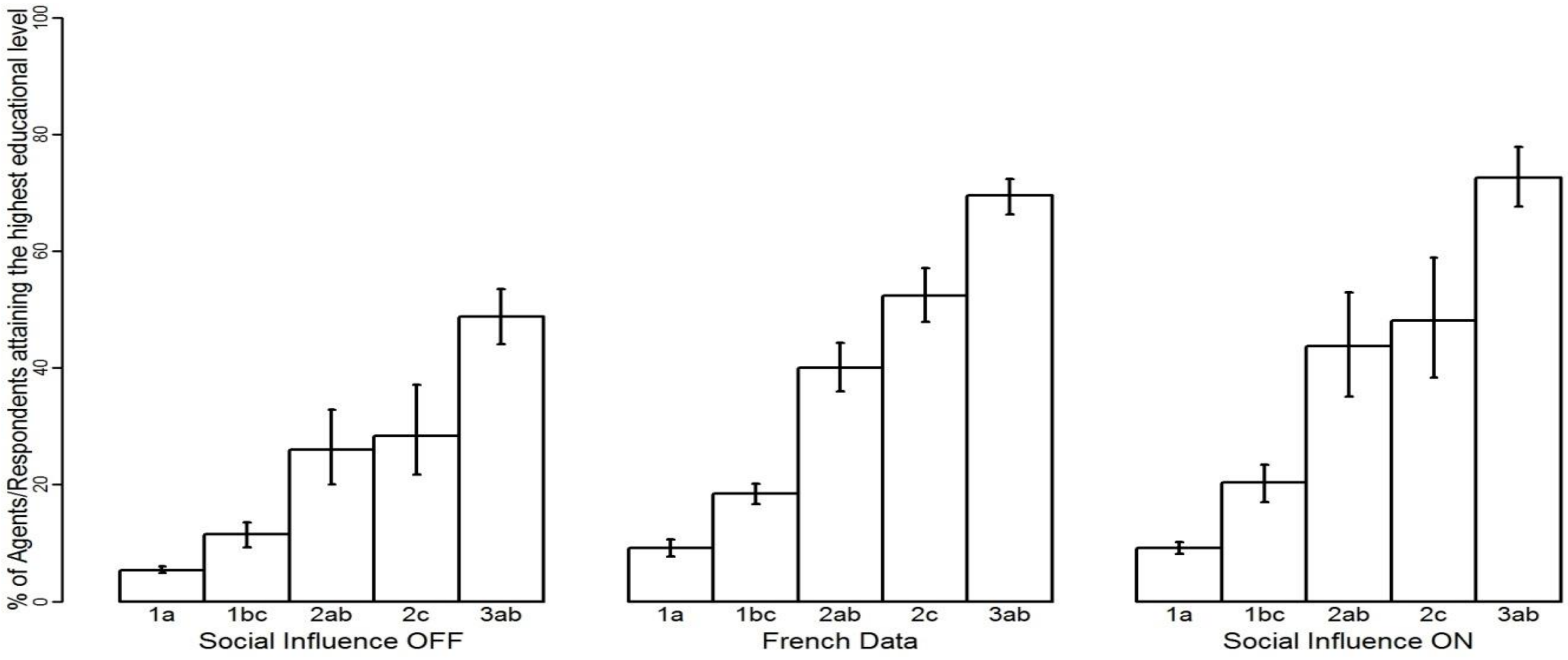


	Emp	"A_i"+"B_i"+Net_i
HLGR(3a)	6.38-8.86	6.86-9
HGGOR(3a)	5.38-8.13	5.44-10.09
DI		11.04-13.28





1. Inter-generational Educational Mobility –Artificial Counterfactual



Percentages of agents attaining the highest educational level within the five agent groups averaged over 100 replications of the model (bars give the values within which fall 95% of the model replications) when the social influence term (SI) is turned off/on.

Social differentiation of micro-level properties accounts for the largest part of the French empirical pattern but…

	"Straw Man"	Ability	+Benefits	+Net
DI	42-44.18	24.57-26.72	15.89- 18.17	11.04-13.28

≈17 **≈9** **≈5**

…we need **network-based "educational traps"** to account for the strong polarization of educational opportunity

2. The Diffusion of Innovations –The macro-regularties

Complex Contagions and the Diffusion of Innovations: Evidence from a Small-N Study

Gianluca Manzo, Simone Gabbriellini, Valentine Roux & Freda Nkirote M'Mbogori

Journal of Archaeological Method and Theory

ISSN 1072-5369
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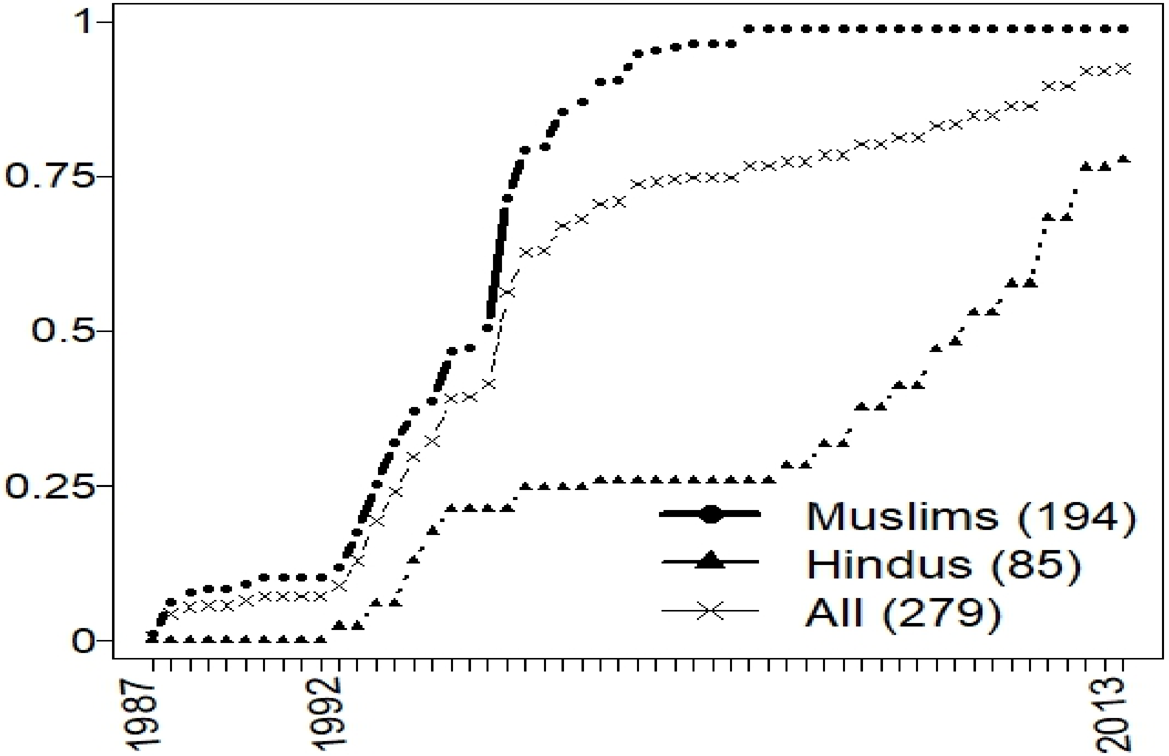
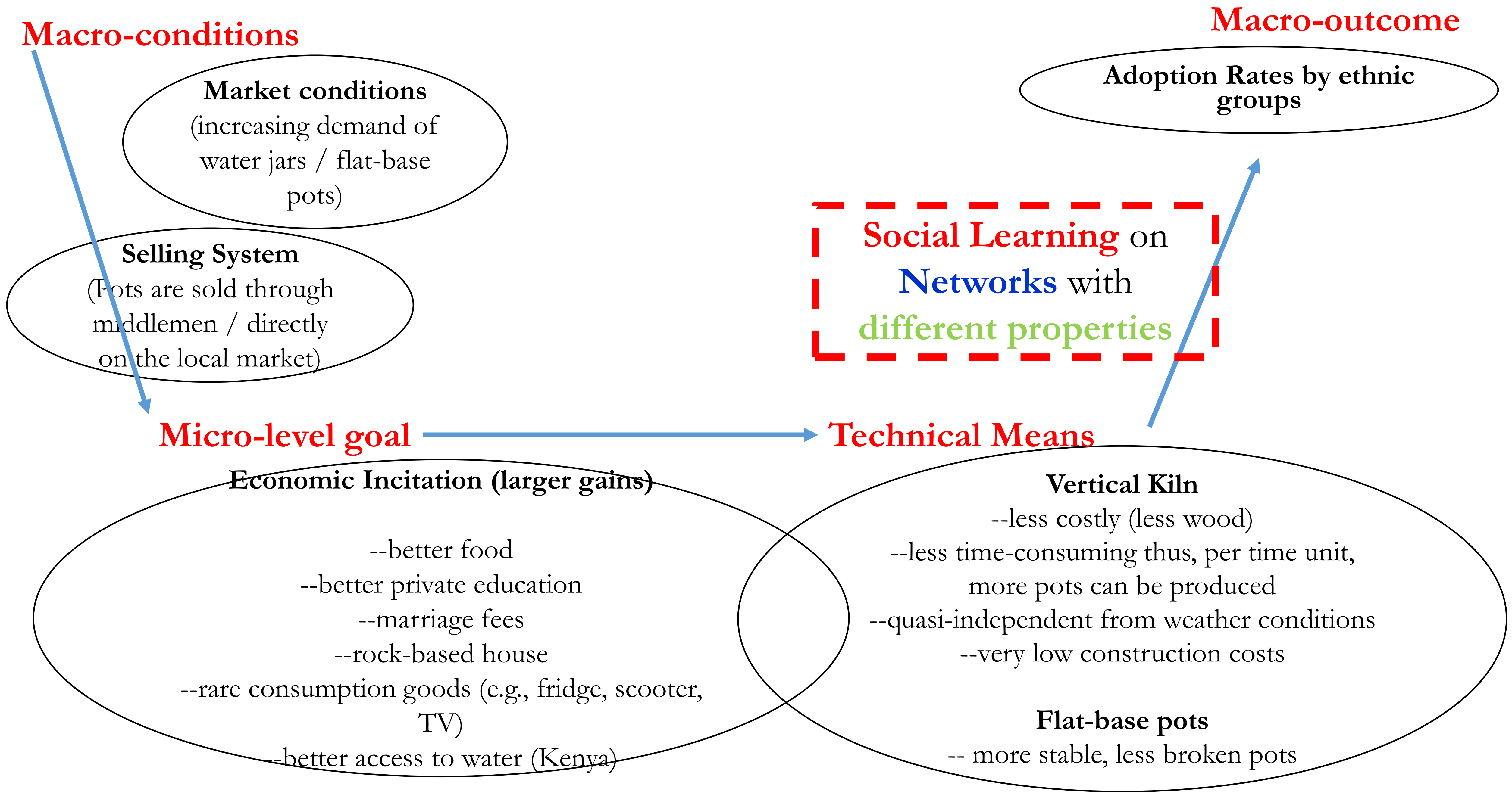
J Archaeol Method Theory (2018)
25:1109-1154
DOI 10.1007/s10816-018-9393-z



Six-month evolution of the cumulative proportions of adoptions of the **vertical kiln** in 19 villages in the Jodhpur region, India.

