Agent-based modelling of social networks: two examples

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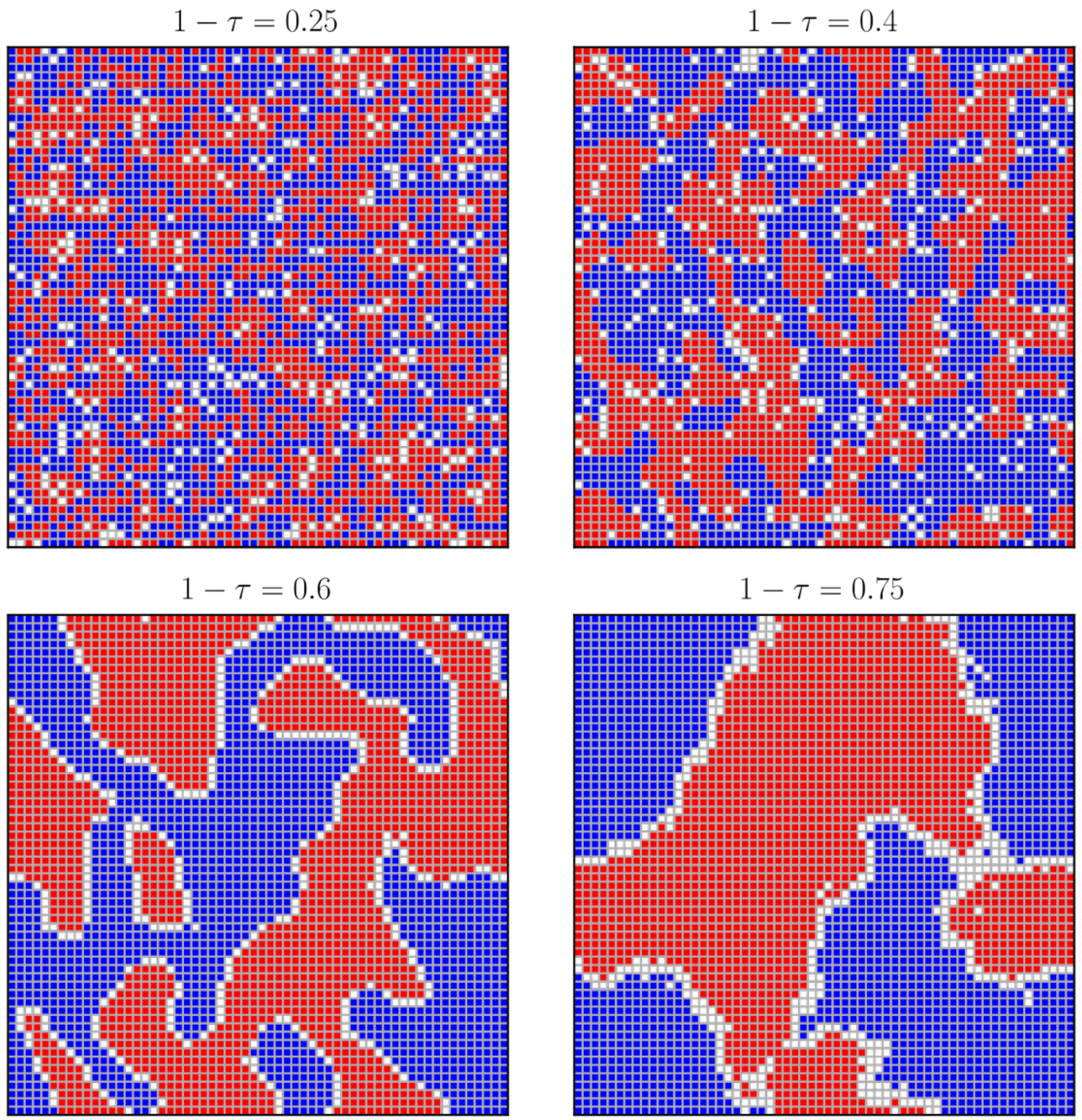
Federico Bianchi

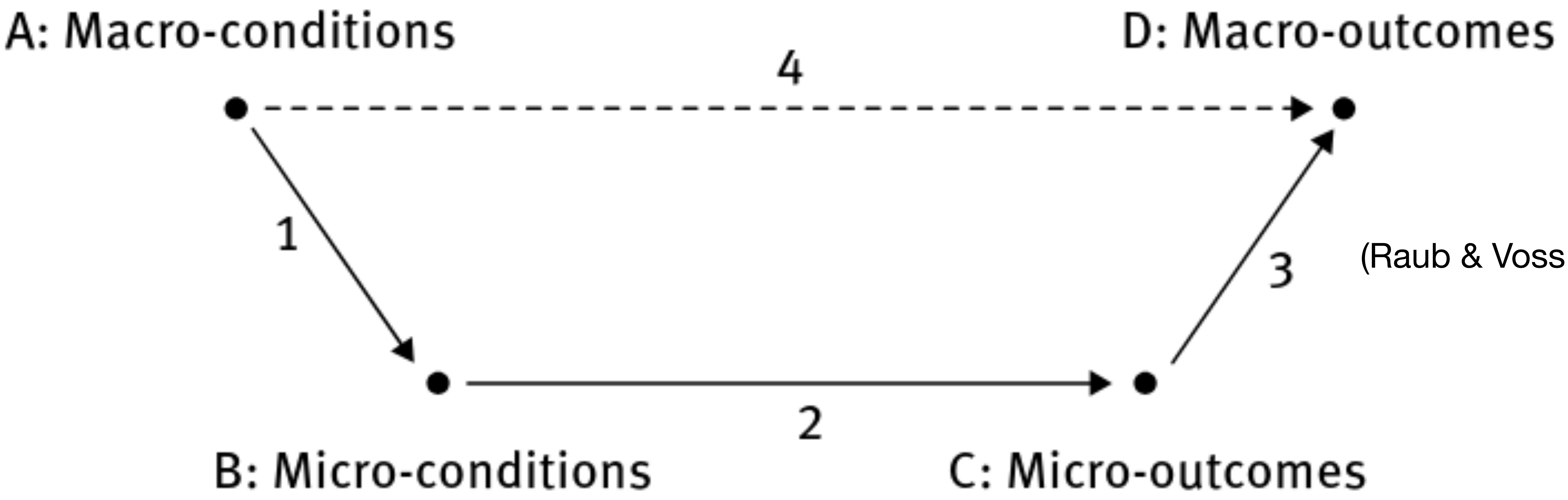
Behave Lab, Department of Social and Political Sciences, University of Milan

Agent-based models (ABM)

- **Computational, dynamic models** that formalize a population of **interdependent social actors** (i.e., *agents*) with specific **properties**, interacting according to a set of **behavioural rules** within certain **environmental constraints** (Gilbert & Troitzsch, 2005; Squazzoni, 2012; Hedström & Manzo, 2015)
- Agent-based modelling (ABM): in social scientists' toolbox since the 1990s (Macy & Willer, 2002; Bianchi & Squazzoni, 2015)
- Underused in social network research — now fit to model empirical social networks



