

# Agent-based Models of Social Dynamics: Principles, One Example, and Challenges.

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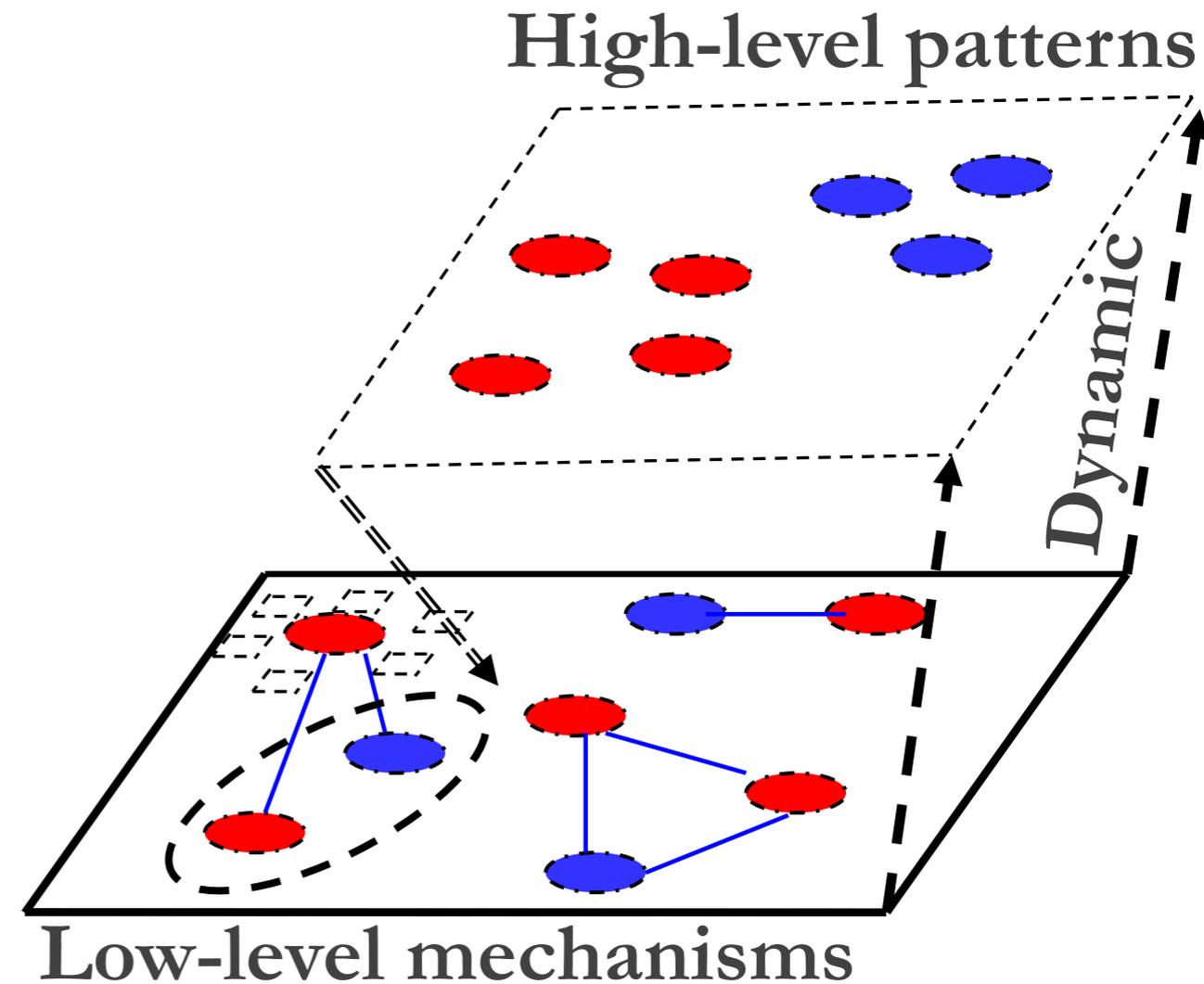
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Agent-based Models of Social Dynamics:

**Principles**, One Example, and  
Challenges.

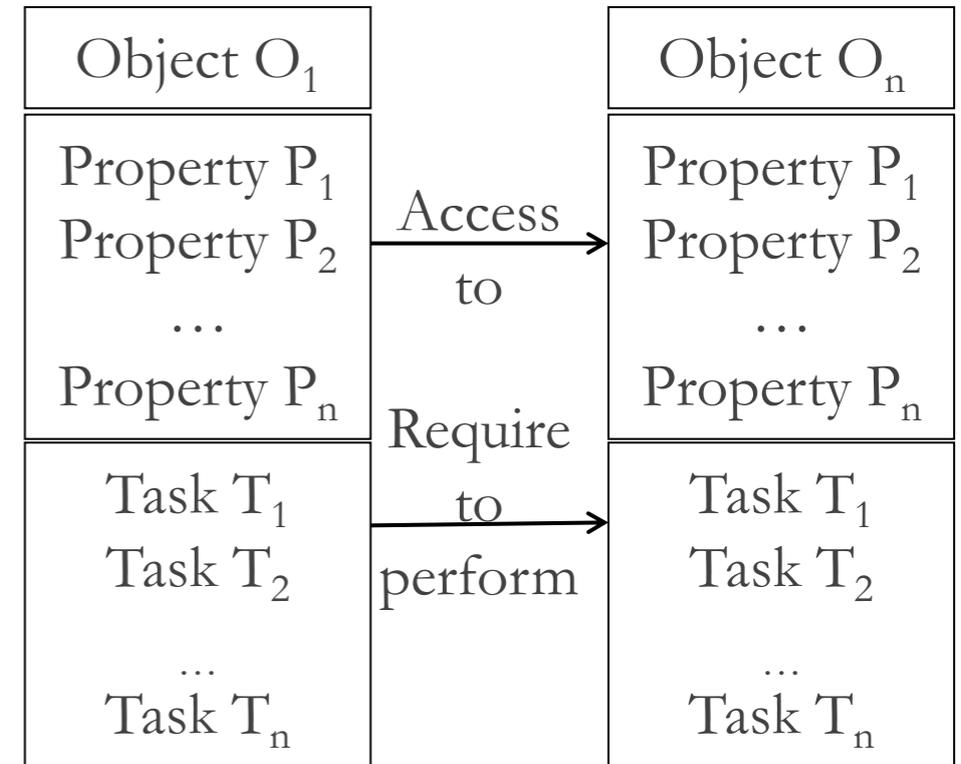
# What is an Agent-based Model (ABM)?

- 1/ Several types of elementary entities;
- 2/ Entities can move;
- 3/ Entities can have several properties;
- 4/ Entities can be related by ties;
- 5/ Entities execute tasks/rules  
(deterministic or stochastic)
- 6/ Entities can belong to several level of analysis
- 7/ The entities' behavior can depend on the behavior on one (or more of other) entity(ies)
- 8/ Global state of the system can feedback into the entities' behaviour
- 9/ A variety of temporal scheduling is possible



# Why is an ABM a computational model?

“Objects are defined as computational entities that encapsulate some **state**, are able to perform **actions**, or methods, on this state, and **communicate** by message passing”.



“A class is a **collection** of things with similar **properties**” (Wooldridge 2009, pp. 5,108)

# A synthetic definition

“Agent-based models (ABM) consist of autonomous, interacting computational objects, called agents, often situated in space and time”

De Marchi & Page (ARPS, 2014)

Agents –identical or endowed with unique attributes (heterogeneity)

Agents –a few or millions

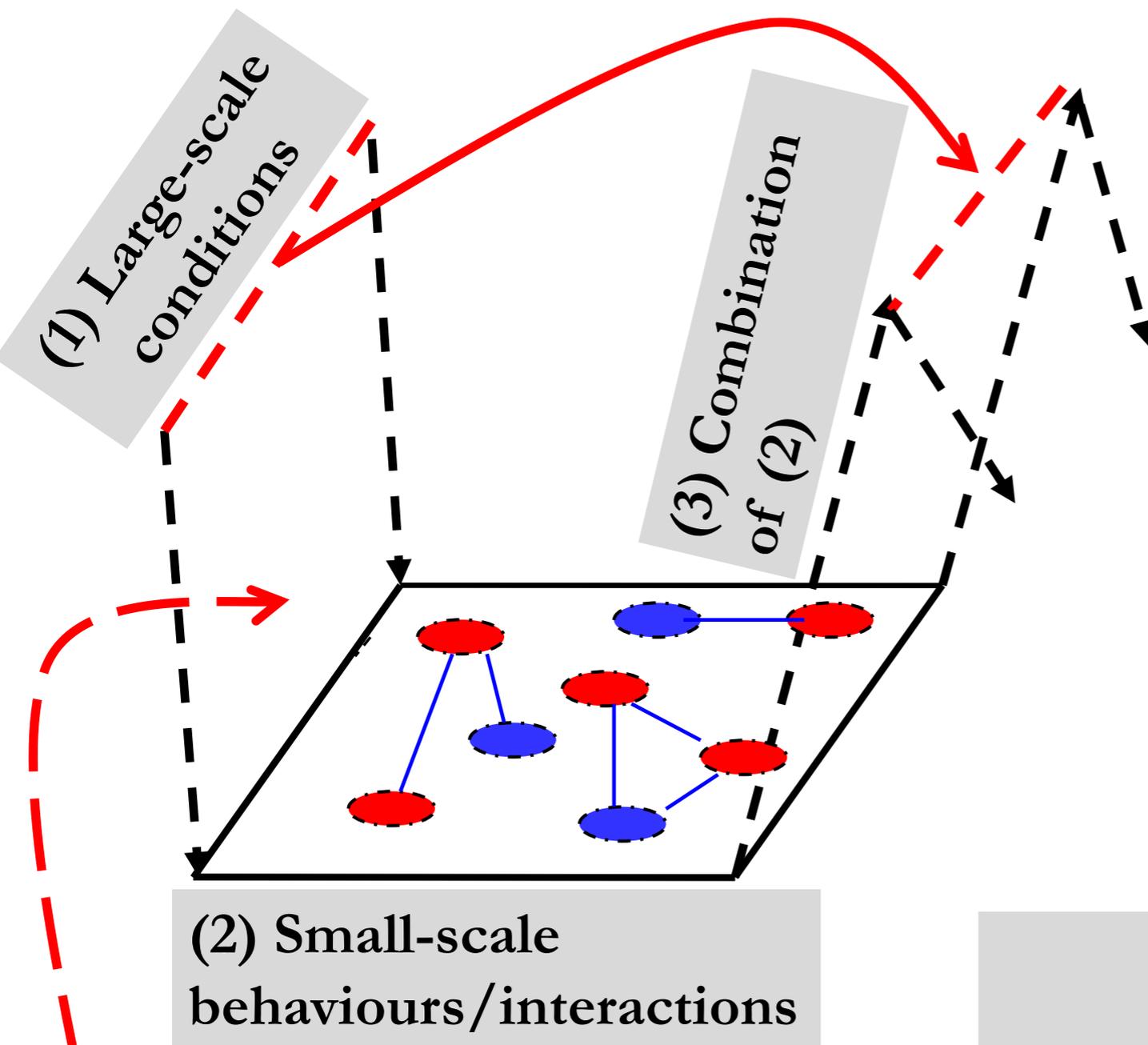
Agents –rule-based (simple or complex)

**Agents –do not necessarily represent “individuals”**

Environment –social networks and/or geographical space

Unpacking aggregates –bottom-up or micro-macro mapping

# Why are sociologists interested in ABMs?



**ABM is especially flexible to model this kind of analytical structures**

→**Micro-to-Macro Problem**←

“(…) the major theoretical obstacle to social theory built on a theory of action is not the proper refinement of the action theory itself, but the means by which purposive actions of individuals **combine** to produce a social outcome”