2. The Diffusion of Innovations –Theoretical framework



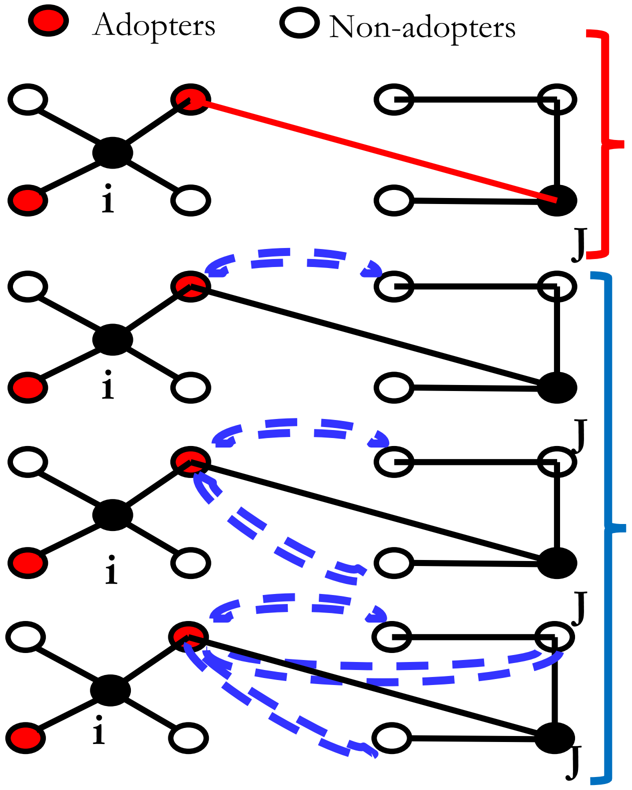
2. The Diffusion of Innovations –Network properties of interest

Bridge *a la* Granovetter

Bridge *with width = 1*

Bridge *with width = 2*

Bridge *with width = 3*



Bridge - **a line** in a network which provides **the *only* path between two points**

(Granotter, 1973: 1364 quoting Harary, Norman, and Cartwright 1965: 198)

→ ***Node-level measure:*** Betweeness centrality

Bridge –A bridge from i to j is the **set of ties** between, on the one hand, the **common neighbors of j and i**, and, on the other side, **neighbors of j but not of i**

Tie-level measure: Bridge width (The width of a bridge is the **size of the abovementioned set** [Centola and Macy, AJS, 2007, 713])

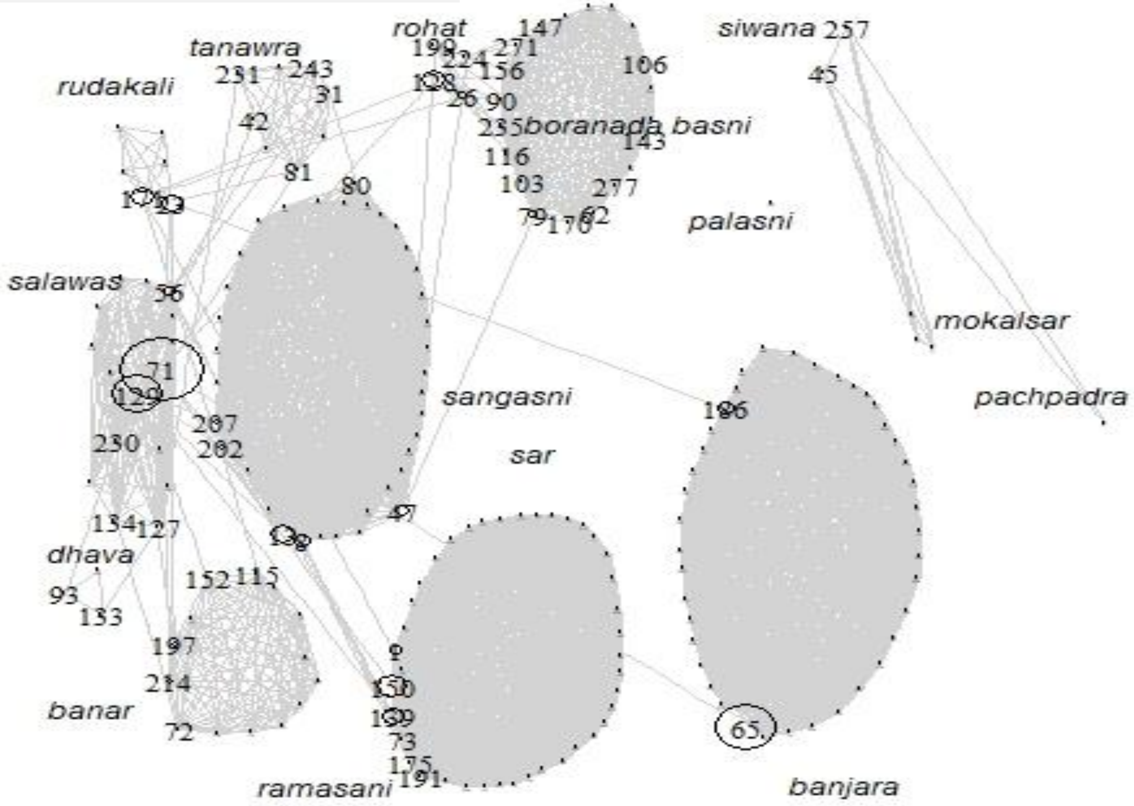
Existing studies –

- Analytical (e.g. Young, PNAS 2011)
- Simulation (e.g. Watts and Strogatz, Nature 1998; Centola and Macy, AJS 2007; Flache and Macy, JMS 2011; Centola, AJS 2015)
- On-line lab Experiment (Centola, Science 2010)

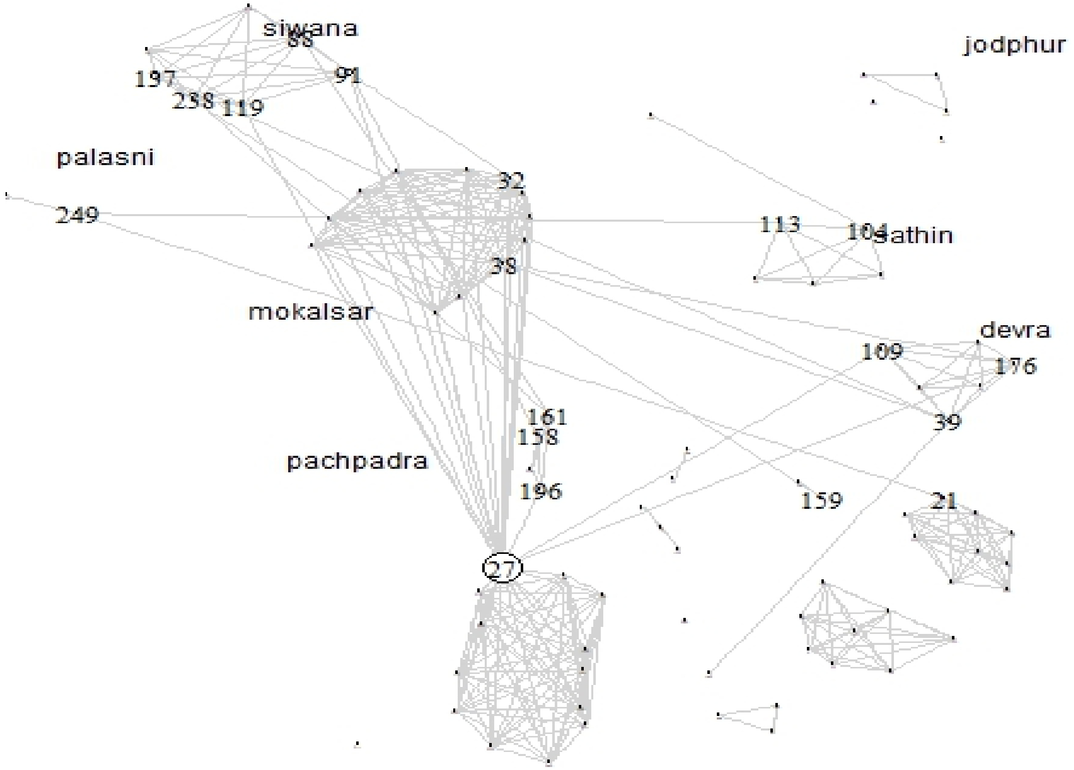
→ "(…) recent studies on the diffusion of behavior have shown that the **lack** of "**wide bridges**" in social networks can significantly **inhibit** the level of adoption in a population (…)" (Centola, Science, 2011, 1271)