ABMs are models of social interaction



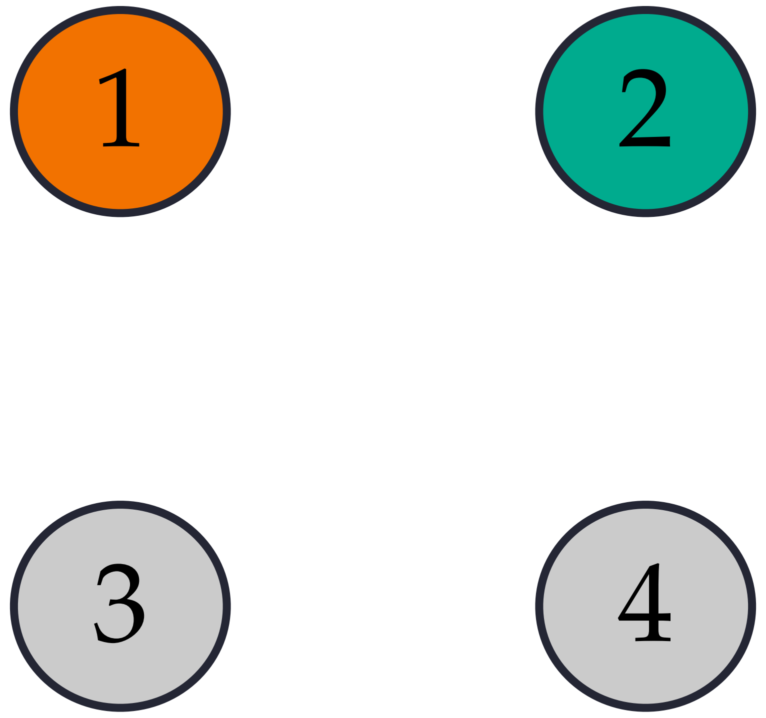
(Raub & Voss, 2017)

ABMs model social interaction between agents (B —> C) given macro-level conditions (A) and test its explanatory power of generating macro-level outcomes (D) via computer simulation

ABMs can model social networks

Time t

1 2

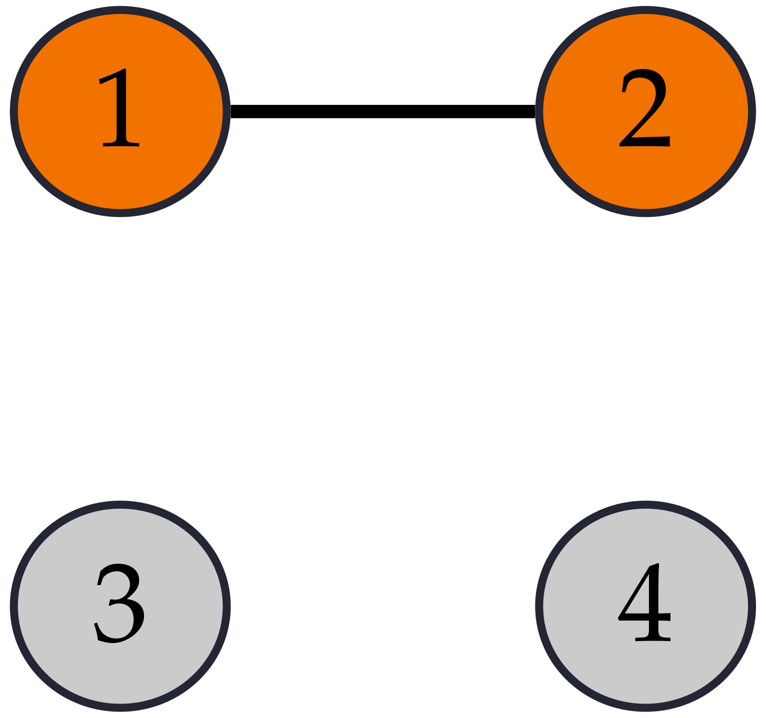


Age = 35
Gender = F
Politics = left
Neighbours = ( )

Age = 47
Gender = F
Politics = right
Neighbours = ( )