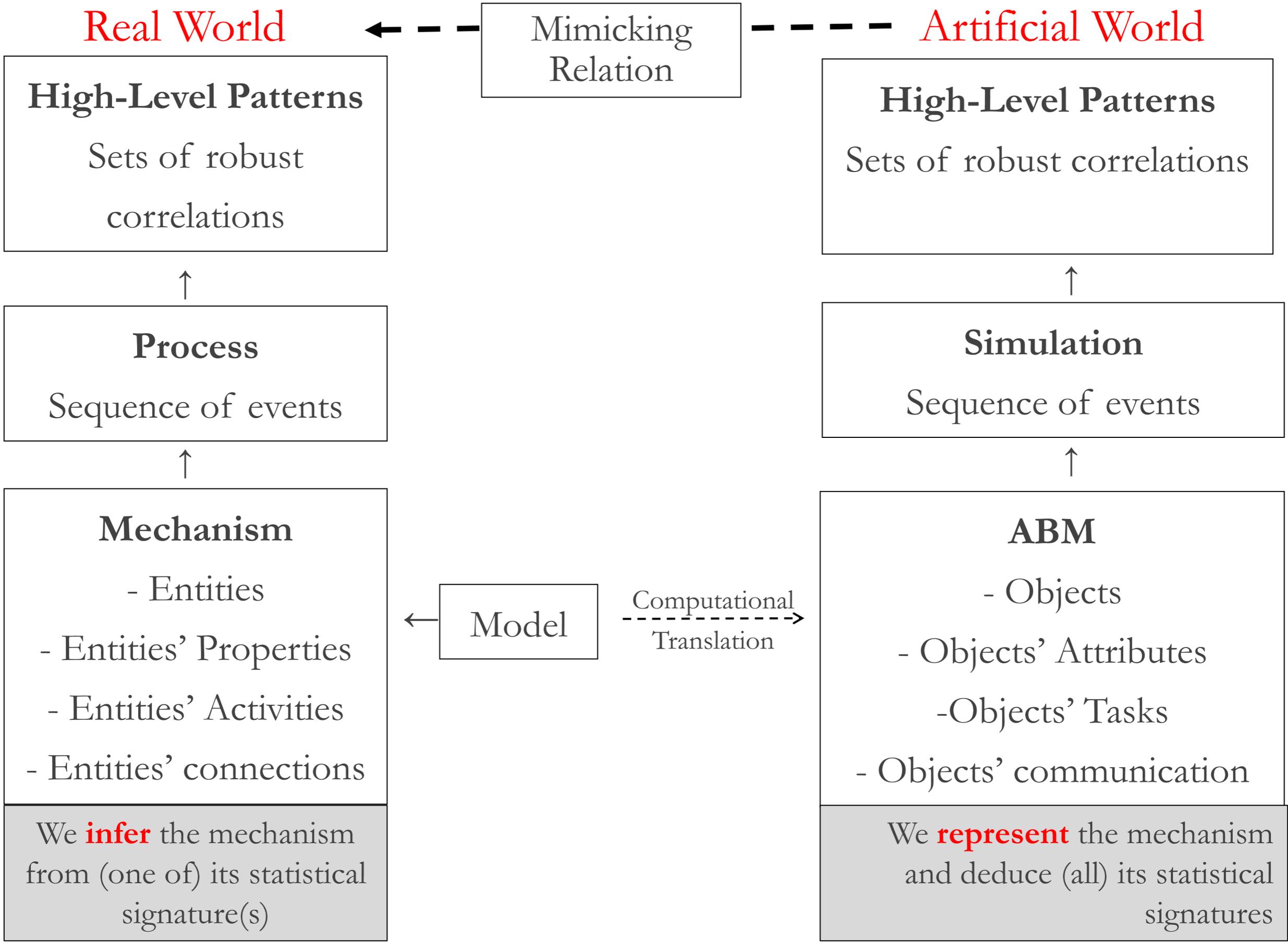
Coleman J. (1986). *American Journal of Sociology*, 91, 1320–1321.

→**Micro-to-Macro non-linearity**←

“Connections and interactions between individuals can amplify or reinforce direct influences on agents”

(Durlauf S., Cohen-Cole E. 2004)

# ABMs as a research strategy



# An Epistemological Note

“Perhaps one day people will interpret the question, “**Can you explain it?**” as asking “**Can you grow it?**”

Artificial society modeling allows us to “**grow**” social structures *in silico* demonstrating that certain sets of **microspecifications** are **sufficient** to generate the **macrophenomena** of interest...”

Epstein J., 2006, *Generative Social Science. Studies in Agent-Based Computational Modeling*, p. 8

“Well, the computer changes epistemology, it changes the meaning of “to understand”.

To me, **you understand something only if you can program it.** (You, not someone else!). Otherwise you don't really understand it, you only think you understand it”.

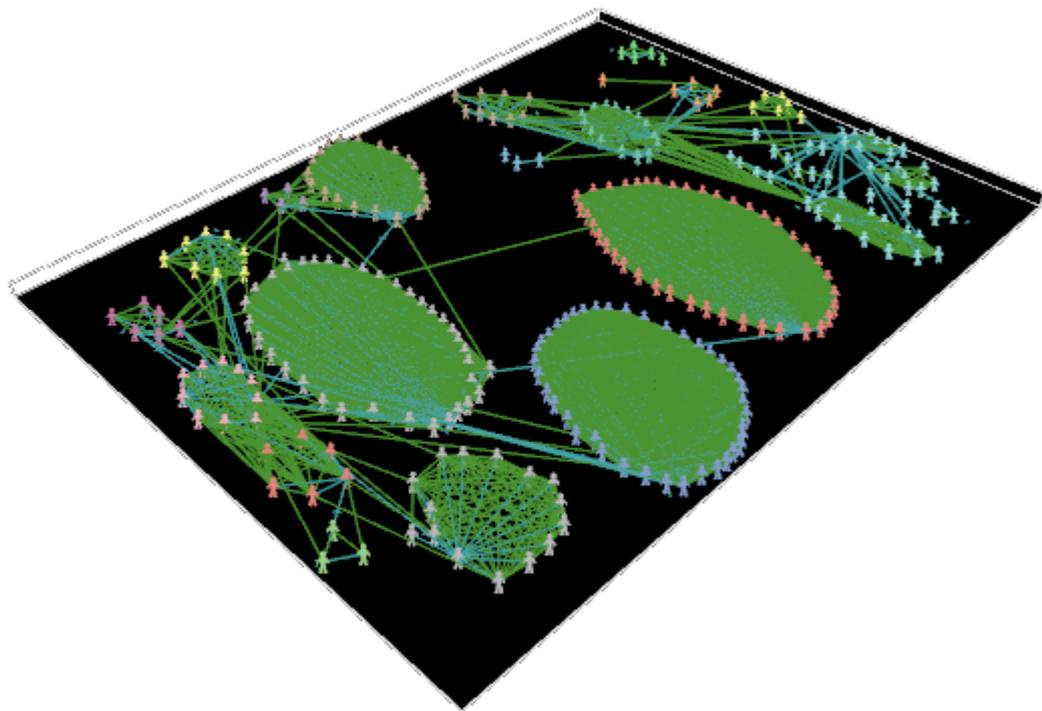
Chaitin, G. 2006 [2005]. *Meta Math!: The Quest for Omega*. Vintage Books, p. xiii

# Should you want to read more on these general points :

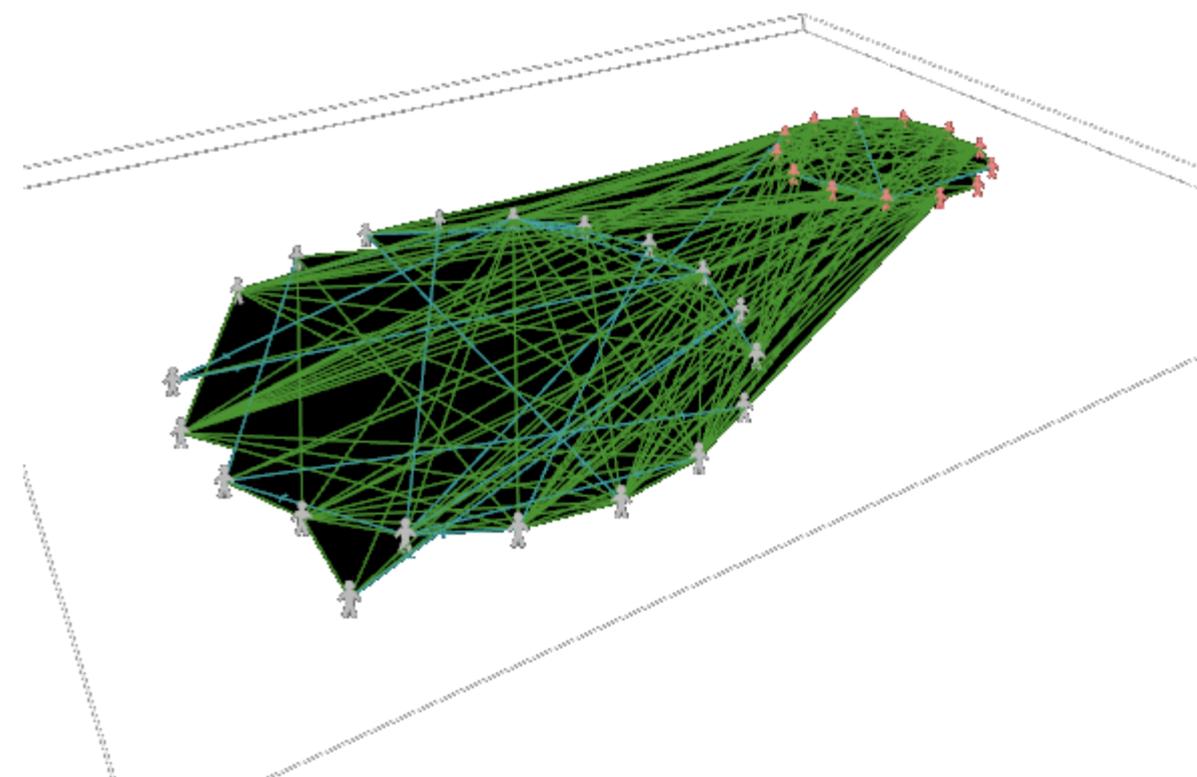
G. Manzo (2014) The Potential and Limitations of Agent-based Simulation: An introduction. *Revue Française de Sociologie* , 55,4, 653-688

G. Manzo (2014) “Data, Generative Models, and Mechanisms: More on the Principles of Analytical Sociology”. In Manzo, G. (2014) (ed.) *Analytical Sociology: Actions and Networks*, Chichester, UK: John Wiley & Sons, 4-52.

Agent-based Models of Social Dynamics:  
Principles, One Example, and  
Challenges.