2. The Diffusion of Innovations –Kinship Network

Muslims (n=194)
Density=0.14 AvDe=27.87



Hindus (n=85)
Density=0.08 AvDe=7.08



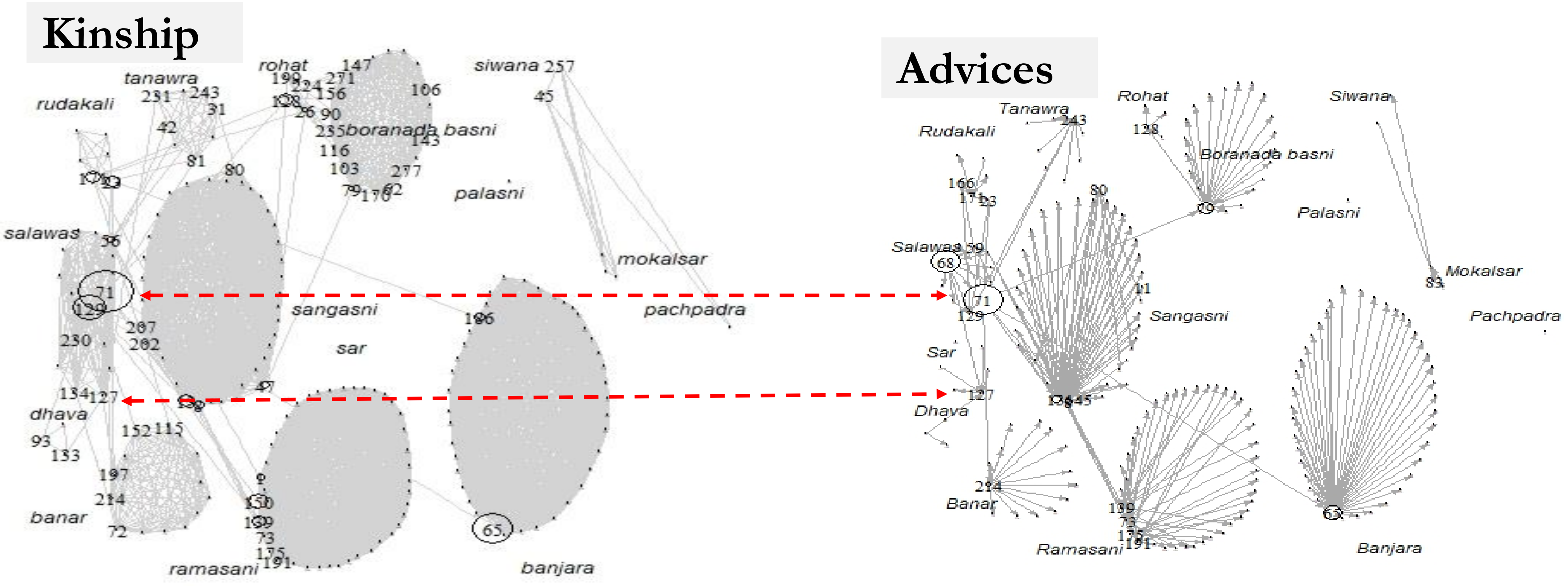
Strong Ties

– More **<u>kinship brokers</u>** among Muslims, who build extensive across-village ties
(27% [53 in absolute number] *versus* 22% [19 in absolute number]

– Longer **<u>kinship chains</u>** among Muslims
(99.5 vs 95.2 –96.4 vs 73 – 82.5 vs 41.2)

– Less (6% *vs* 11%) but larger **<u>kinship bridges</u>** among Muslims
(average width: 16.37 *vs* 8.30 // SD width 13.33 *vs* 4.58)

2. The Diffusion of Innovations –Kinship/Advice Net Ovelap –Muslim potters



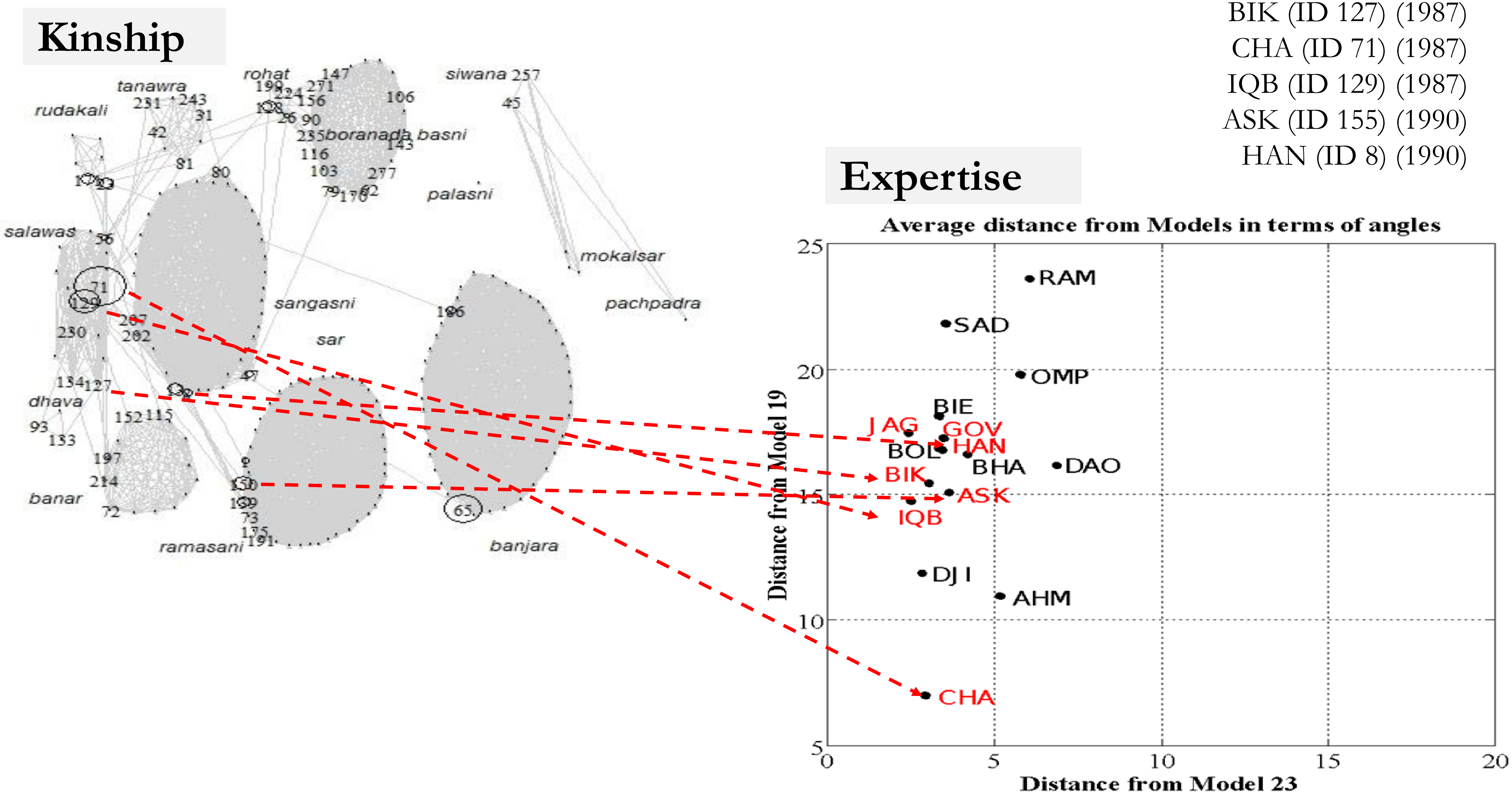
Overlap=0.96 // QAP=0.254 (p<.001)

Overlap(first cross-village diffusion links)=0.65 // QAP=0.246 (p<.001)

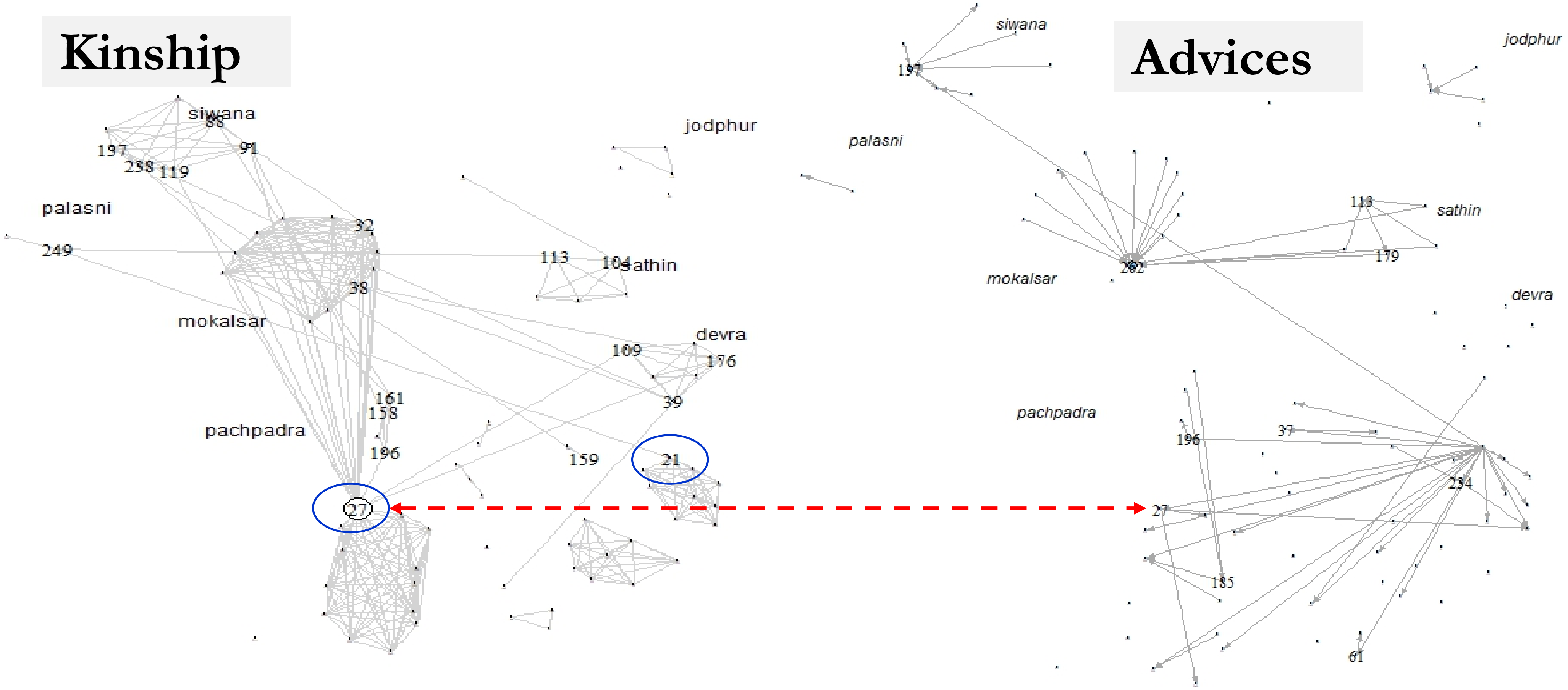
BC cor= 0.66 //BC cor (rank)=0.45

2. The Diffusion of Innovations –Central Potters and Expertise –Muslim potters

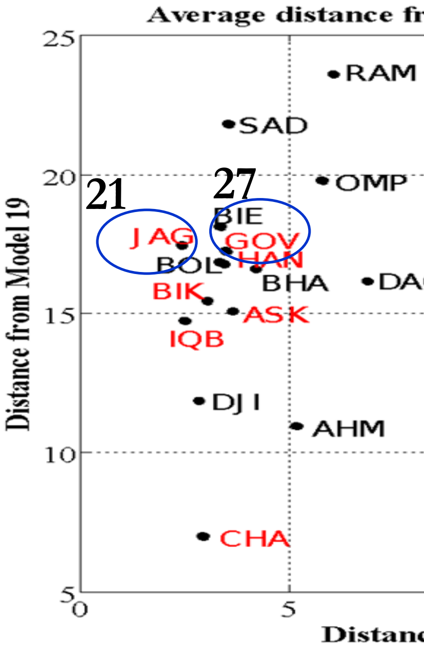
BIK (ID 127) (1987)
CHA (ID 71) (1987)
IQB (ID 129) (1987)
ASK (ID 155) (1990)
HAN (ID 8) (1990)