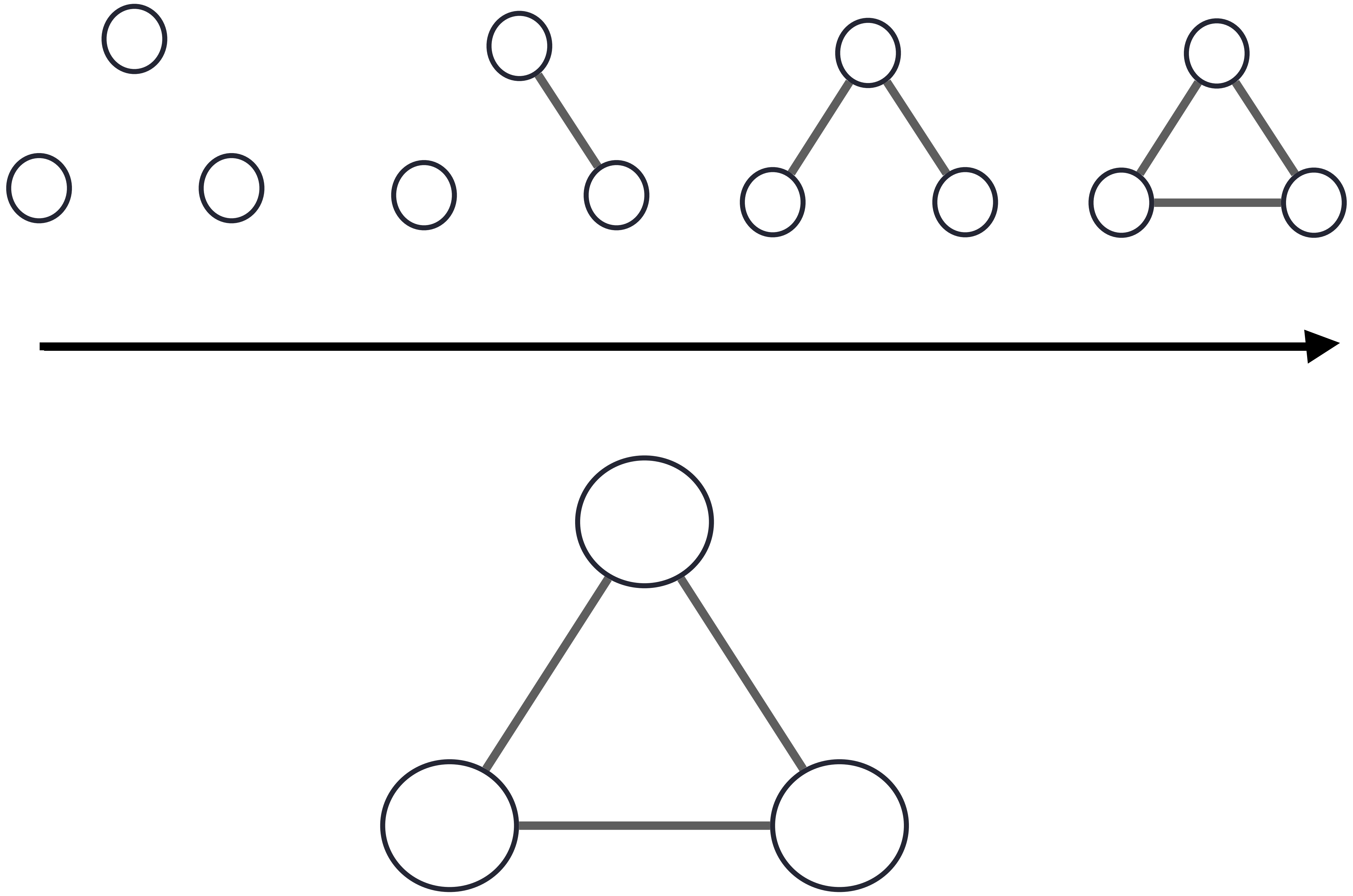
Time $t + 1$

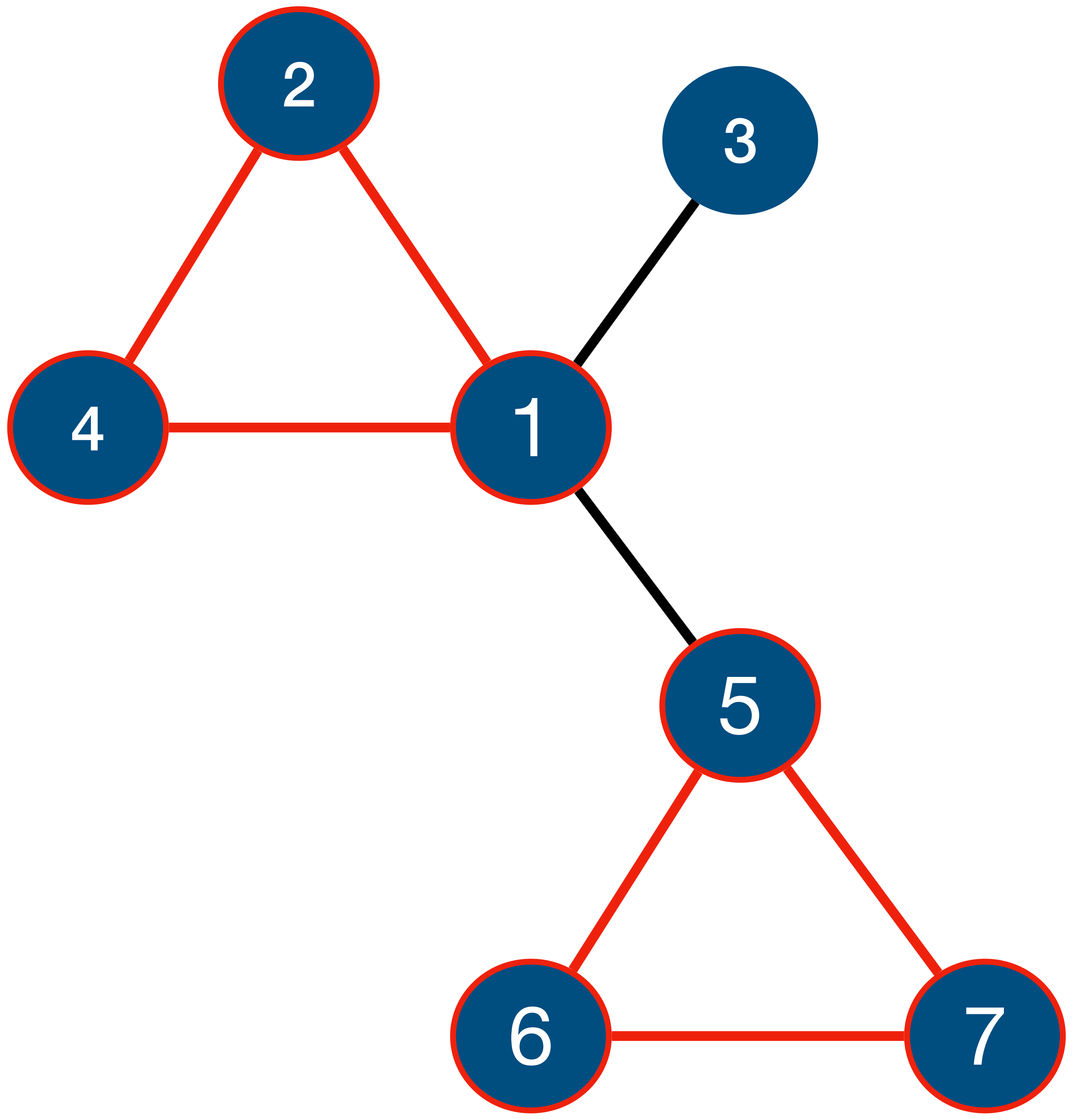
1 2



Age = 35
Gender = F
Politics = left
Neighbours = (2)

Age = 47
Gender = F
Politics = left
Neighbours = (1)





Common statistical network models

- Prevalence or incidence of the "**archeological traces**" of unobserved, past relational processes (White, 1970, 2008; Lusher et al., 2013)
- **Mathematical tractability**: sufficient statistics of local configurations + parameters estimated via robust algorithms (maximum likelihood or method of moments)

$t = 0$

1. Complying to a solidarity norm (Lindenberg, 2015)

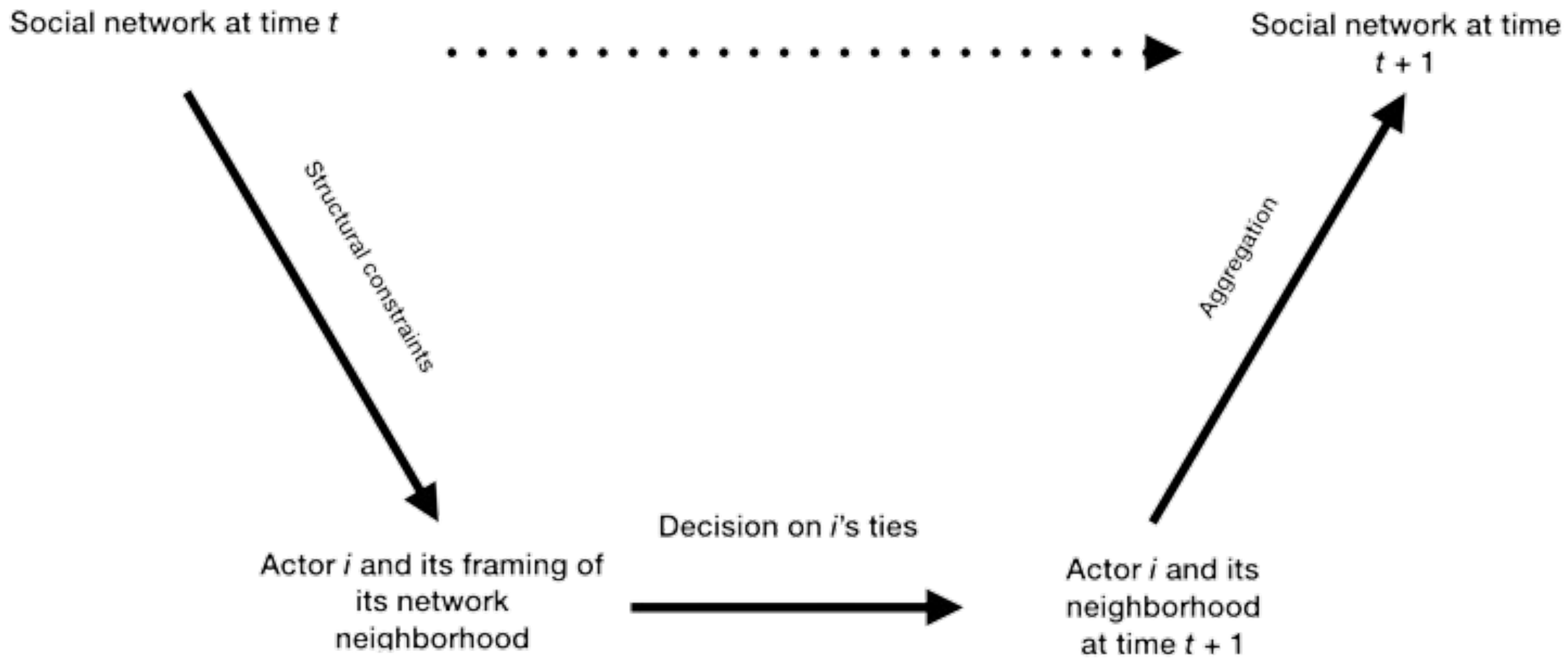
2. Strategically investing in a long-term relationship (Coleman, 1991)