**Complex Contagions** in Non-western Societies: Explaining **Diffusion Dynamics** among Indian and Kenyan **Potters**.



*In collaboration with:*

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CRFJ - Jerusalem  
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National Museum of Kenya  
(Nairobi)

# Empirical Data

|       | # of Potters | Religion   | Social context   | District                     | Data Collection (2013, 2014, 2015) | Sample   | Main information collected   |
|-------|--------------|--|--|------------------------------|------------------------------------|--|--|
| India | 279          | - Muslims<br>- Hindus  | - 19 Rural (partly semi-desertic) villages<br>- 1 urban center | Jodhpur & Barmer (Rajasthan) | 89 in-depth interviews             | 20 villages -> 342 households -> 74% of active households (460) in the Jodhpur and Barmer districts (across 47 villages) | - When a potter adopted<br>- From whom she learn                     |
| Kenya | 33           | - Mukurino<br>- Other Religion (Pentecostal, Apostoli, PCEA) | - 2 rural villages   | Kiaritha (Ishihara)          | 33 in-depth interviews             | 2 villages -> 33 potters -> almost 100% of the Ishihara region   | - Potters' Kinship Connections<br>- Potters' reasons to adopt/reject |

# Type of Innovations

## Indian Villages

## Kenyan Villages

Open Firing

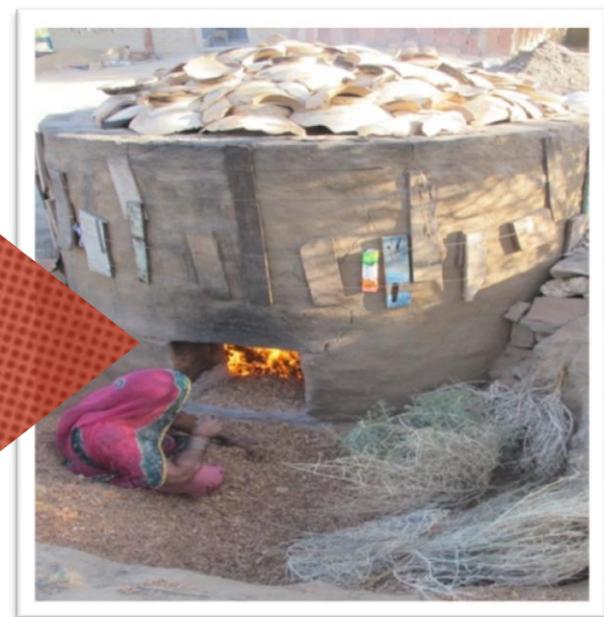
Vertical Kiln

Round-Base Pot

Flat-Base Pot



1987

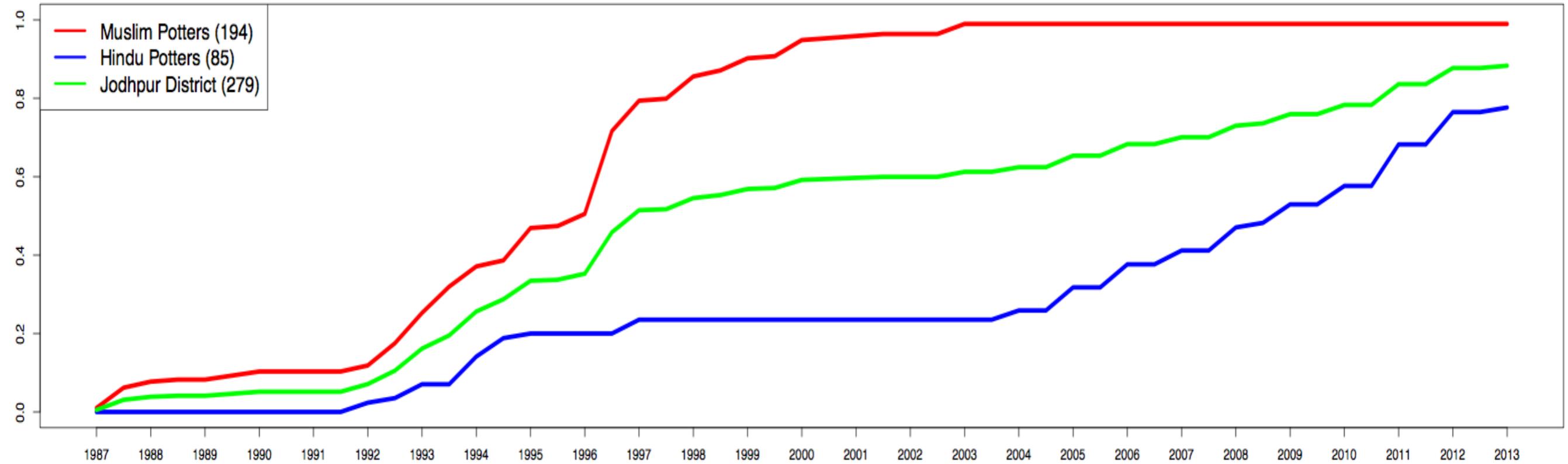


1997

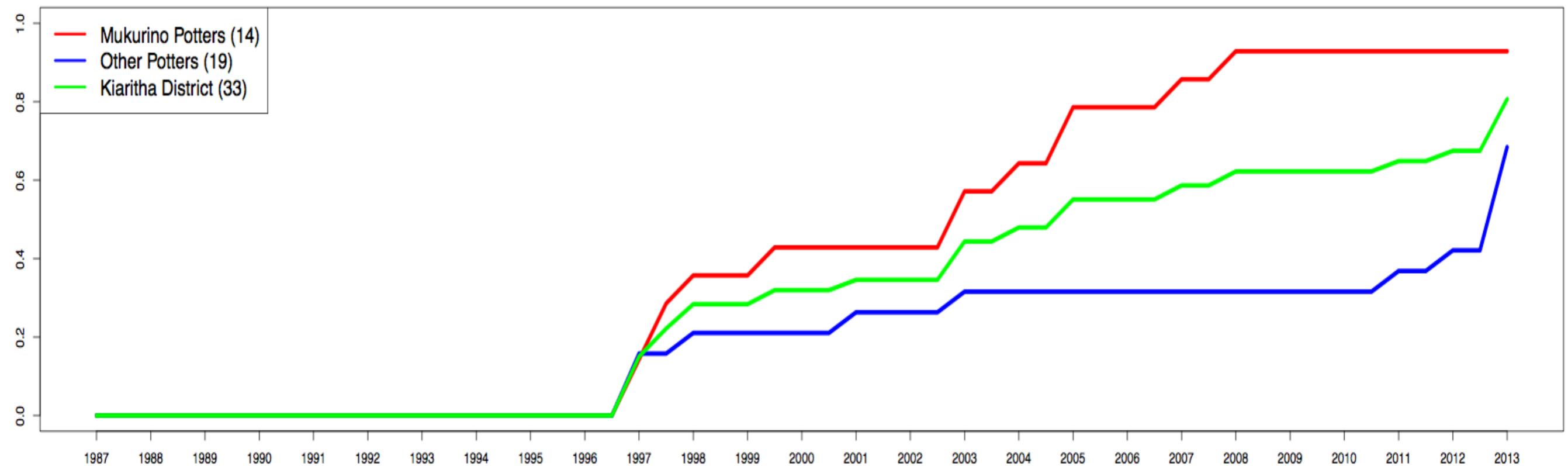


# Puzzling Large-scale Patterns

## Rate of adoption of the vertical kiln (Indian Villages)



## Rate of adoption of Flat-base Pots (Kenyan Villages)



# Theoretical Orientation

Focus –“graph-theoretic conditions under which contagion causes the innovation to spread throughout the network” (P. Young, PNAS, 2011, p. 5)

## H1: The strength of weak ties

- “Intuitively speaking, this means that **whatever is to be diffused** can reach a larger number of people, and traverse greater social distance (i.e., **path length**), when passed through **weak ties** rather than strong” (Granovetter, AJS, 1973, p. 1366)
- ***Small-world topologies***: a few **long connections** greatly reduce the **average path length** of a regular network, and favor quick diffusion of disease (Watts & Strogatz, Science, 1998)

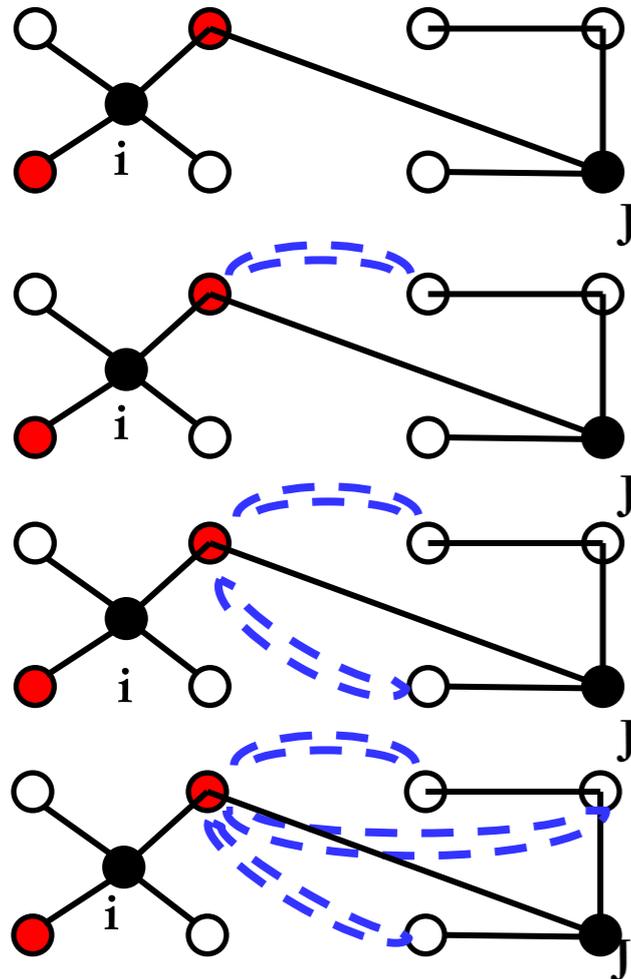
## H2: The strength of strong ties

- ❖ “(...) when activation requires **confirmation or reinforcement from two or more sources** [**complex contagions**], the **transitive structure** that was **redundant** for the spread of information now becomes an essential pathway for diffusion” (Centola and Macy, 2007, 709)
- ❖ ***Bridge width***: larger bridges increases local tie redundancy, thus increasing the probability of being exposed to a plurality of activated neighbors, which ultimately favor large and quick diffusion (Centola AJS, 2015)

# Complex Contagions

## Local-net-centred view

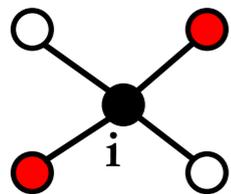
● Adopters ○ Non-adopters



***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***

***Bridge width*** - The width of a bridge is the **size of the abovementioned set** (Centola and Macy, AJS, 2007, 713)

## Ego-centred view



***Network threshold*** – “the proportion of prior adopters in an individual’s personal network of direct personal contacts when the individual adopts” (Valente 1995: 70).