GOV (ID 27)
JAG (ID 21)
(First trial of the kiln in 1995)



Expertise

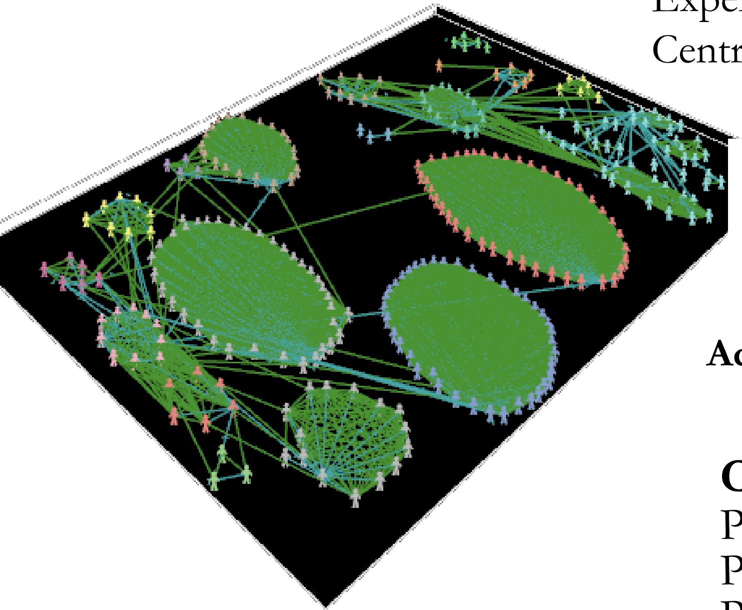


Overlap=0.60 // QAP=0.247 (p<.001)

Overlap(first cross-village diffusion links)=0.20 // QAP=0.082 (p<.01)

BC cor= 0.17 // BC cor (rank)=0.20

2. The Diffusion of Innovations –The Agent-Based Model



Empirically-calibrated Attributes

Village
Religion
Age
Expertise
Centrality on kinship net

Call (at each iteration)

Adopter (A)

↑

Call
Pr (age)
Pr (expertise)
Pr (centrality)
Random

→ **Frequency**

<u>**Simulated time:**</u> 1 iteration ~ 1 day → 180 iteration ~ 6 months
0.5 or 0.25 talk / iteration
1 talk / iteration → 180 interactions/6 months
2, 3 or 4 talks / iteration

Physical Distance

Average geographical distance among villages –63.40 Km (M); 108.94 (H)

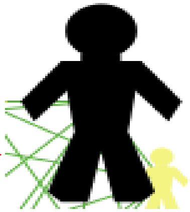
$$\Pr(PA) = \left(\frac{1}{|V_A - V_{PA}|}\right)$$

Or

$$\Pr(PA) = \left(\frac{1}{|SPL_{A,PA}|}\right)$$

Average shortest path length –
L (giant component): 3.28 (M) 2.30 (H)
L/L_0 : 0.39 (M) 0.53 (H)

Relational Distance



Potential Adopter (PA)

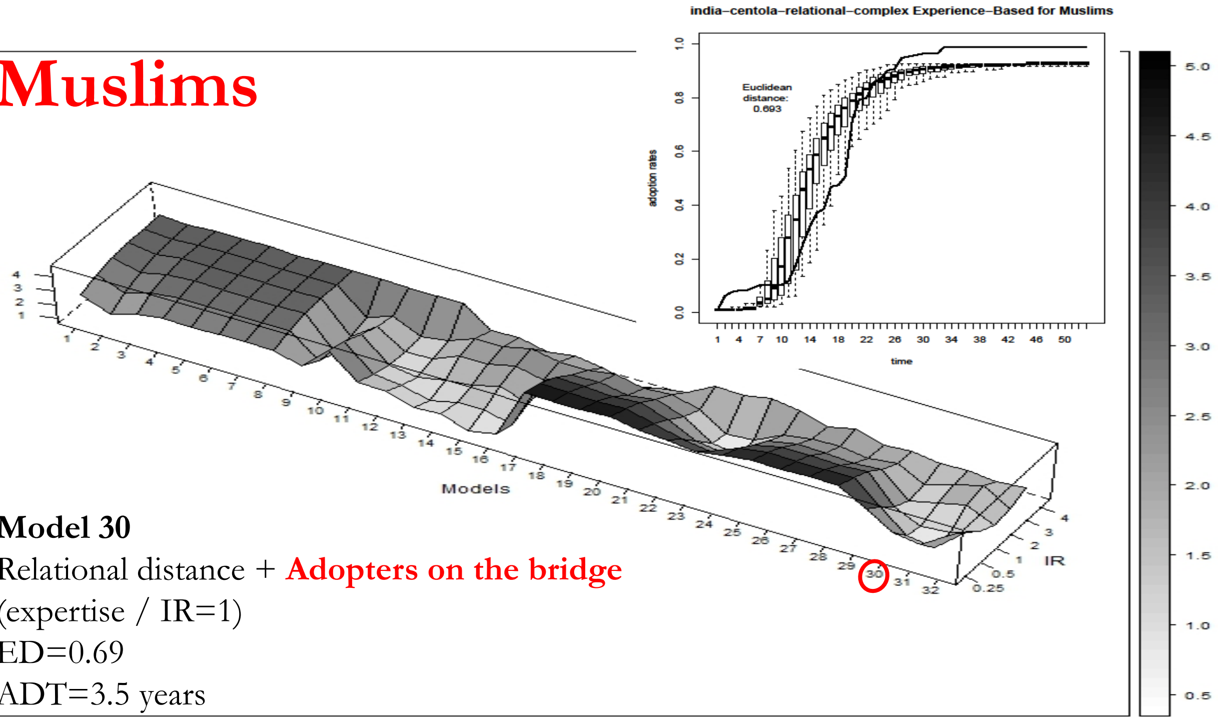
A [***Simple contagion***] One exposure suffices (Hägerstrand 1967)

B [***Complex contagion 1***] Increasing function of proportion of activated direct neighbors, each of them weighted by their (kinship) centrality (Garip/DiMaggio 2012, 107)

C [***Complex contagion 2***] Increasing function of A-PA bridge width

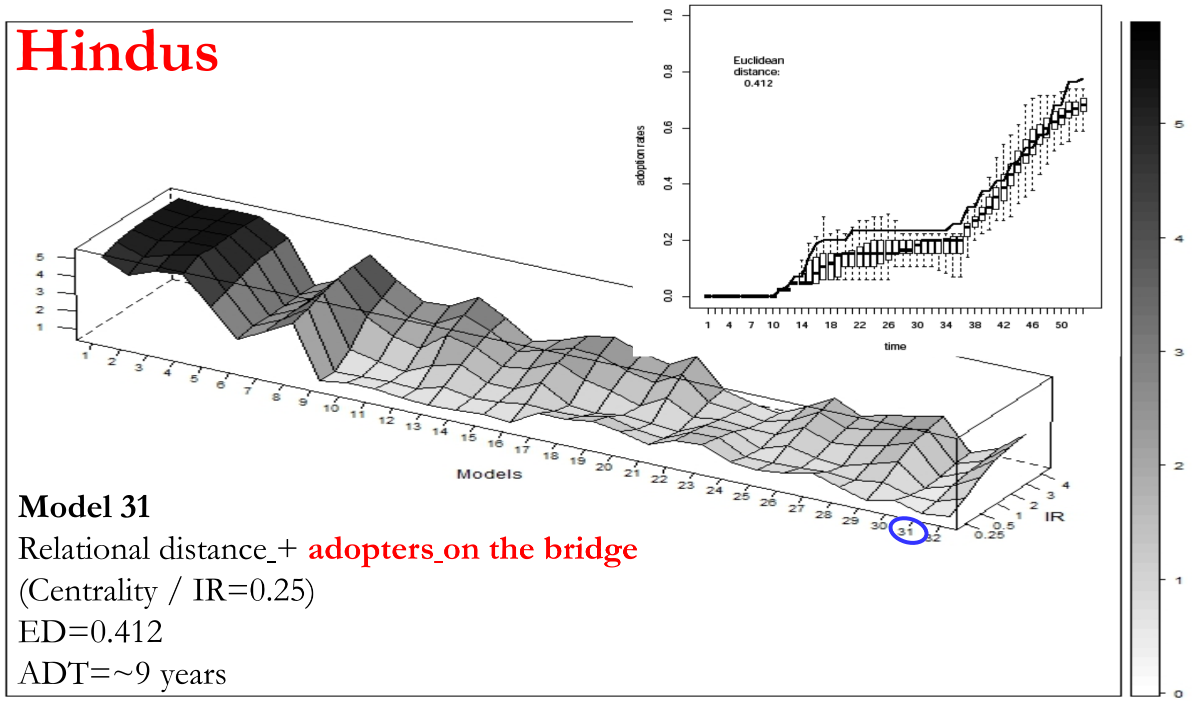
D [***Complex contagion 3***] Increasing function of proportion of activated nodes involved by the A-PA bridge width

Muslims



Model 30
Relational distance + **Adopters on the bridge**
(expertise / IR=1)
ED=0.69
ADT=3.5 years

Hindus



Model 31
Relational distance + **adopters on the bridge**
(Centrality / IR=0.25)
ED=0.412
ADT=~9 years