3. Controlling one's reputation (Buskens & Raub, 2005)

$t = 1$

Disentangling different mechanisms underlying network patterns

- Statistical models of social networks usually provide **underdetermined evidence of causal mechanisms**
- "Network patterns" (Robins, 2015) or "network mechanisms" (Stadtfeld & Amati, 2021) underlie different possible causal mechanisms



ABMs can model mechanisms of network formation/ influence

- Identifying the **causal mechanisms** of social network evolution
- Patterns of **social actors' inter(actions)** bringing about regular network structures or compositions
  - **Motives** behind decisions (goals or preferences)
  - **Context framing** (cognition and culture; Fuhse & Gondal, 2024)
  - **Types of ties** (events or states; Borgatti et al., 2009)

Real mechanism
- Actors
- Actors' properties
- Actors' (inter)actions
- Actors' relationships

➡

Agent-based model
- Agents
- Agents' attributes
- Agents' rules of behaviour
- Agents' structural constraints

- "**Structural homology**" with causal mechanisms (Manzo, 2014):
    - **Cognitive** or **cultural** constituents of actors' decisions
    - Social **interactions**
    - **Institutional**, **relational**, or **spatial** constraints
- High **flexibility** —> wide **granularity** range of agent modelling (Wooldridge & Jennings, 1995)
    - **Social** characteristics: autonomy, interdependence, embeddedness, heterogeneity
    - **Cognitive** characteristics: reactivity, proactivity, heuristic-based rationality, adaptiveness

ABM:

flexibility and granularity

Building on shifting sands: Complex contagion and negative ties hinder malaria outdoor preventive measure adoption in a hard-to-reach population in Meghalaya, India

Federico Bianchi*, Elisa Bellotti**, Francesco Renzini*, …, Sara Albert***

* Behave Lab, Department of Social and Political Sciences, University of Milan, Italy
** Mitchell Centre for Social Network Analysis and Department of Sociology, University of Manchester, UK
*** Indian Institute of Public Health in Shillong, India

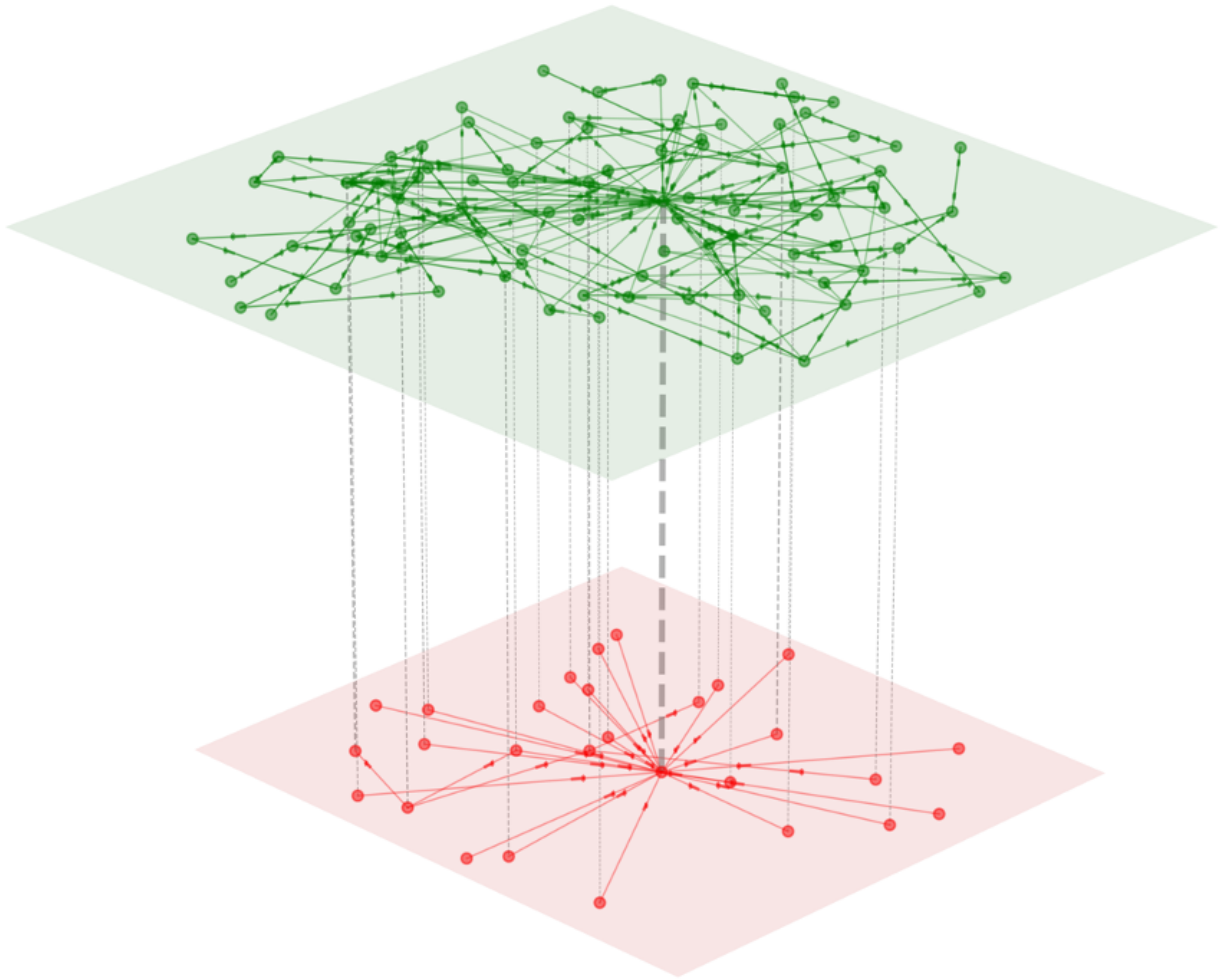
Low adoption of malaria preventive measures in hard-to-reach populations