# Can complex contagions on larger bridges explain our diffusion curves?

## 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)

## Our study -

Quasi-natural experimental data + Agent-based computational models

### Complex Contagion

Learning and reinforcement through several other potters

We partly know who provides information to whom

### Social (Kinship) Networks

Weak ties: initiate initiators  
Strong ties redundancy: facilitate/impede innovation

Mesurable and comparable across sub-communities

**SNA**

### Complex decision

Adopting {  
Kiln  
New shape

We do not know the entire sequence of actions and reactions, thus the connection between micro-behaviours and large-scale patterns is unclear

**ABM, given SNA**

## **a. Descriptive SNA**



# Social Norms - Marriage Rules

## Muslim

### Within each village

- # One common ancestor
- # Marriage rule: endogamous

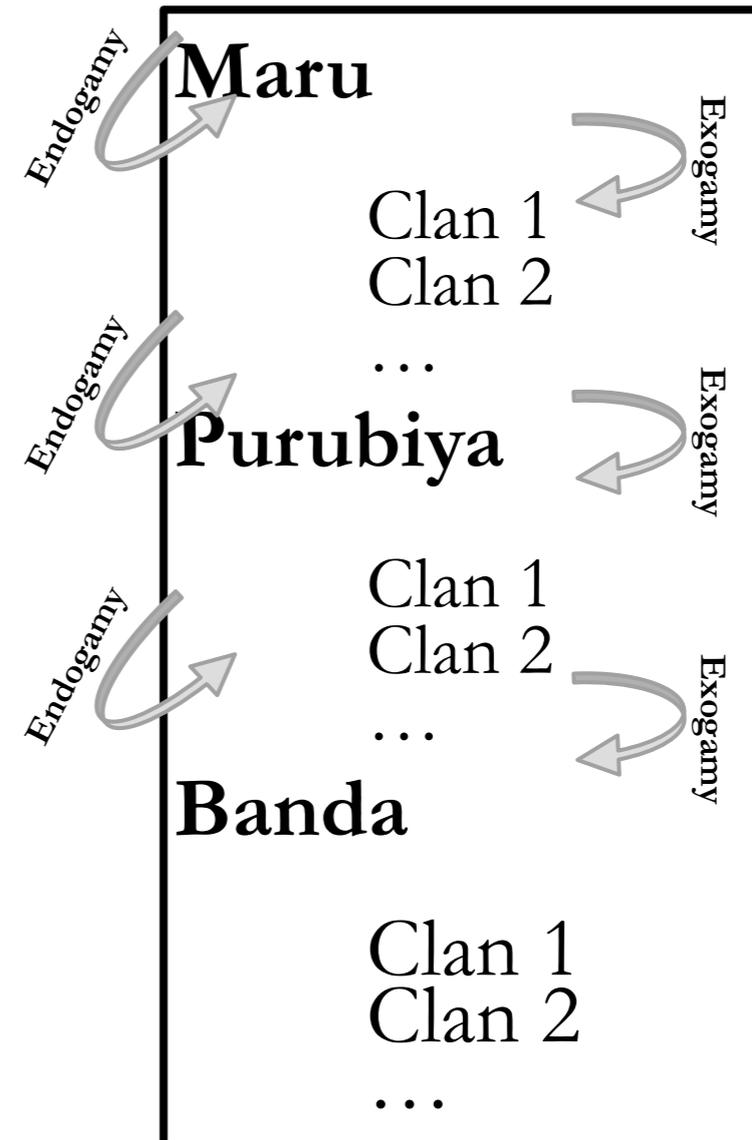
### Across villages

- # Bhaipa/Genait villages
- # Cross-cousin marriages



All family-related (within villages) & dense inter-villages family links

## Hindu



Family-related along caste-based lines, and, within castes, along clan-based lines (within villages) & sparse inter-villages links (see Kramer 1989)

→ Rao, Rogers, and Singh (1980) – Empirical evidence of caste-based diffusion networks among Hindu

# India – Kinship Network

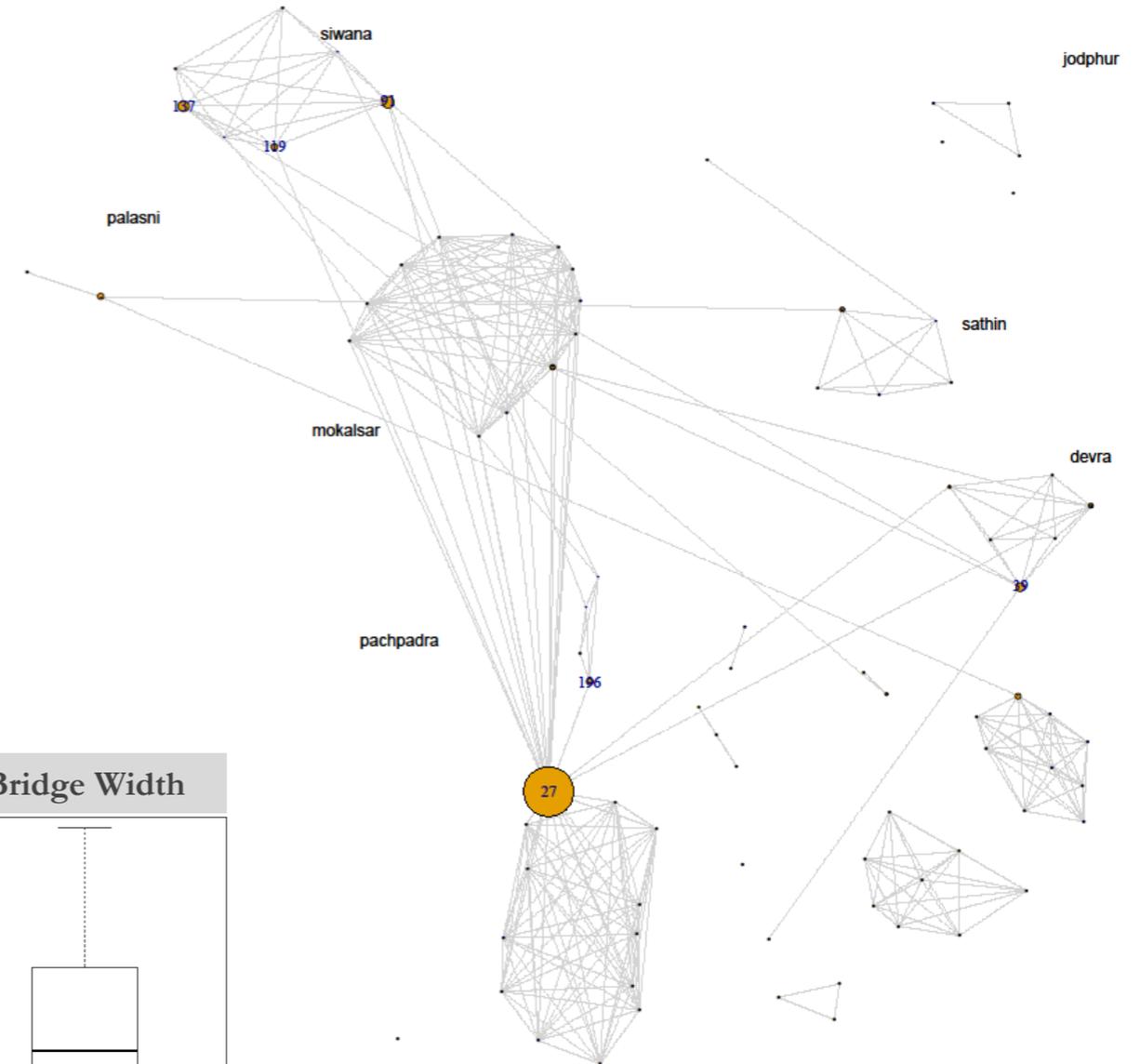
**Muslims (n=194)**

Density=0.14 AvDe=27.87



**Hindu (n=85)**

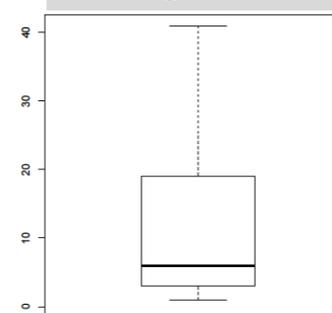
Density=0.08 AvDe=7.08



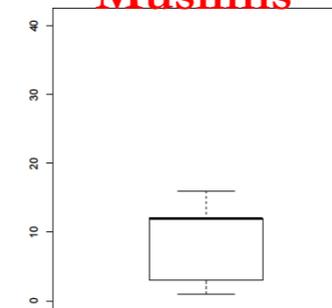
## Strong Ties

- Numerous and powerful kinship brokers among Muslims
- Longer kinship chains among Muslims (5-step reachability: 82% vs 6%)
- Less (6% vs 10%) but larger kinship bridges among Muslims (average width: 13.37 vs 8.30)