3. Virus Propagation –The macroscopic stilized fact

Halting SARS-CoV-2 by Targeting High-Contact Individuals

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[2] European University Institute, Via dei Roccettini 9, San Domenico di Fiesole (Florence) 50014, Italy
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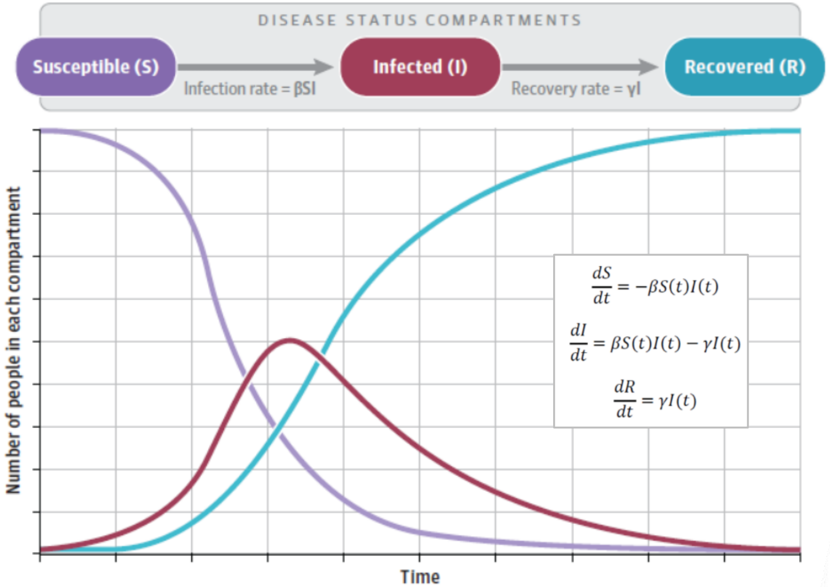
Received: 05-06-2020 Accepted: 10-09-2020 Published: 31-10-2020

Abstract: Network scientists have proposed that infectious diseases involving person-to-person transmission could be effectively halted by interventions targeting a minority of highly connected individuals. Could this strategy be effective in combating a virus partly transmitted in close-range contact, as many believe SARS-CoV-2 to be? Effectiveness critically depends on high between-person variability in the number of close-range contacts. We analyzed population survey data showing that the distribution of close-range contacts across individuals is indeed characterized by a small proportion of individuals reporting very high frequency contacts. Strikingly, we found that the average duration of contact is mostly invariant in the number of contacts, reinforcing the criticality of hubs. We simulated a population embedded in a network with empirically observed contact frequencies. Simulations showed that targeting hubs robustly improves containment.

Keywords: Agent-Based Computational Models, Complex Social Networks, Virus Diffusion, Immunization Strategies, Epidemiological Models

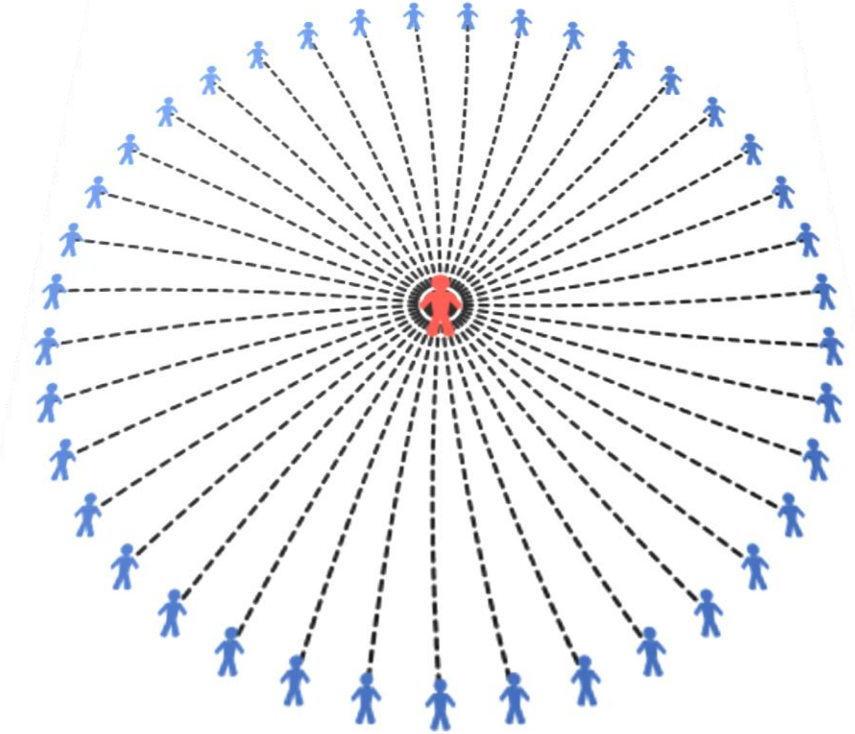
How would this **curve change** if the underlying **network of contacts** had a **broad degree distribution**, and we could **intervene** on it by exploiting the **friendship paradox**?



Tollens & Luong 2020 (*JAMA Guide to Statistics and Methods*)

Star Net (1 actor → 39 contacts & 39 actors → 1 contacts

Aactors' average degree → 1.95
Actors' contacts' average degree → 38.05



Friendship Paradox –"the mean number of friends of friends is always greater than the mean number of friends of individuals" (Feld 1991: 1465)

***Ego*'s contacts on average ≈ <k>**

Contacts of *ego*'s contacts on average ≈ <k> + $\frac{Var(k)}{\langle k \rangle}$

Friendship Paradox & Degree Heterogeneity-"The mean among friends is much greater than the mean among individuals if there is much variation in the population." (Feld 1991: 1470)

3. Virus Propagation –Close-range contact distributions (France 2012)

(Comes-F survey, 2012) Direct contact = talk to someone, in person, at a distance lower than 2 meters, with or without physical contact

Jour 1 : |_|_| |_|_|

Carnet des contacts

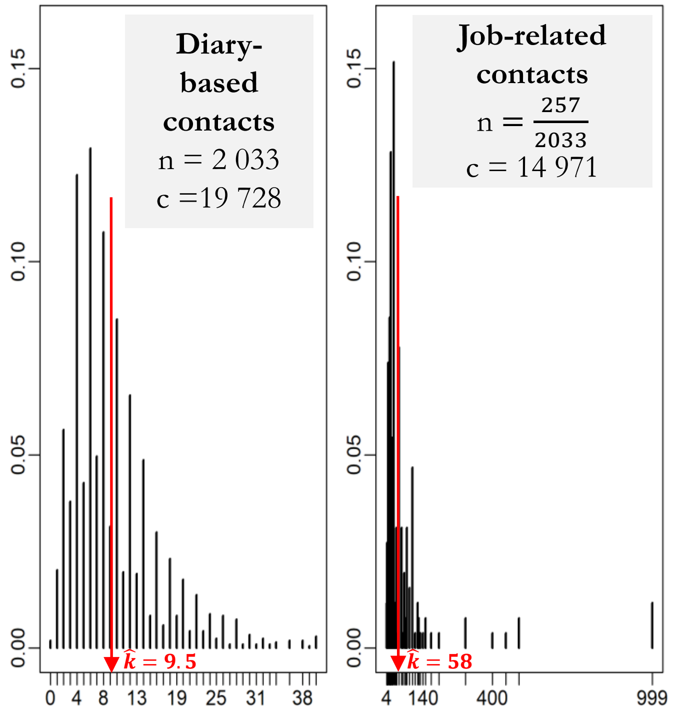
	Âge (ou fourchette) de la personne rencontrée	Sexe		Lieu(x) de contacts noter tous les lieux où la personne a été en contact avec vous							À quelle fréquence rencontrez-vous cette personne ?					A-t-elle touché votre peau ?		Durée totale des contacts avec une même personne				
		Féminin	Masculin	Domicile, véhicule ou autres lieux privatifs	École, collège, lycée ou tout autre lieu d'études	Lieux de travail clos (bureau, atelier)	Chez des proches en lieux clos	Autre lieux clos (restaurant, commerce, …)	Transport collectif	Lieux ouverts (parc, rue) y compris pour le travail (chantier, voie publique…)	(presque) chaque jour	Quelques fois par semaine	Quelques fois par mois	Quelques fois par an ou moins souvent	1ère fois	Oui	Non	Moins de 5 min	5 -15 min	15 min - 1 h	1-4 h	4H ou plus
Utilisez une ligne par personne rencontrée et avec laquelle vous avez eu au moins un 'contact'																						
01	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5
02	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5
03	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5
04	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5
05	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5
06	_ / _	☐1	☐2	☐1	☐2	☐3	☐4	☐5	☐6	☐7	☐1	☐2	☐3	☐4	☐5	☐1	☐2	☐1	☐2	☐3	☐4	☐5

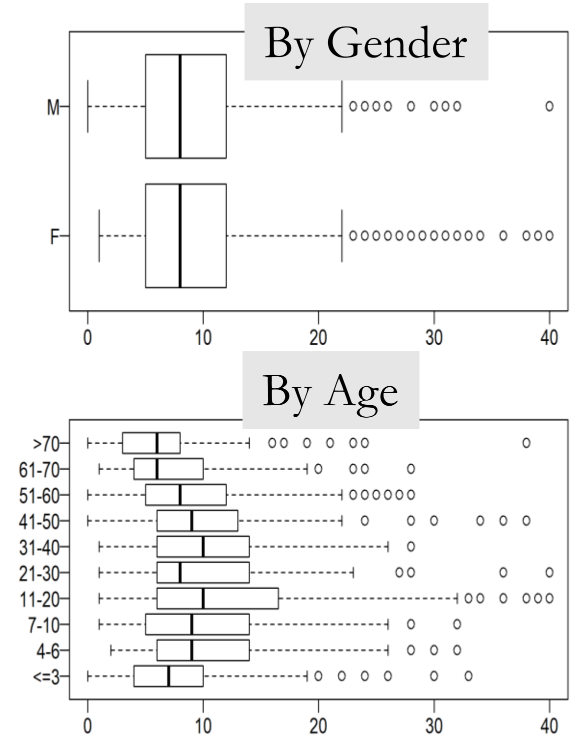
8. Exercez-vous une profession qui entraîne beaucoup de contacts *(clients pour les commerciaux, les coiffeurs…, patients pour les personnels soignants, élèves ou étudiants pour les professeurs…)* ?