- **Malaria** is still to be fully eradicated: Epicenters are often located among **hard-to-reach populations** in the Global South
- Geographical marginalization + low socio-economic status —> poor access to health care
- resistance to instituzionaled health practices (cultural/religious beliefs) despite top-down policy —> **low adoption rate of key preventive measures**
- **Meghalaya (North-Eastern India)**: mountainous area with patches of tropical forest - **Tribal population** (Garo and Khasi-Jaintia) —> **lack of fine-grained data**

Data

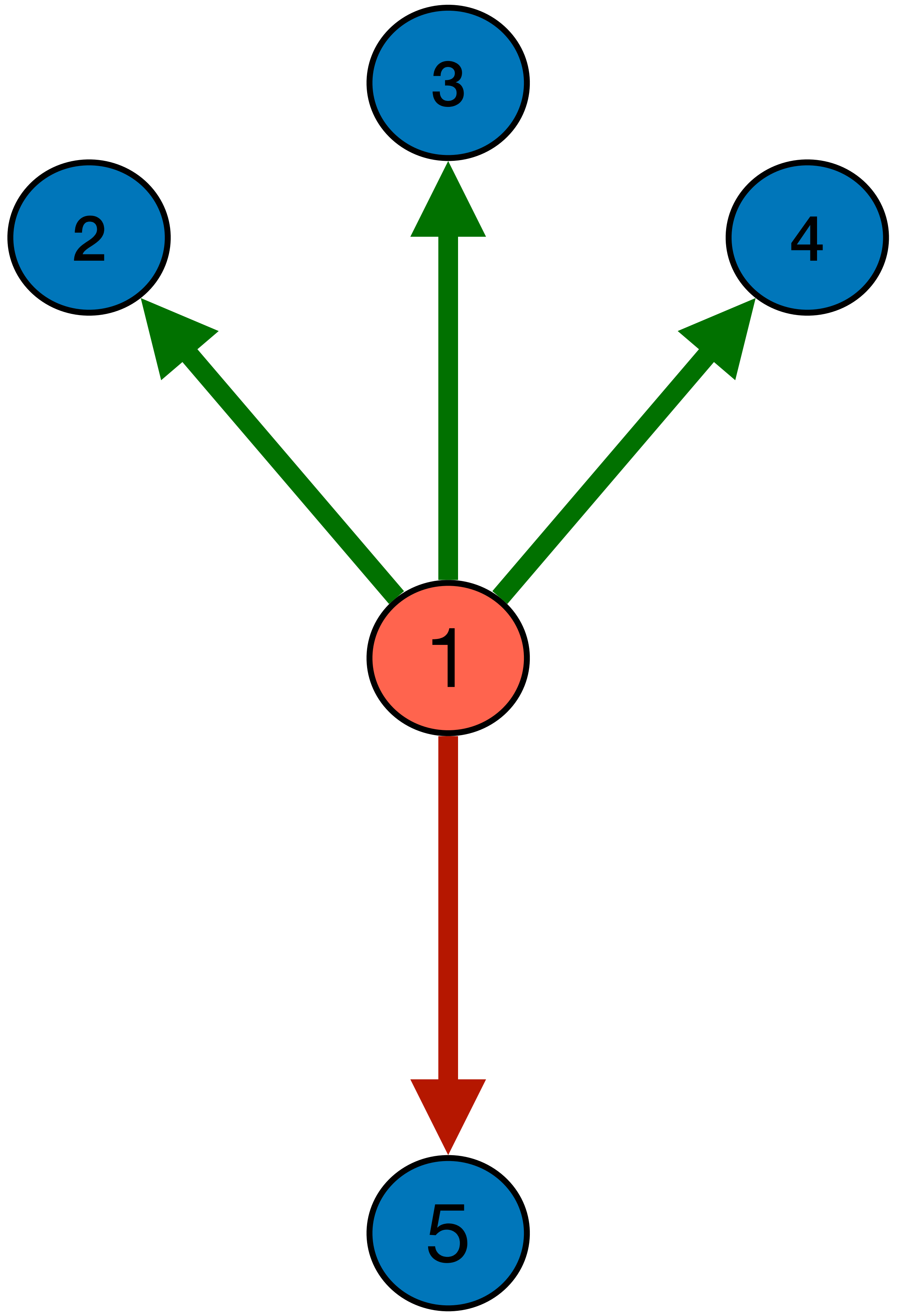
- Data collection: 2020-2021 face-to-face questionnaire administration
- Network data:
    - **Positive ties**: Who do you talk to about health?
    - **Negative ties**: Who do you avoid talking to about health?
- Individual data: **Cream use** (yes/no)

- **cream adoption rate = 14.96%**
- # individuals (nodes) = 98
- # positive ties = 272
- avg. degree (positive ties) = 2.78
- # negative ties = 27
- avg. degree (negative ties) = 0.28