Bridge Width



Muslims

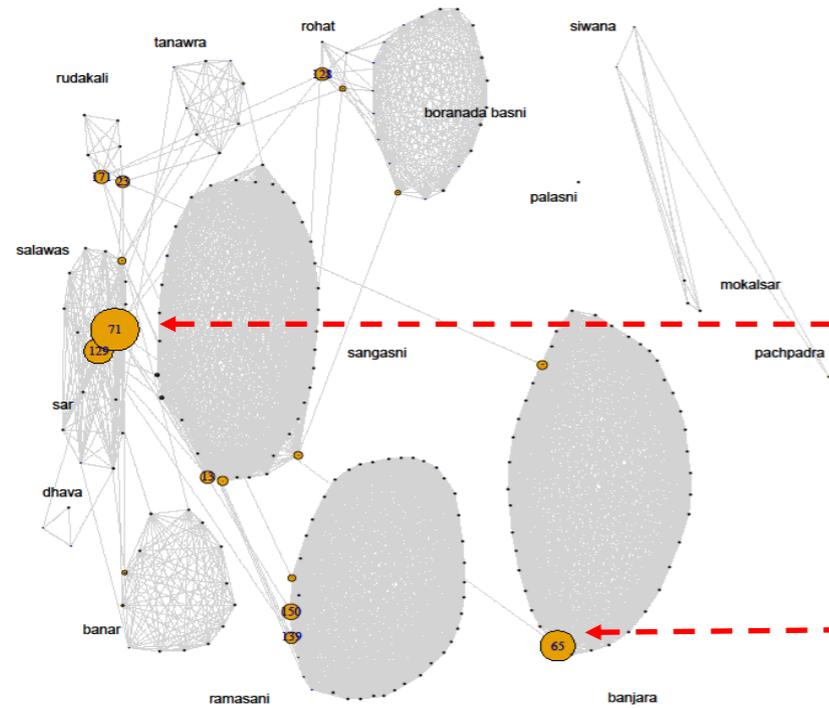


Hindu

**Larger structural opportunities for helping and advising**

# India – Kinship / Diffusion Nets Overlap

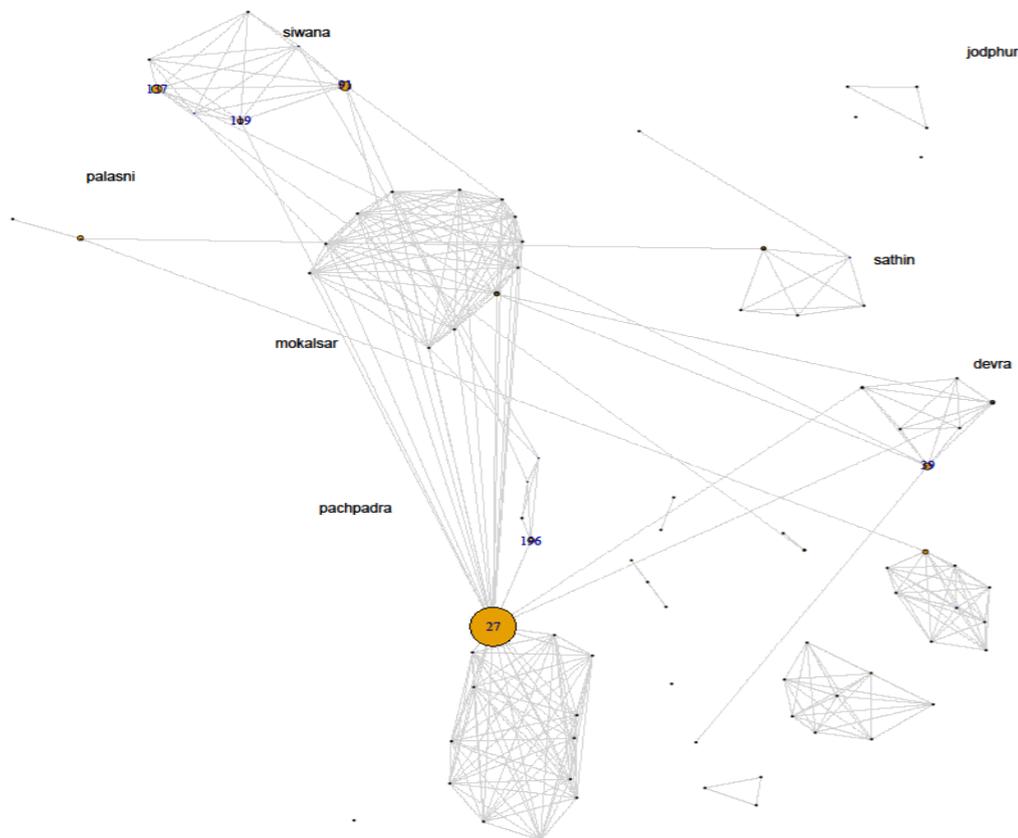
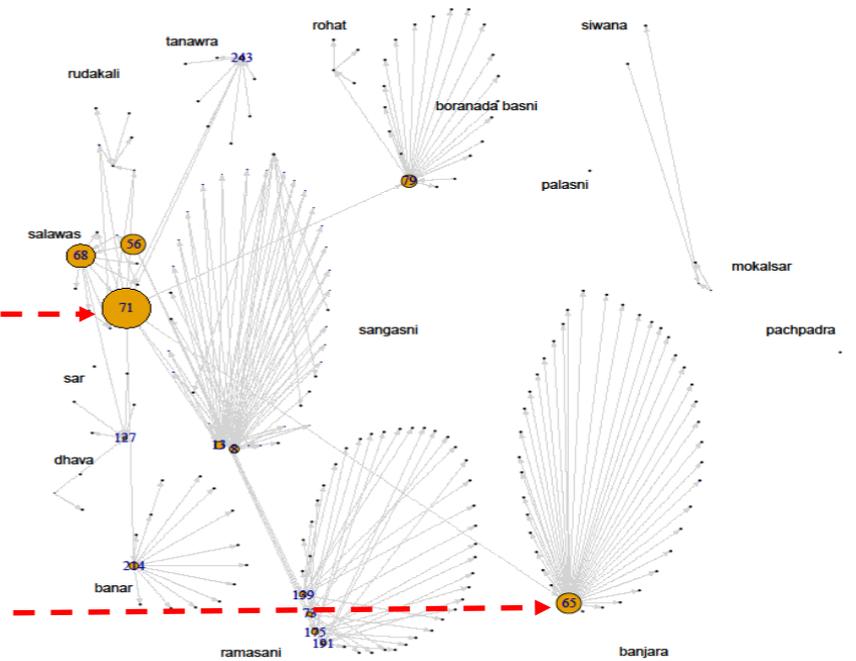
## Kinship Networks



## Muslims

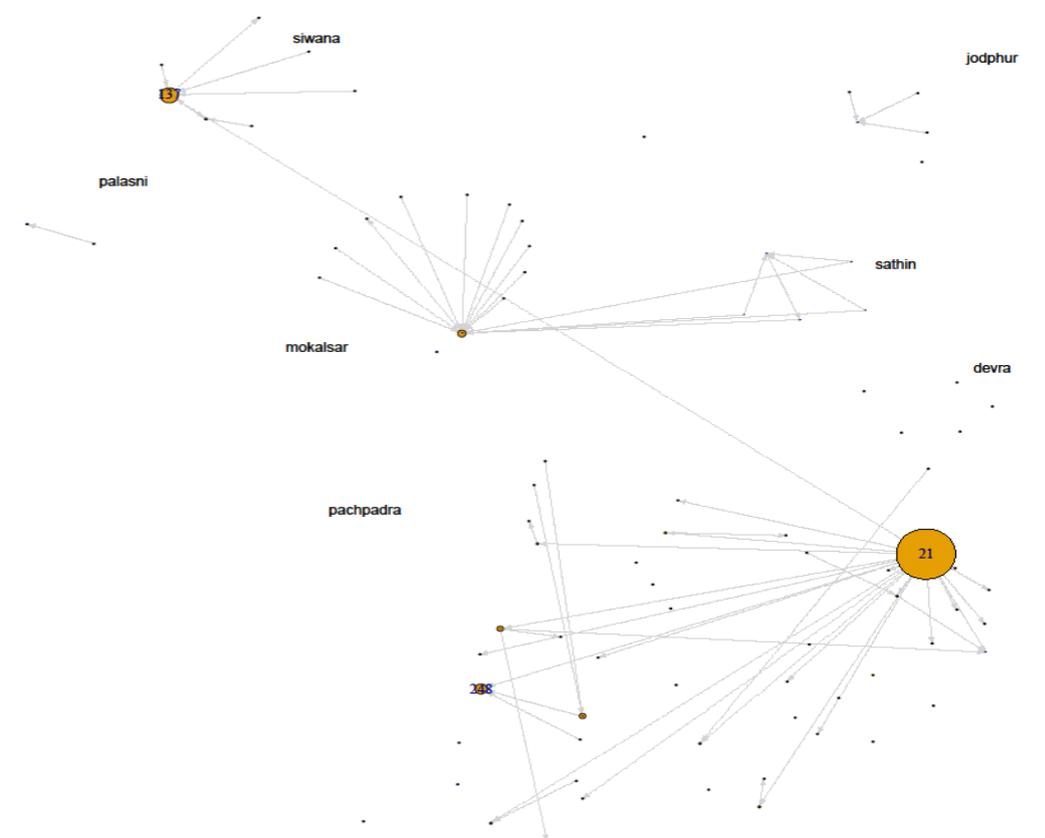
BC cor= 0.66  
QAP=0.96  
QAP<sub>(first cross-village diffusion links)</sub>=0.65

## Diffusion Networks



## Hindus

BC cor= 0.17  
QAP=0.60  
QAP<sub>(first cross-village diffusion links)</sub>=0.20



# Some pieces to solve the puzzle...

**Puzzle** – Larger and faster diffusion among Muslim potters

## What we have learned:

**1** – Kinship networks seem to lie behind advice networks

**2** – Kinship networks differ across Muslims and Hindus

**2a** – Muslim kinship network is more reachable

**2b** – Muslim kinship network is more locally redundant (larger bridges)

It seems there is a **correlation** between **more dense strong ties** among Muslims and **faster diffusion** of the kiln among them.

## Questions:

Are larger bridges among Muslim sufficient to explain the macroscopic differences in the diffusion curves ?

What is the precise contagion process operating on this network?

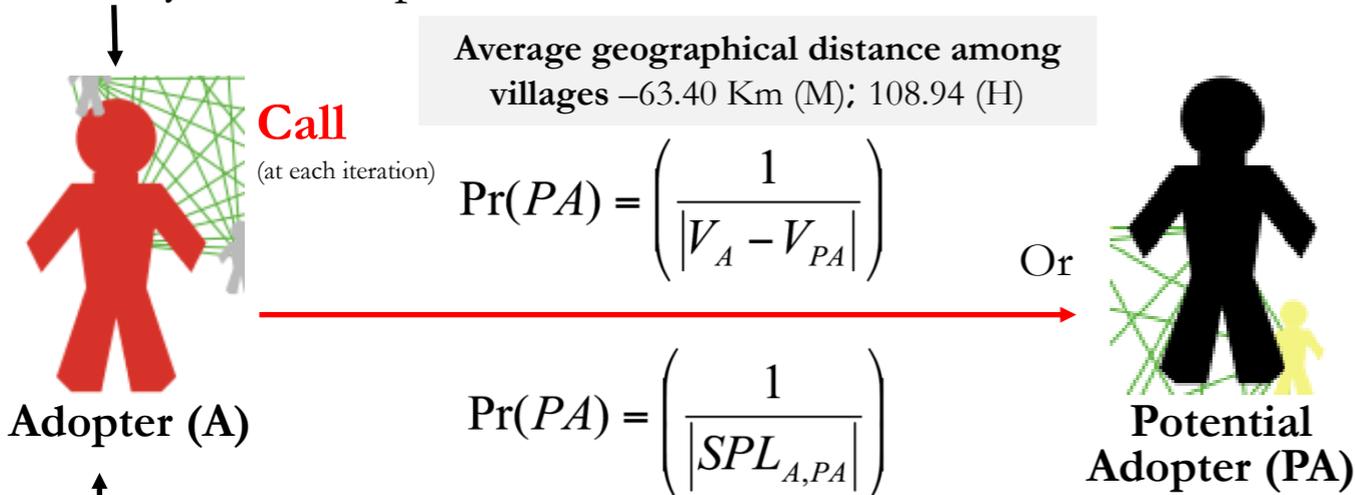
**b. ABM, given Descriptive SNA**

# The Agent-based models

## Empirically-calibrated

### Attributes

- Village
- Religion
- Age
- Expertise
- Centrality on kinship net



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<sub>0</sub>: 0.39 (M) 0.53 (H)

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

↳ **Frequency**  
**Simulated time:** 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

## PA Choice

- 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

# Model Search

## 8 model combinations

1. Physical distance / deterministic, single contagion
2. Relational distance / deterministic, single contagion
3. Physical distance / complex contagion 1
4. Relational distance / complex contagion
5. Physical distance / complex contagion 2
6. Relational distance / complex contagion 2
7. Physical distance / complex contagion 3
8. Relational distance / complex contagion 3

## 4 adopter-calling strategy

1. as function of potters' age
2. as function of potters' expertise
3. as function of potters' kinship centrality
4. random

## 6 possible interaction rates

1. 0.25 interactions per iteration
2. 0.50 interactions per iteration
3. 1 interaction per iteration
4. 2 interactions per iteration
5. 3 interactions per iteration
6. 4 interactions per iteration