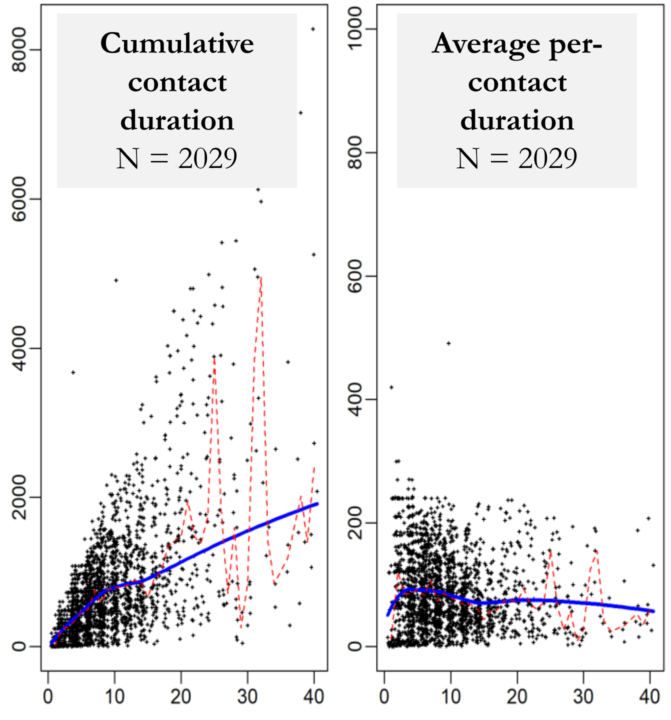
- Oui ……………☐1 ➔ *Passez à* **8a** *et* **suivantes**
- Non …………☐2 ➔ *Allez directement en page 3*

8a. À combien estimez-vous en moyenne le nombre de ces personnes (clients, patients, élèves,...) que vous rencontrez par jour :

|______| personnes







3. Virus Propagation –Network Algorithm and Statistics

Network generation algorithm

Configuration model (without duplicate links nor self-links) combined with a **triadic closure generative mechanism** (see step 5.1 below)

1/ Each agent is given a degree precisely equal to the number of close contacts per day that was observed in the French survey;
2/ Source agents are ordered in descending order of the to-be-generated degree;
3/ For each of them, we randomly pick available destination agents;
4/ Each time a connection is made, the degree of the two newly connected agents is increased by one;
5/ as soon as an agent reached the to-be-generated degree:
5.1/ **we went through all its neighbors and connected each of the agent's neighbor pairs with probability *p***
5.2/ the source agent was excluded from the search algorithm.

Network based on **diary-recorded contacts**

COMES 2021

	Average degree	Median degree	Stdev degree	Clustering coef	Deg-clust corr	Av path length	Diameter
	Degree-Calibrated (DC) networks (mean/sd 100 net realizations)						
p=0	9.72 (0.00)	8 (0.00)	6.56 (0.00)	0.01 (0.00)	-0.06 (0.01)	3.47 (0.00)	6 (0.00)
p=0.5	9.72 (0.00)	8 (0.00)	6.56 (0.00)	0.43 (0.00)	-0.62 (0.01)	4.38 (0.03)	7.45 (0.50)
p=1	9.72 (0.00)	8 (0.00)	6.56 (0.00)	0.57 (0.01)	-0.56 (0.01)	5.52 (0.09)	10.10
	Erdős-Rényi (ER) network (mean/sd 100 net realizations)						
	9.65 (0.50)	9.72 (0.10)	3.11 (0.10)	0.00 (0.00)	0.00 (0.03)	3.60 (0.01)	6.06 (0.24)

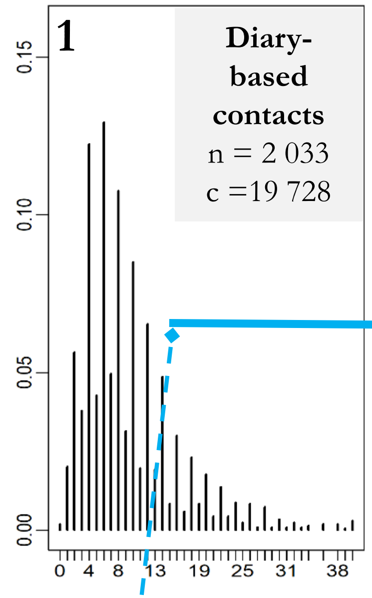
British data

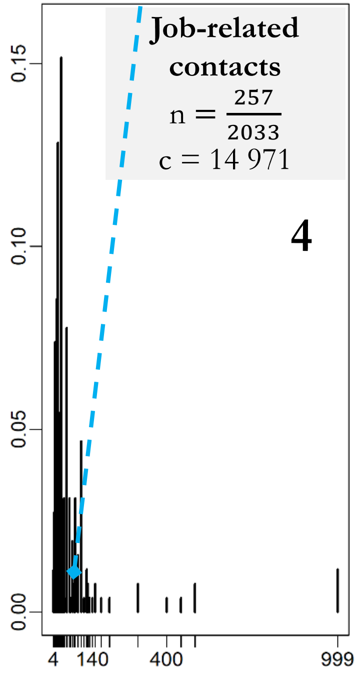
Qualitative relationship between CC and APL & Hubs and APL

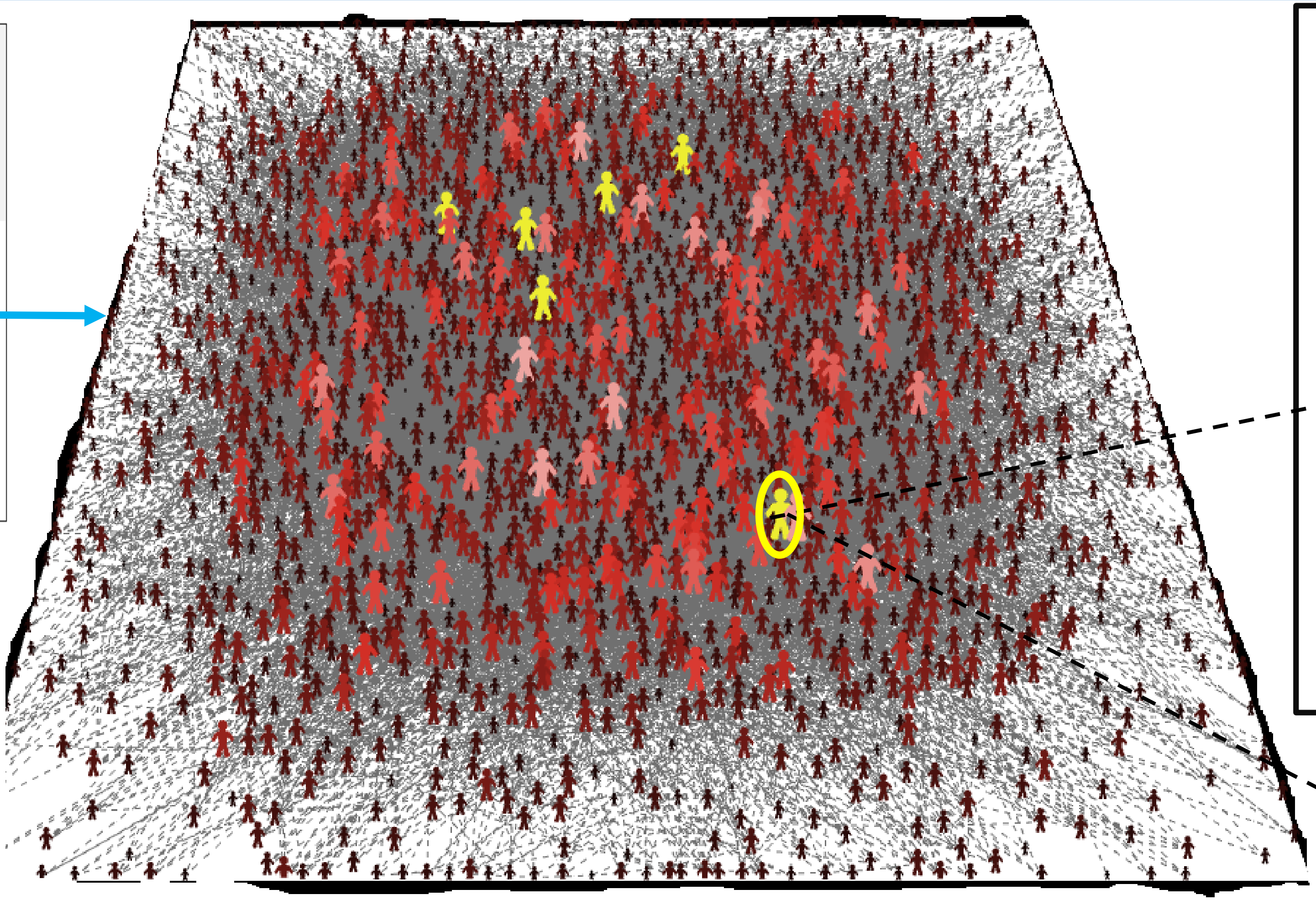
Network based on **diary-recorded contacts + job-related extra contacts (up to 134)**