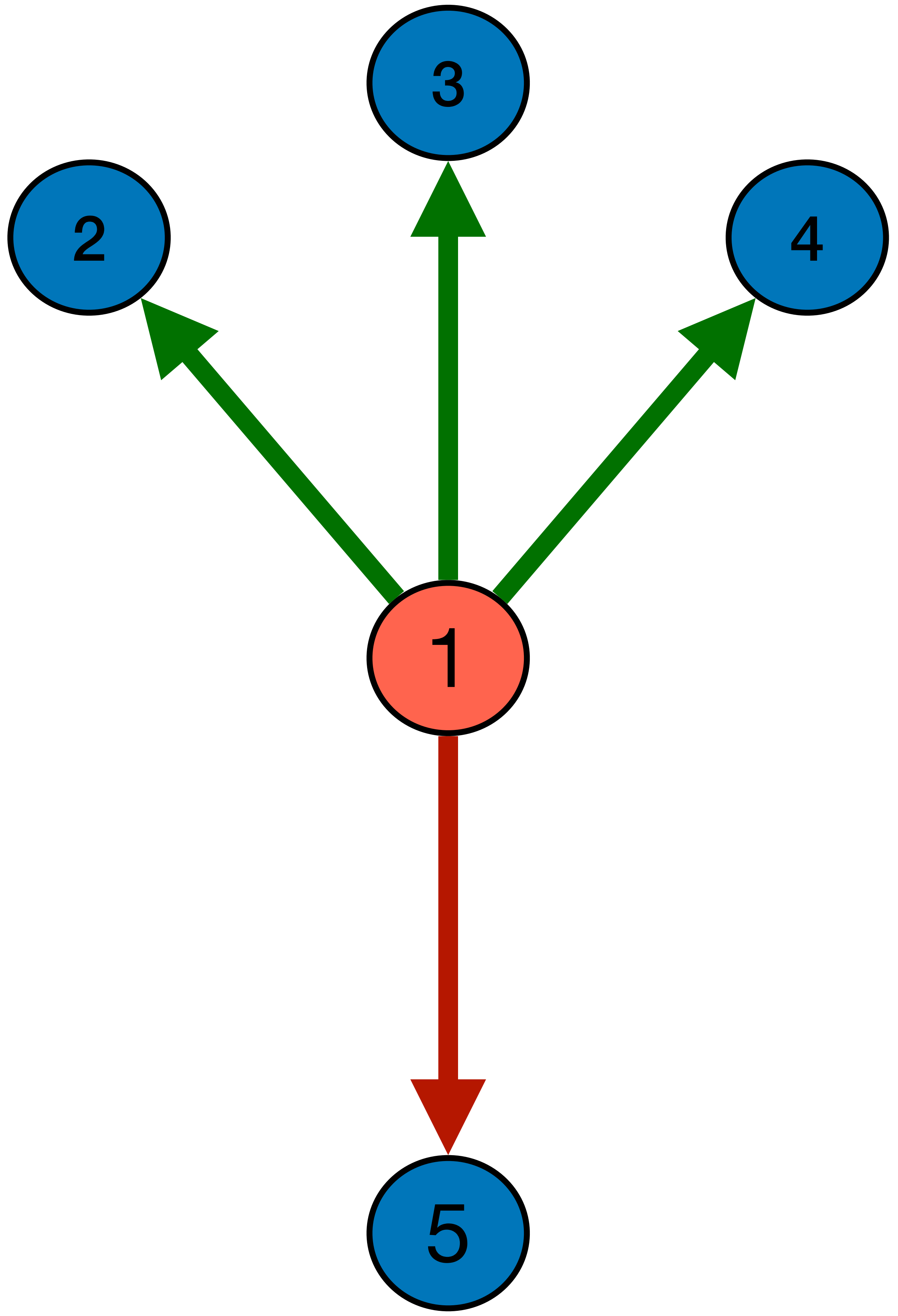
Complex contagion + negative influence

- Obstacles to preventive measure (**insecticidal cream**) **adoption**:
  - stigmatized (misalignment with traditional health culture)
  - easily observable behaviour
  - small, tight community (tribal villages)
- **Dual-side diffusion mechanism**:
  - **Complex (threshold-based) contagion**: strong reinforcement from **adoption** by **positive ties** (Centola & Macy, 2007)
  - **Negative influence**: **adoption** by **negative contacts**
- Assuming **idiosyncratic** case characteristics:
  - positive impact of within-household adoption (fixed effect)
  - Positive tie with ASHA (Accredited Social Health Activist) increases propensity to use
  - Positive tie with traditional healer decreases propensity to use