186 modeling options ·  
100 replications each  
= 186.100 simulations

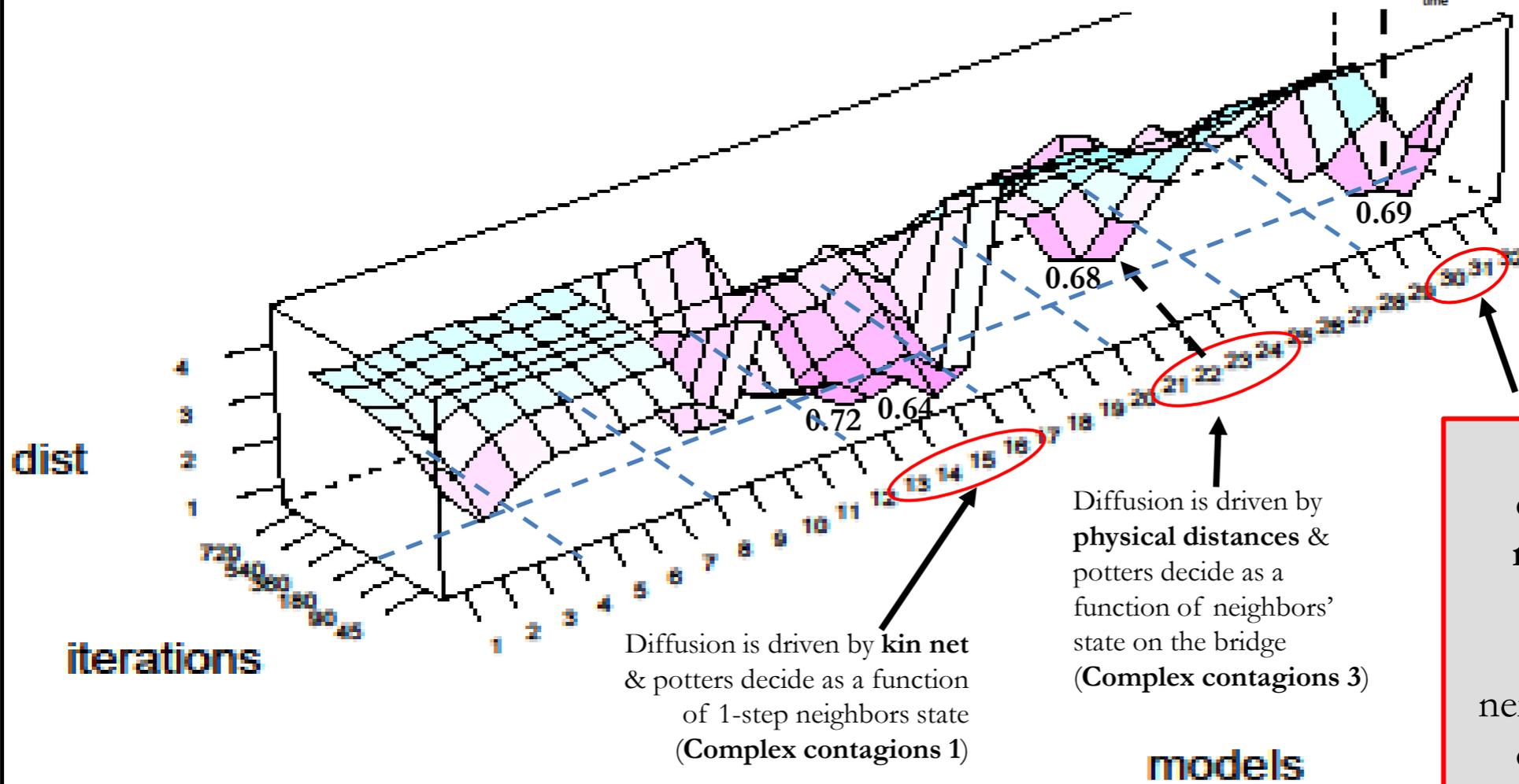
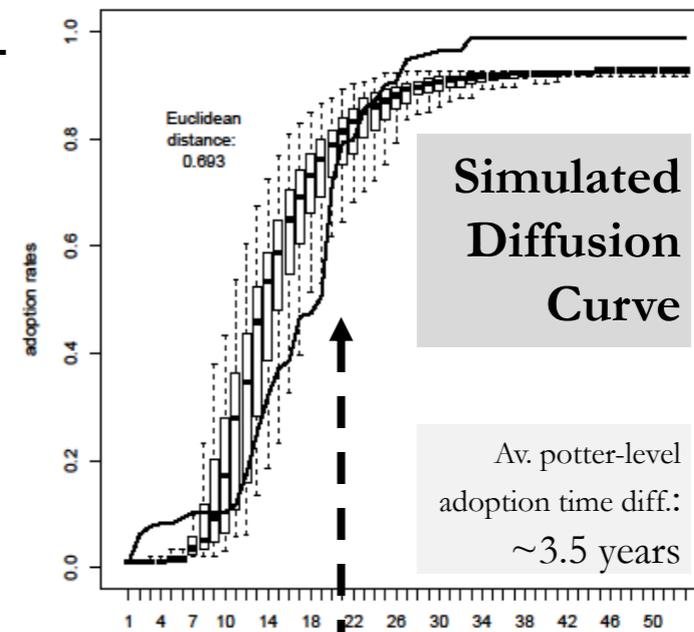
## –Output measures–

1/ Euclidian distance between simulated and empirical **diffusion curves**

2/ Average difference between simulated and empirical **potter-level adoption times**

→ We look for the model option(s) that minimize(s) these two statistics at the same time

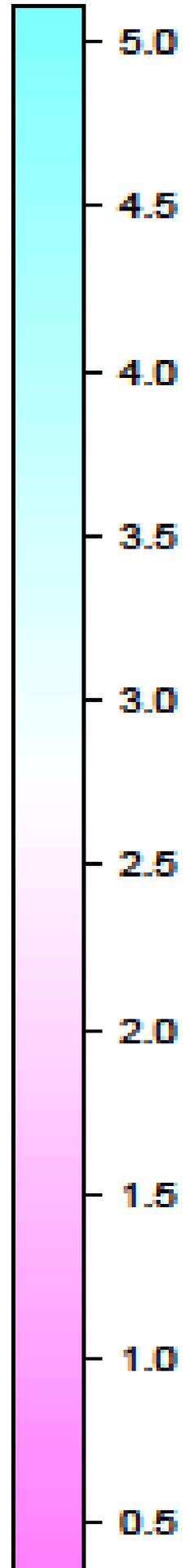
# Muslim Potters



Diffusion is driven by **kin net** & potters decide as a function of 1-step neighbors state (**Complex contagions 1**)

Diffusion is driven by **physical distances** & potters decide as a function of neighbors' state on the bridge (**Complex contagions 3**)

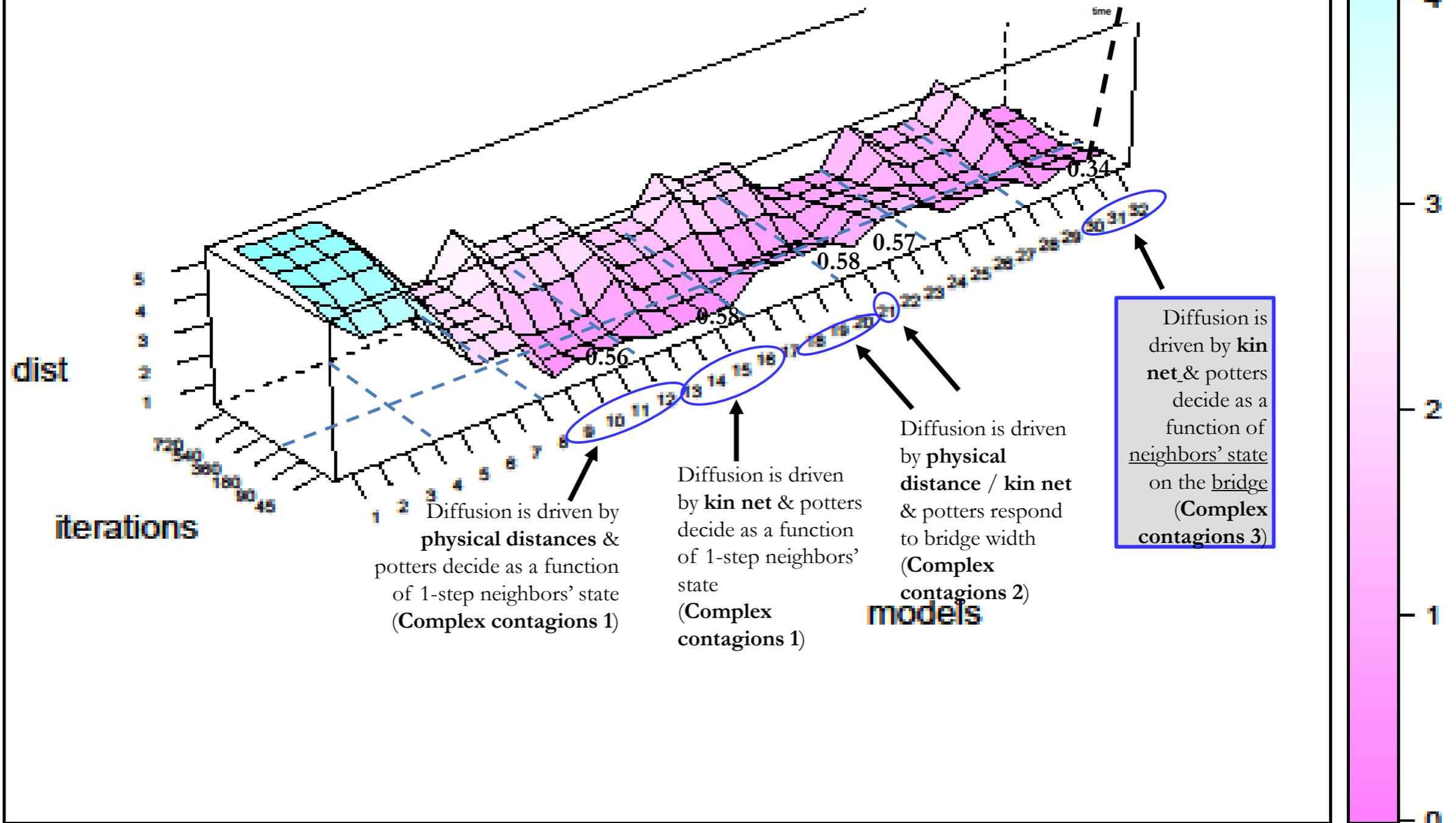
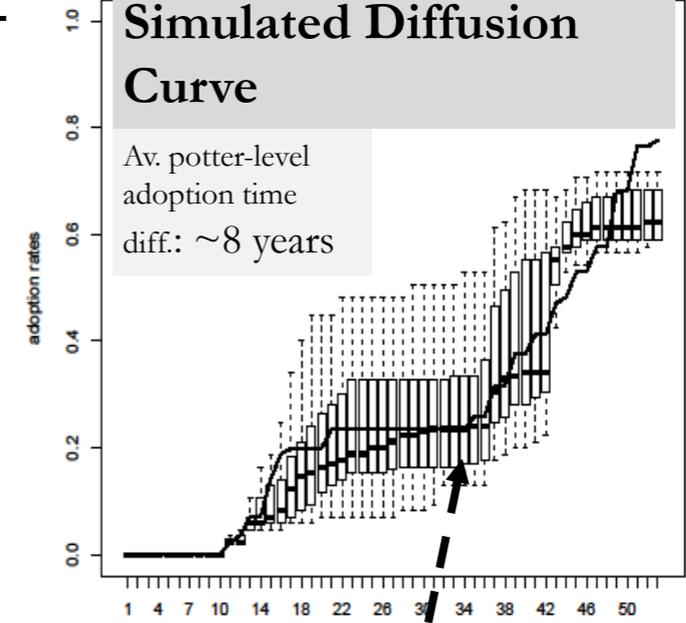
Diffusion is driven by **kin net** & potters decide as a function of neighbors' state on the bridge (**Complex contagions 3**)



# Hindu Potters

## Simulated Diffusion Curve

Av. potter-level adoption time  
diff: ~8 years



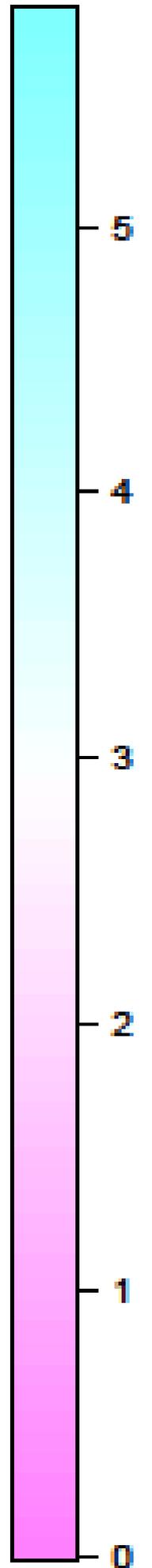
Diffusion is driven by physical distances & potters decide as a function of 1-step neighbors' state (Complex contagions 1)

Diffusion is driven by kin net & potters decide as a function of 1-step neighbors' state (Complex contagions 1)

Diffusion is driven by physical distance / kin net & potters respond to bridge width (Complex contagions 2)