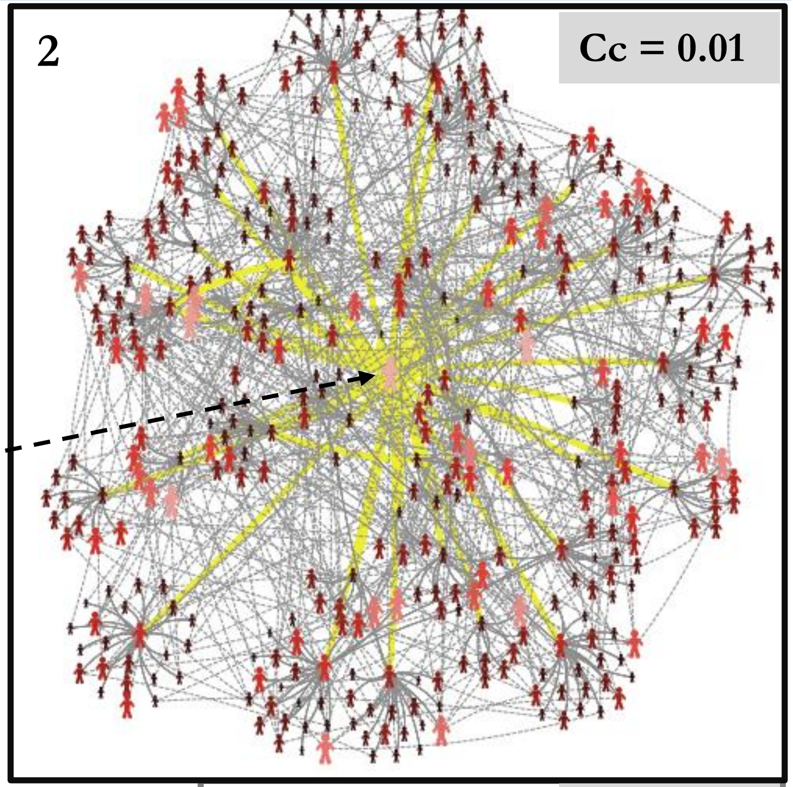
	Average degree	Median degree	Stdev degree	Clustering coef	Deg-clust corr	Av path length	Diameter
	Empirical-degree (ED) networks (mean/sd 100 net realizations)						
p=0	14.87 (0.00)	9.00 (0.00)	19.58 (0.00)	0.04 (0.00)	-0.15 (0.01)	2.83 (0.00)	4.8 (0.40)
p=0.5	14.72 (0.04)	9.00 (0.00)	19.19 (0.04)	0.42 (0.01)	-0.50 (0.00)	3.29 (0.02)	5.01 (0.01)
p=1	14.77 (0.04)	9.00 (0.00)	19.38 (0.12)	0.50 (0.01)	-0.44 (0.01)	3.60 (0.08)	6 (0.62)
	Erdős-Rényi (ER) network (mean/sd 100 net realizations)						
ER	14.86 (0.14)	14.89 (0.31)	3.86 (0.14)	0.01 (0.01)	-0.00 (0.03)	3.09 (0.01)	5 (0.00)

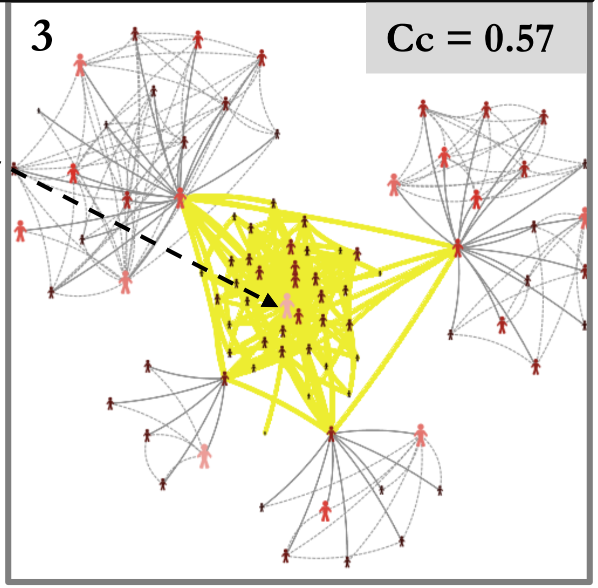
3. Virus Propagation –The Agent-based Models











5

S_i, t=0 → E_i, t=1→4 → I_i, t=5→9 $\xrightarrow{N\sim<0993>\ [0.090,\ 0.096]}$ (*Science* 2020) R_i, t ~ $P<15>[7,42]$ (*WHO* 2020)

Infect each direct contact

N[0.03, 0.02] → R_0= 1.52

π ~ N[0.05, 0.02] → R_0= 2.53

N[0.07, 0.02] → R_0= 3.55

Science, November 2020 /
India –Tamil Nadu & Andhra Pradesh
≈ 85 000 (index cases) → ≈ 575 000 (contacts)
0.047 < π > 0.107
≈ 1343 (index cases) ≈ 18 500 (contacts)
0.012 (Health) **0.026** (Community) **0.09** (Household)

3. Virus Propagation –Network Interventions

Network Immunization

Choice of a set of nodes who cannot catch (vaccine) nor transmit the disease (isolation).
(Cohen & Havlin 2010: ch. 15)

At **each iteration** t
b [1, 3, 5, 10]
S- or I-agents → R-state

S_i, t=0 → E_i, t=1→4 → I_i, t=5→9 → R_i, t ~ P<15>[7,42] (*WHO* 2020)

N~<0993> [0.090, 0.096] (*Science* 2020)

Infect each direct contact

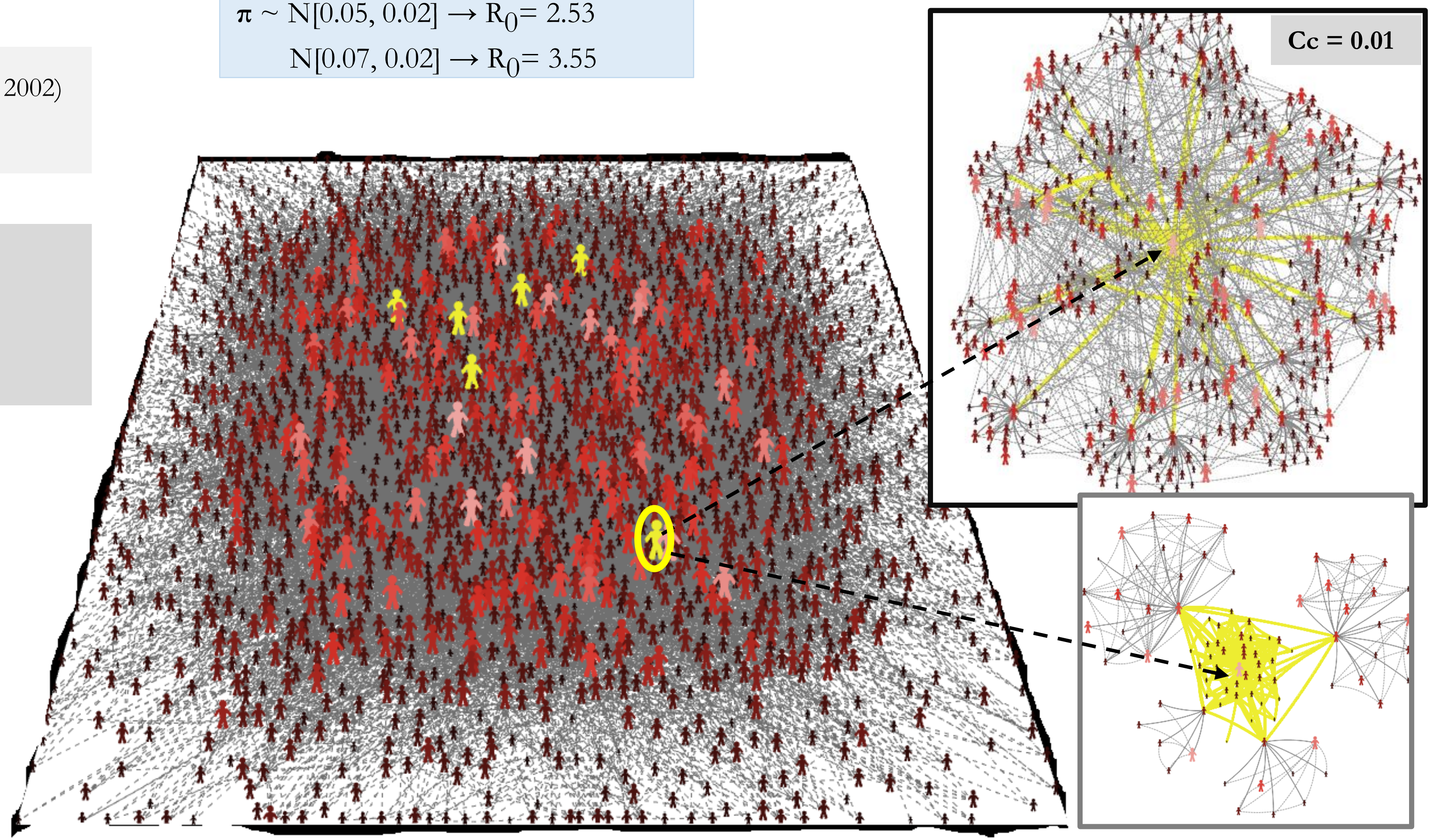
N[0.03, 0.02] → R_0= 1.52
π ~ N[0.05, 0.02] → R_0= 2.53
N[0.07, 0.02] → R_0= 3.55

1/ **Uniform immunization** (Pastor-Satorras&Vespignani 2002)
Random selection (NO-TARGET strategy)

2/ **Degree-based immunization** (Barabasi 2002)
Reverse order of agents' degree, from the highest to the lowest (HUB-TARGET strategy)