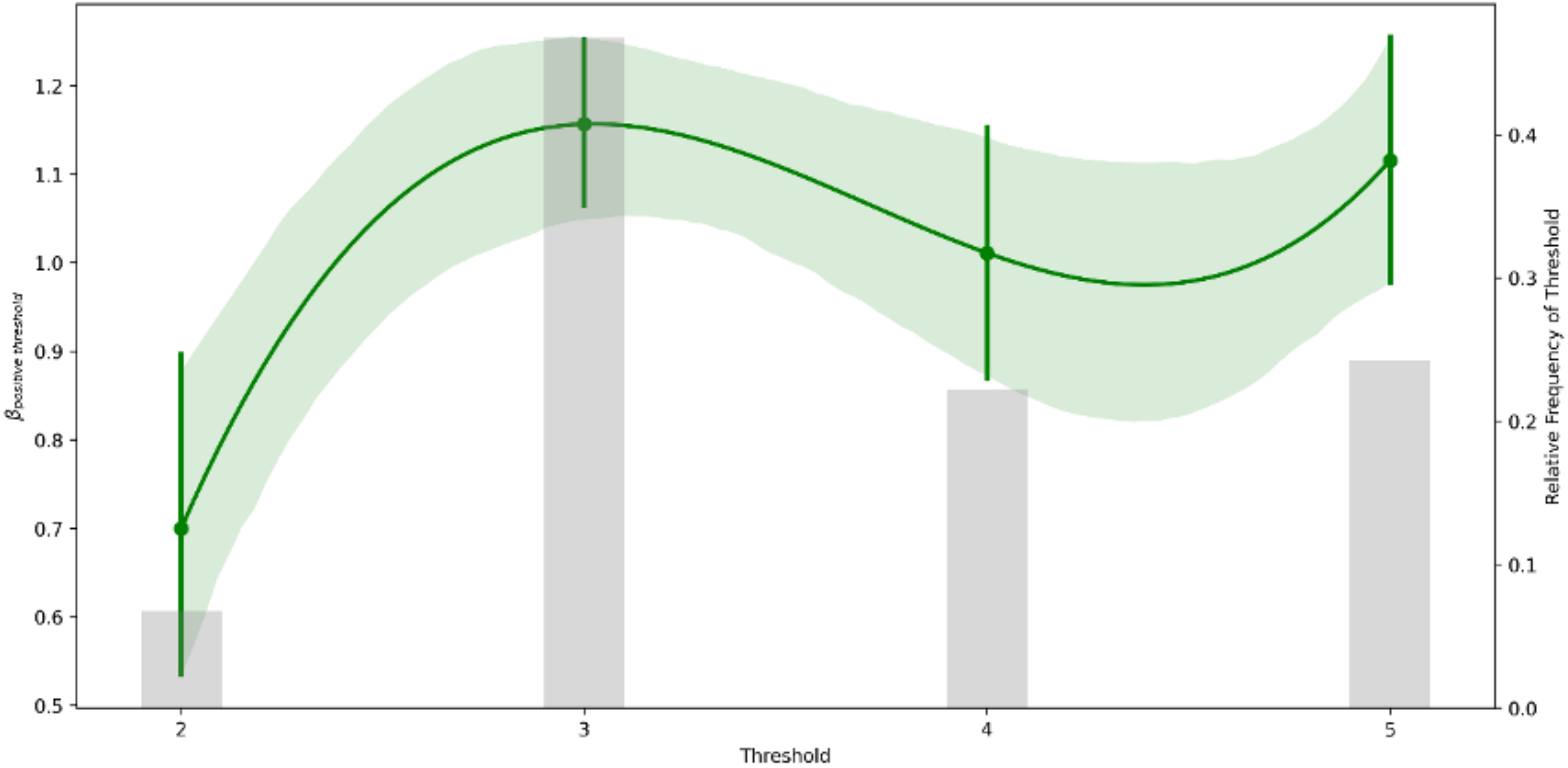


ABM of complex contagion + negative influence

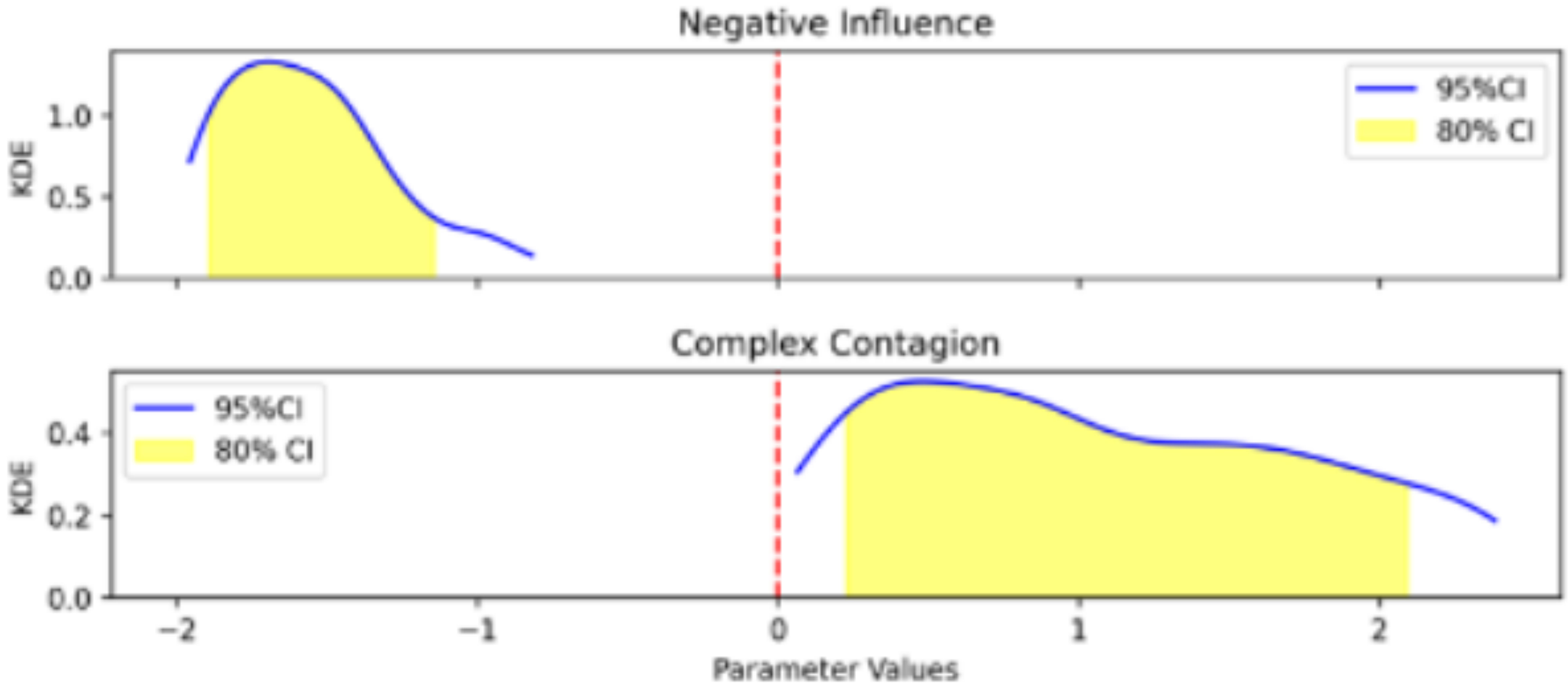
- **ABM of the diffusion** process in the empirically-observed networks (Bianchi & Renzini, *forthcoming*)
- Model of villagers' **cream use** as a binary-choice model (Mc Fadden, 1978): **logistic objective function** of personal networks' composition
- **Estimating**:
  - **threshold levels** for cream use contagion
  - impact of threshold-based **positive influence**
  - impact of **negative influence** (= adoption by one negative contact)
- **Assuming:**
  - positive impact of within-household adoption (fixed effect)
  - ASHA and traditional healers as stubborn agents