Diffusion is driven by kin net & potters decide as a function of neighbors' state on the bridge (Complex contagions 3)

models



# Indian Case –To sup up

**Puzzle** – Larger and faster diffusion among Muslim potters

## Empirical data

- a** – Muslim kinship network is **more reachable** and information **go through central nodes**
- b** – Muslim kinship network is **more locally redundant** (larger bridges)

## Simulation

- a** – **Structural differences alone**, plus a deterministic contagion process at the dyadic level, is not sufficient to account for the macroscopic diffusion curves
- b** – **Probabilistic reinforcement from multiple neighbors lying on local bridges** (i.e. complex contagions) are necessary (and sufficient) to generate the macroscopic diffusion curves

## Implication

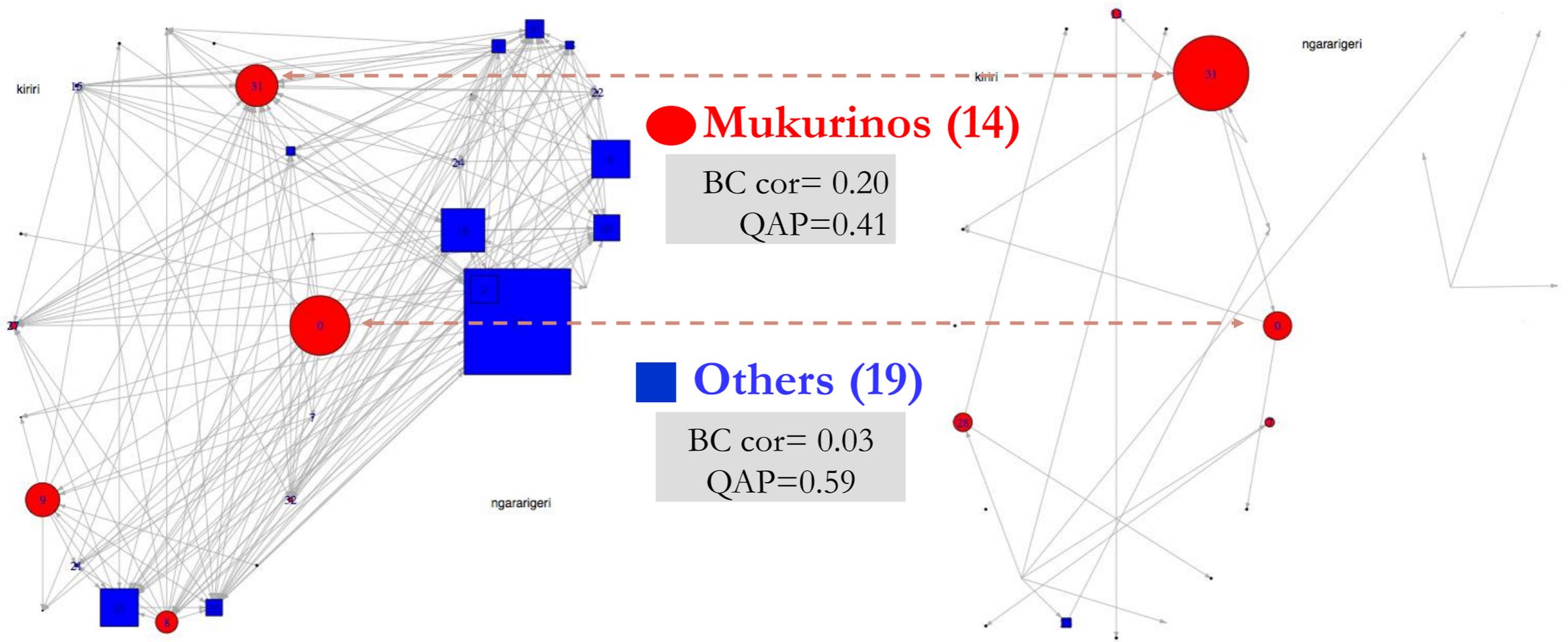
**Local bridges** sustain diffusion depending on **other structural features** and the **level of uncertainty** about the innovation

→ **Local bridges among hindu potters reinforce doubts**

(e.g.: first adopter in larger Hindu village went back to open firing some years after having adopted the vertical kiln)

**“Out-of-sample” test: the Kenyan  
case.**

# Kenya – Kinship / diffusion Net Overlap



## Kinship Networks

Density:  
Mukurinos=0.26  
Others=0.51

1. More and stronger brokers among Others
2. Longer chains among Mukurinos (3-step reachability: 42% vs 21%)
3. **Less (42% vs. 45%) and narrower bridges among Mukurinos (average width: 7.15 vs 10.66)**

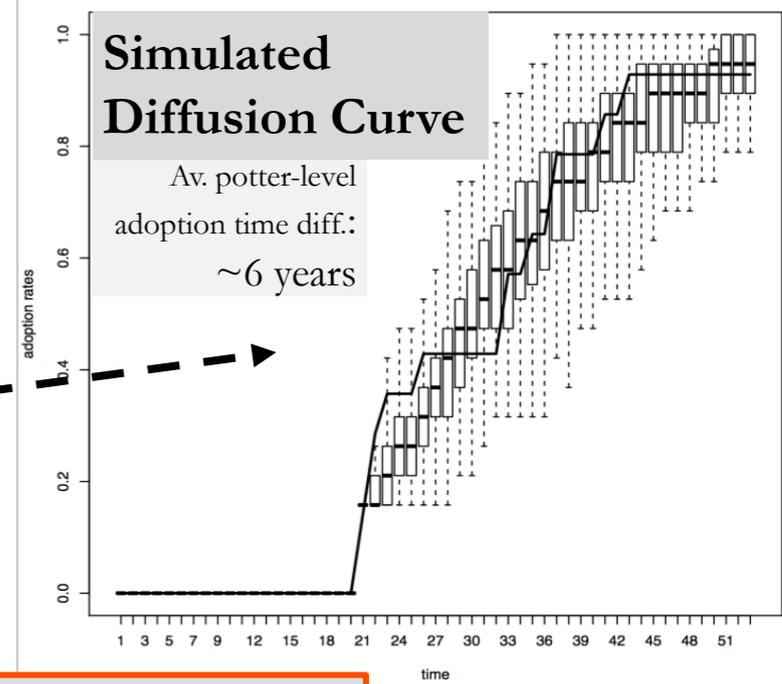
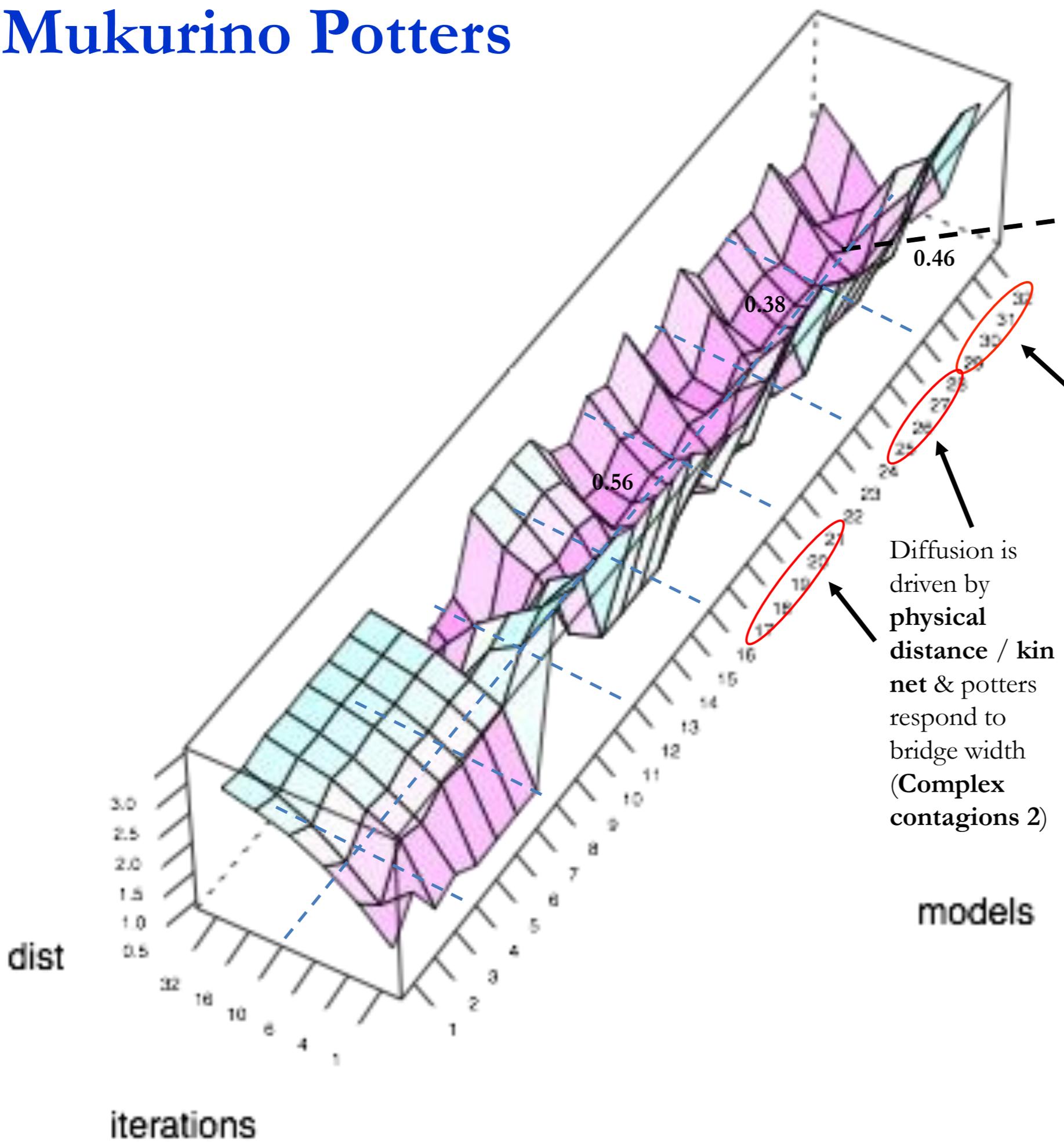
## Diffusion Networks

Density:  
Mukurinos=0.04  
Others=0.02

1. More and stronger brokers among Mukurinos
2. Longer chains among Mukurinos (1-step reachability: 50% vs 15%)
3. **More (13% vs. 9%) but narrower bridges among Mukurinos (average width: 5.04 vs 6.59)**

NB: In both communities, correspondence between diffusion and kinship ties, but BC correlation is very low for Others. This means that Others learn from potters that are not « opinion leaders » within their community.