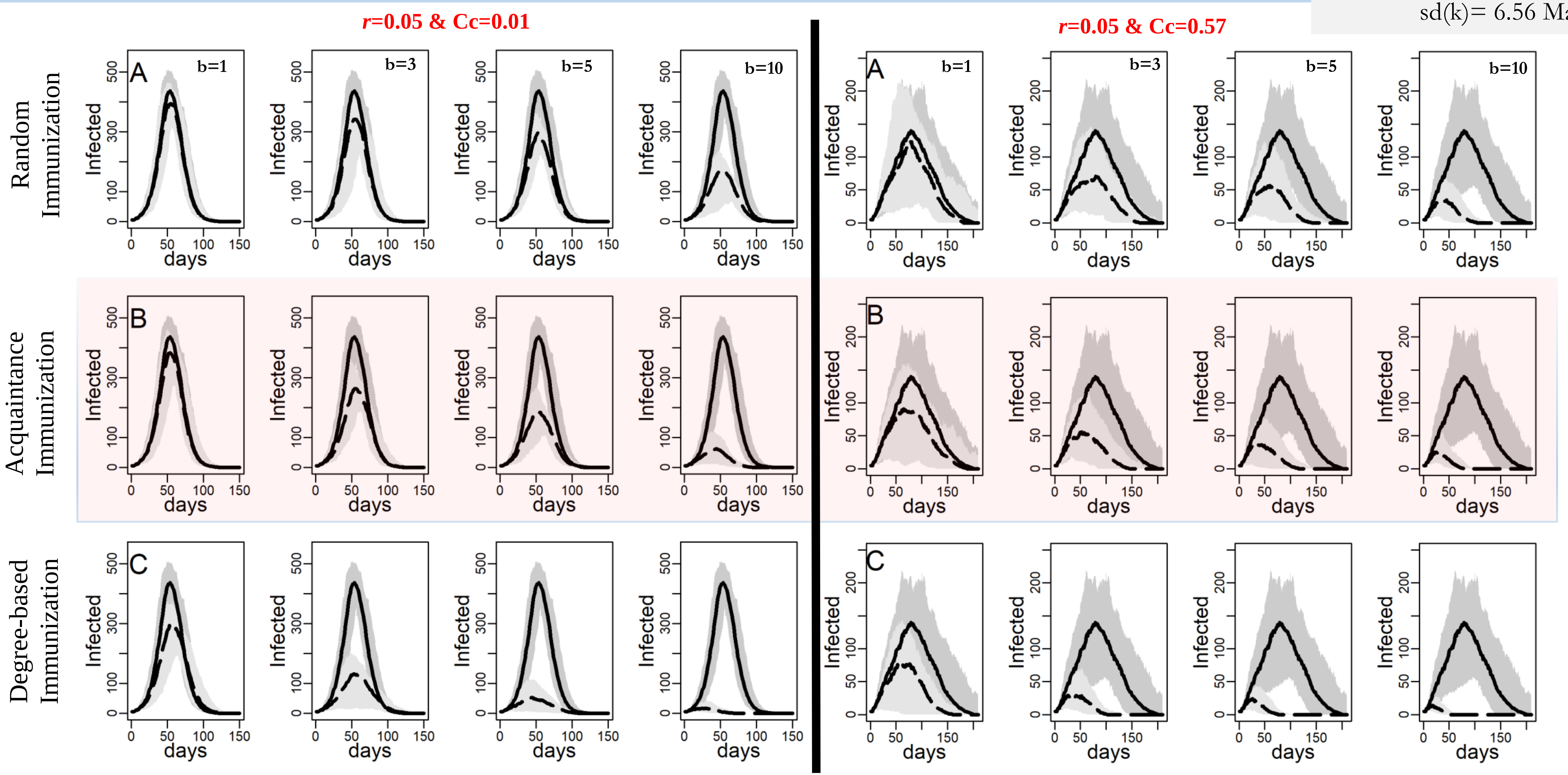
3/ **Acquaintance immunization** (Cohen et al. 2003)
(CONTACT-TARGET strategy)

1. **Random** selection of ***b*** agents
2. **Random** selection of **one of their contacts**
3. **This contact** is immunized



3. Virus Propagation –Simulated Epidemics without (solid) & with (dashed) net interventions

Small-hub Nets <k>=9.72
sd(k)= 6.56 Max(k) = 40

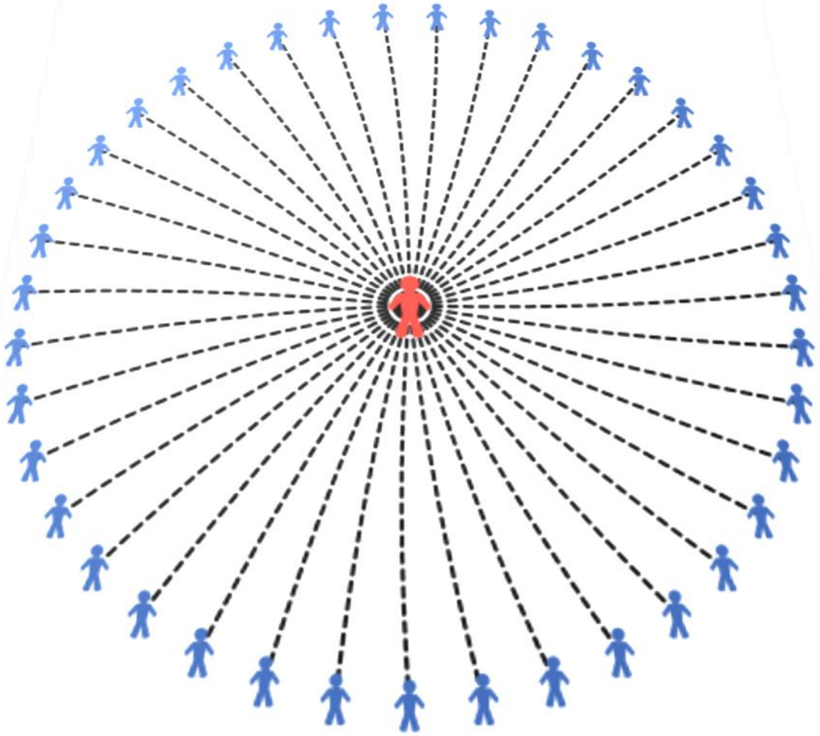


1/ For a given “budget” (*b*, column), targeting reduces, and delay, peaks compared to uniform immunization
2/ Increasing “budget” (*b*, column) makes targeting more and more efficient
3/ Acquaintance immunization is a good approximation for perfect hub targeting
4/ Results are robust across Cc values
From ≈10% to ≈95% peak reduction depending on how many hubs are targeted and how they are targeted

3. Virus Propagation –The Friendship Paradox within empirically-based French contact networks

Star network

1 actor (**red**) → 39 contacts
39 actors (**blue**) → 1 contacts



Agents' average number of contacts → 1.95
Average number of contacts of agents' contacts → 38.05

Friendship Paradox –"the mean number of friends of friends is always greater than the mean number of friends of individuals" (Feld 1991: 1465)

***Ego*'s contacts on average ≈ $\langle k \rangle$**

Contacts of *ego*'s contacts on average ≈ $\langle k \rangle + \frac{Var(k)}{\langle k \rangle}$

Friendship Paradox & Degree Heterogeneity-"The mean among friends is much greater than the mean among individuals if there is much variation in the population." (Feld 1991: 1470)

Diary-based network (Max degree 40) (Cc=0.01)

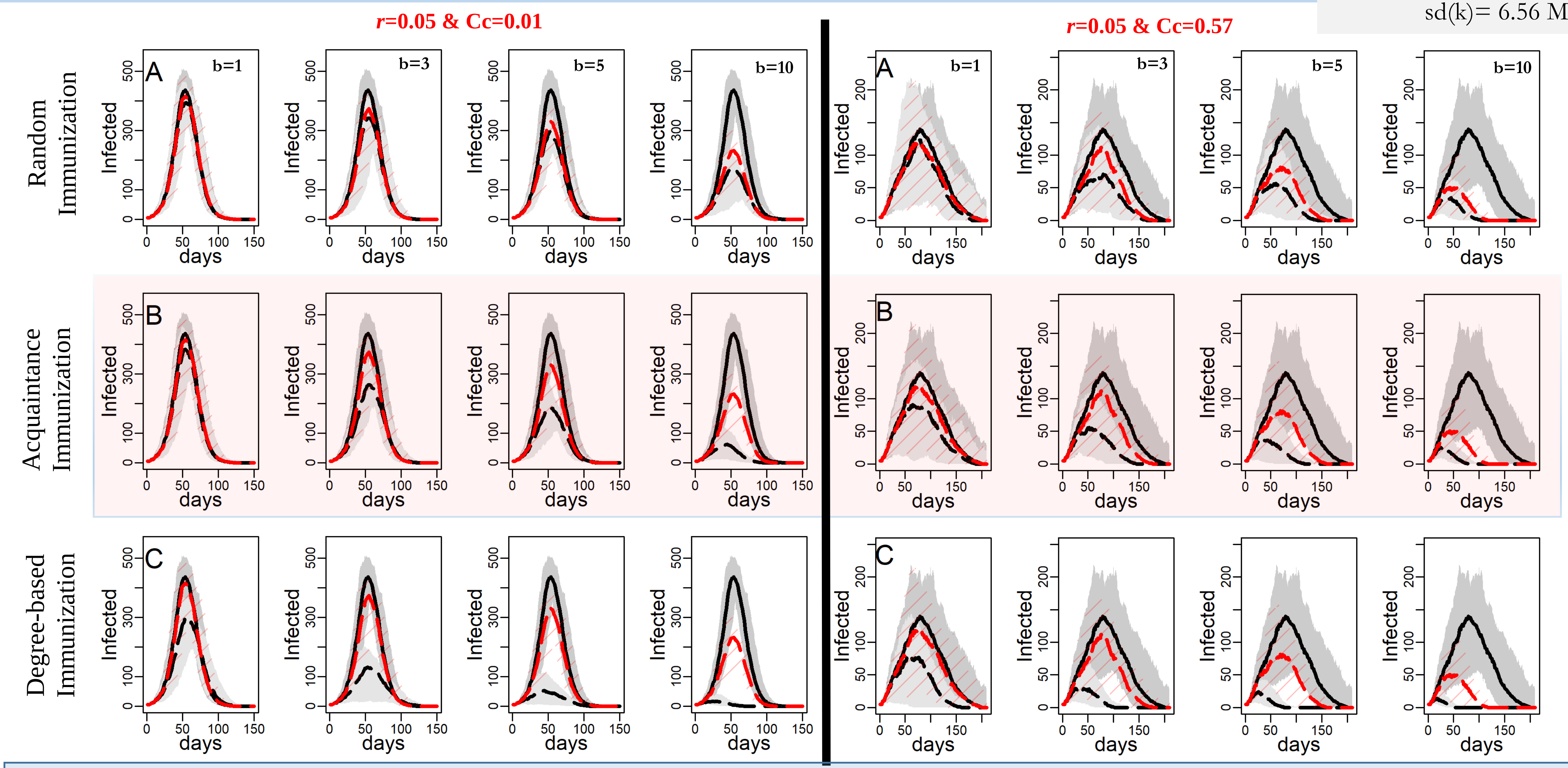
Ego's contacts on average ≈ **9.72**
Contacts of *ego*'s contacts on average ≈ **16.63**

Diary-based+Job-related network (Max degree 134) (Cc=0.04)

Ego's contacts on average ≈ **14.87**
Contacts of *ego*'s contacts on average ≈ **65.03**

3. Virus Propagation –Simulated Epidemics without (solid) & with (dashed) net interventions

Small-hub Nets <k>=9.72
sd(k)= 6.56 Max(k) = 40



Age-based Intervention (To-be-immunized agents are selected according to their age in a reversed order)

→ Prioritizing older people is as effective as the **random selection**

→ Why? Being older is weakly correlated with being a hub…

Linear Correlation coefficient r (Age & Degree) ≈ -0.18

Grazie / Merci / Thank you… for your attention!