# Mukurino Potters

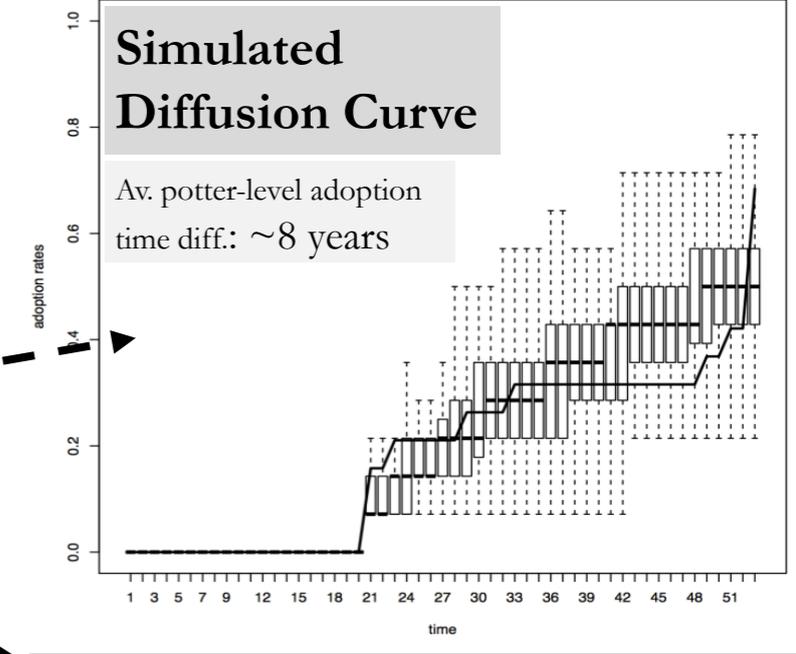
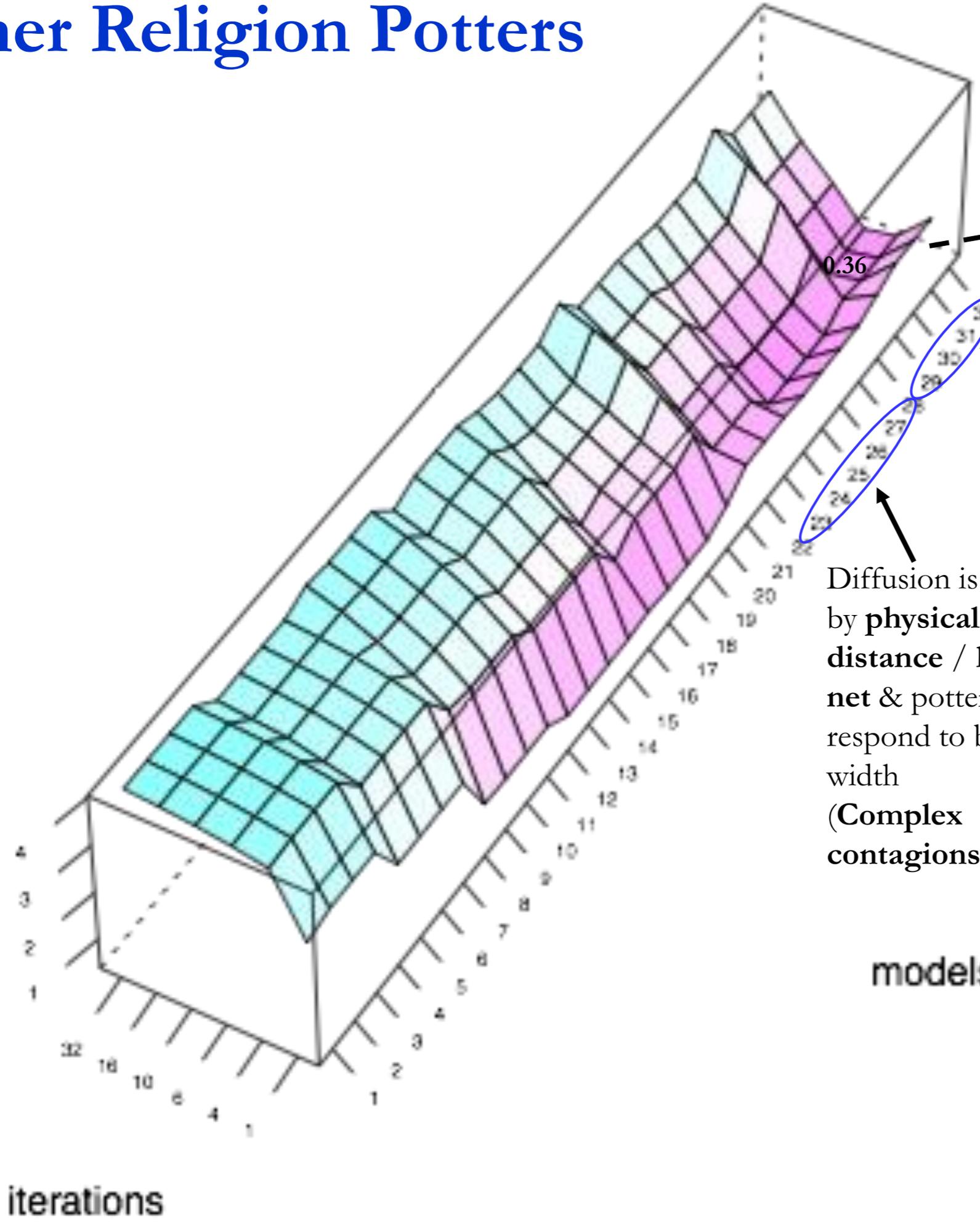


Diffusion is driven by **kin net** & potters decide as a function of neighbors' state on the bridge (**Complex contagions 3**)

Diffusion is driven by **physical distance / kin net** & potters respond to bridge width (**Complex contagions 2**)

models

# Other Religion Potters



Diffusion is driven by **physical distance / kin net** & potters respond to bridge width  
(**Complex contagions 2**)

Diffusion is driven by **kin net** & potters decide as a function of neighbors' state on the bridge  
(**Complex contagions 3**)

models

# Kenyan Case – To sup up

**Puzzle** – Larger and faster diffusion among Mukurino potters

## Empirical data

- a** – Mukurino kinship network is **more reachable** and **information go through central nodes**
- b** – Muslim kinship network is **less locally redundant** (less and narrower bridges)

## Simulation

- a** – **Structural differences alone**, plus a deterministic contagion process at the dyadic level, is not sufficient to account for the macroscopic diffusion curves
- b** – **Probabilistic reinforcement from multiple neighbors lying on local bridges** (i.e. complex contagions) are necessary (and sufficient) to generate the macroscopic diffusion curves

## Implication

**Local bridges** sustain diffusion **depending** on **other structural features** and the **level of uncertainty** about the innovation

→ Local bridges among Other-religion potters reinforce doubts (e.g.: other-religion potters did not receive a special, direct training to make flat-based pots)

# Take-Home Message

## India –Muslims

- (e) Large bridges
- (e) High Reachability
- (e) Strong Opinion leaders
- (e) Initial Positive views
  
- (s) Complex contagions

**Fast diffusion**

## India –Hindus

- Narrow bridges (e)
- Low reachability (e)
- Few opinion leaders (e)
- Initial negative views (e)
  
- Complex contagions (s)

**Slow diffusion**

## Kenya –Mukurinos

- (e) Narrow bridges
- (e) Reachability
- (e) Strong Opinion leaders
- (e) Initial Positive views
  
- (s) Complex contagions

**Fast diffusion**

## Kenya –Other-religion

- Large bridges (e)
- Low Reachability (e)
- No Opinion leaders (e)
- Negative Positive views (e)
  
- Complex contagions (s)

**Slow diffusion**

**Positive views:** e.g. "Janet

embraced the new shape because it required shorter time to make than the traditional one, it fetched more money, they were easy to carry and their demand was higher"

Local tie redundancy (bridges) is not *per se* an innovation facilitator : it only is a structural opportunity.

If **positive views** exist, and certain structural features are present, local bridges can fuel cascade of adoptions.

Otherwise, local bridges can reinforce **doubts**, and trigger cascade of non-adoptions.

**Doubts:** e.g. "Nancy finds the flat

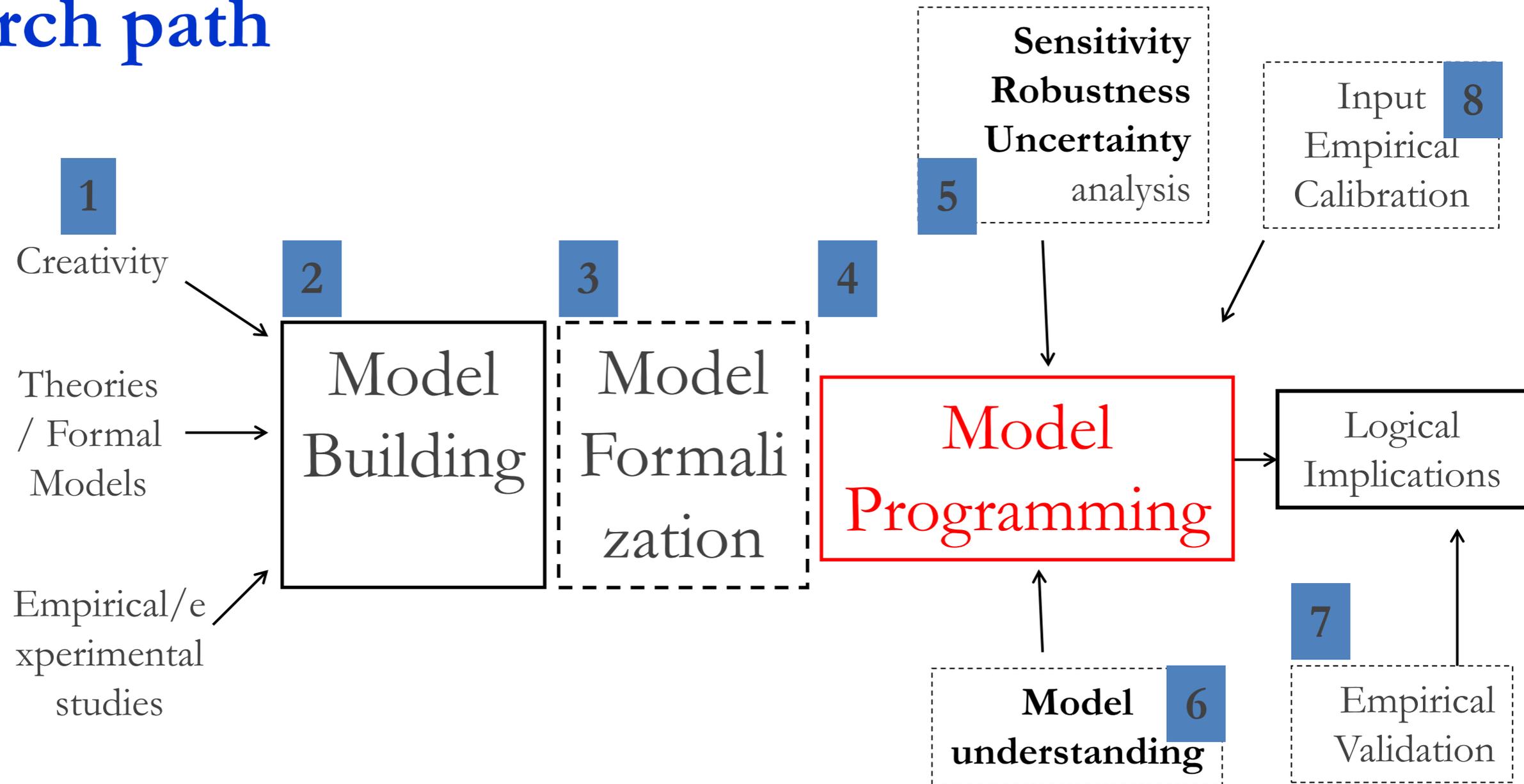
based pots very beautiful but they are not durable. They break quickly and customers complain all the time"

**Should you want to read  
more on a similar study :**

G. Manzo (2013) “Educational Choices and Social Interactions: A Formal Model and A Computational Test”, *Comparative Social Research*, 30, 47-100.

Agent-based Models of Social Dynamics:  
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# ABM Challenges –the ideal research path



Oreskes et al. (1994, 664) : ‘Fundamentally, the reason for modeling is a lack of full access, either in time or space, to the phenomena of interest’

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Thank you very  
much for your  
attention!

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*Critiques and advices are welcome...*