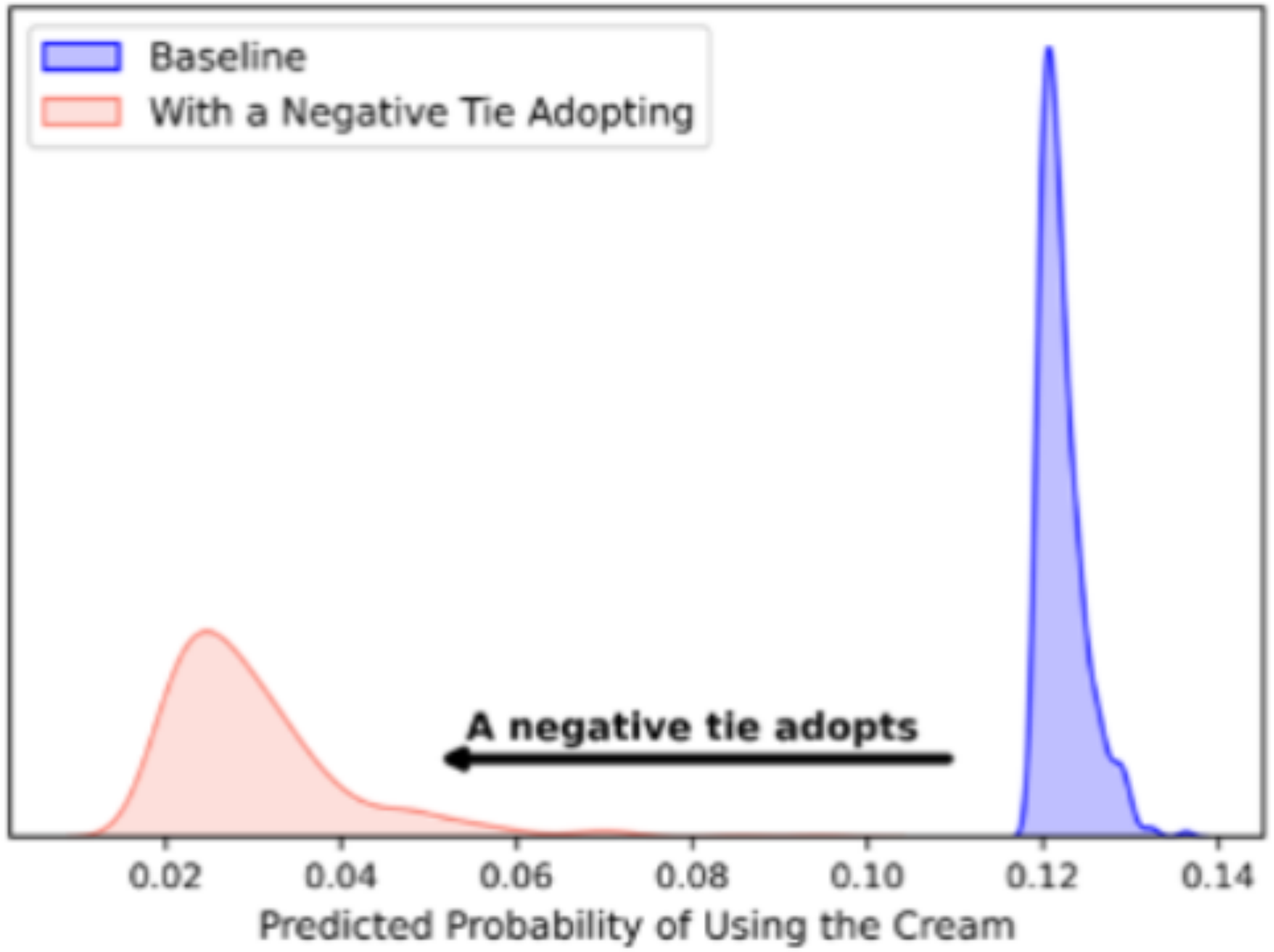
Estimated threshold

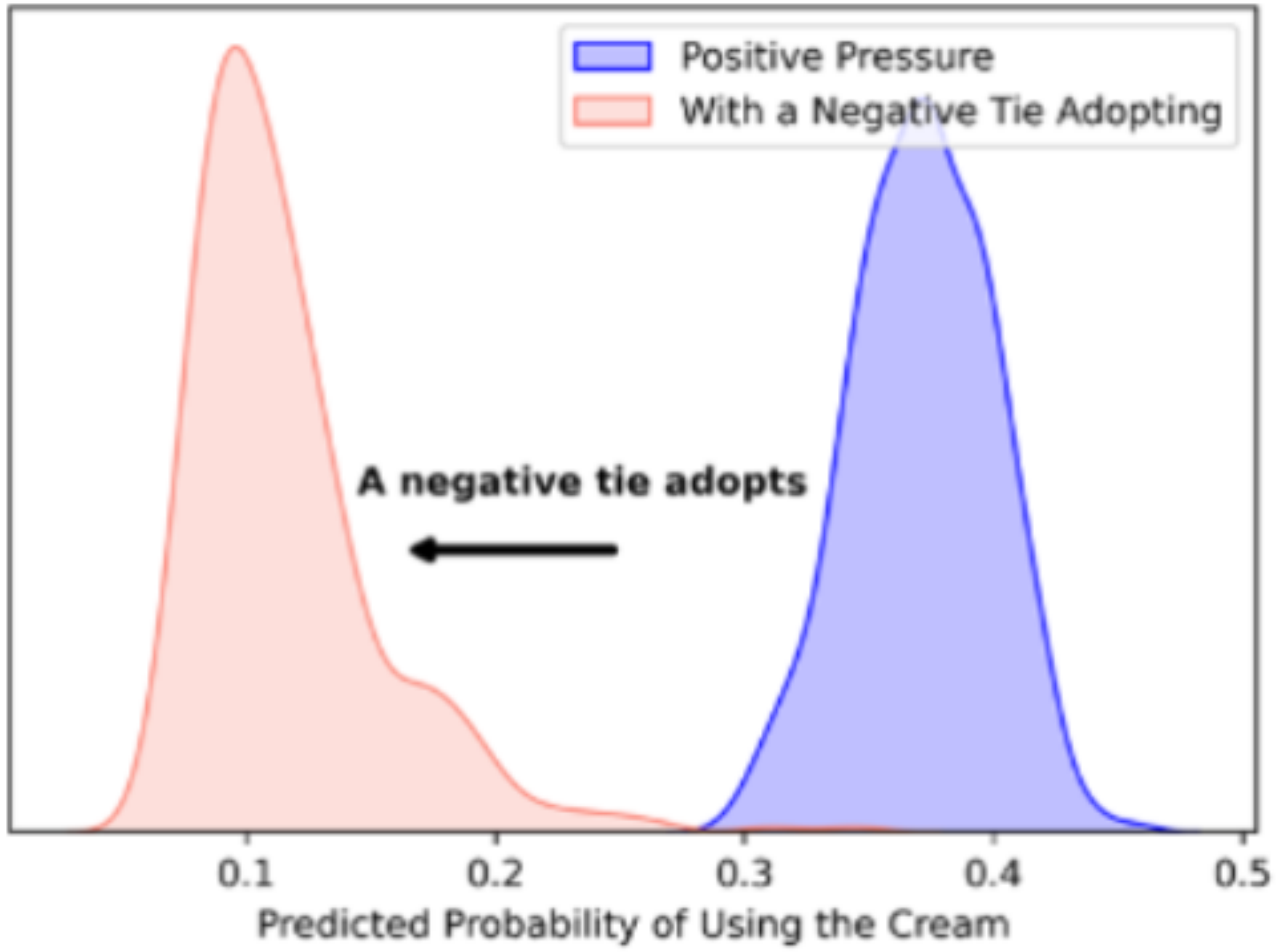


Impact of diffusion mechanism



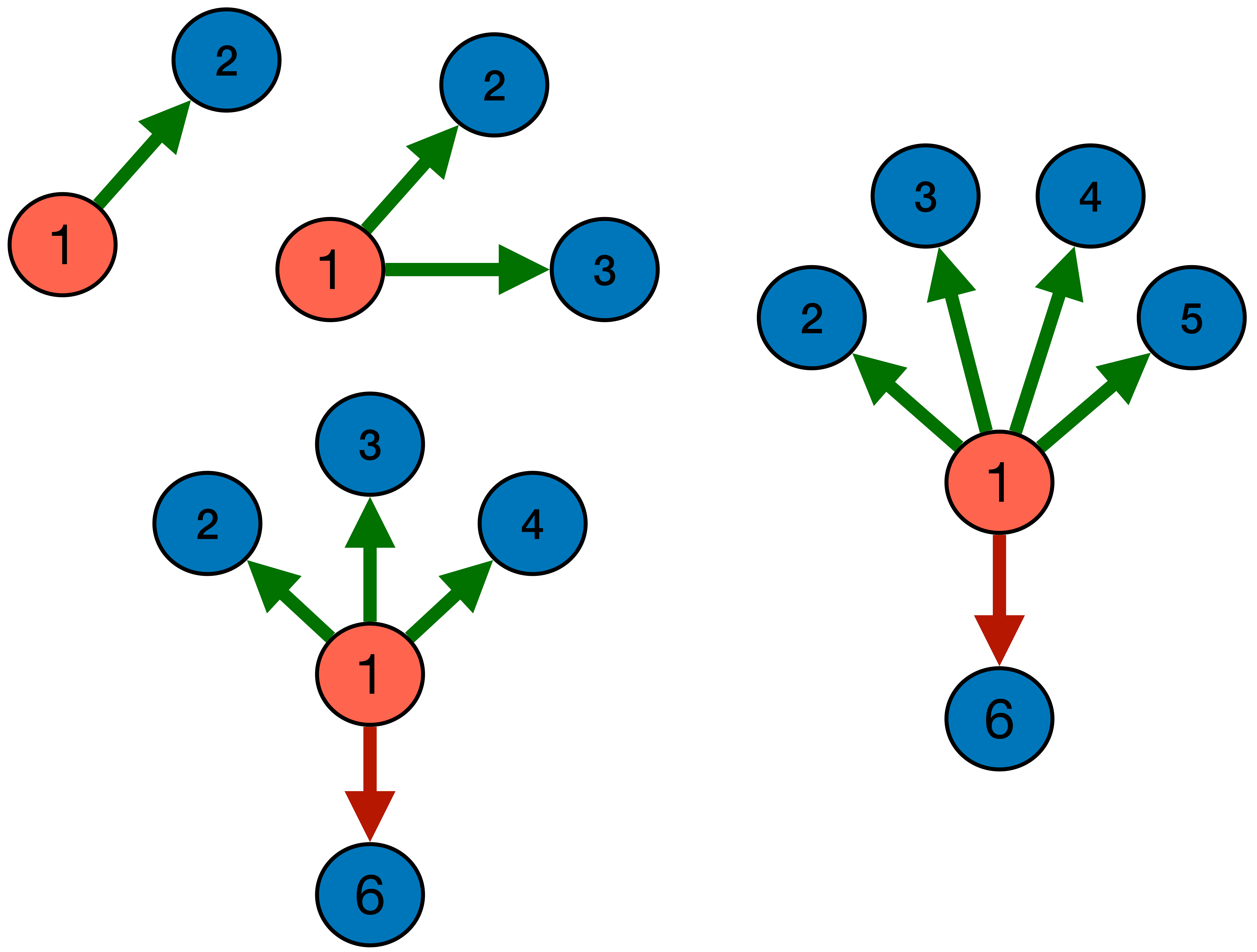
Impact of diffusion mechanism



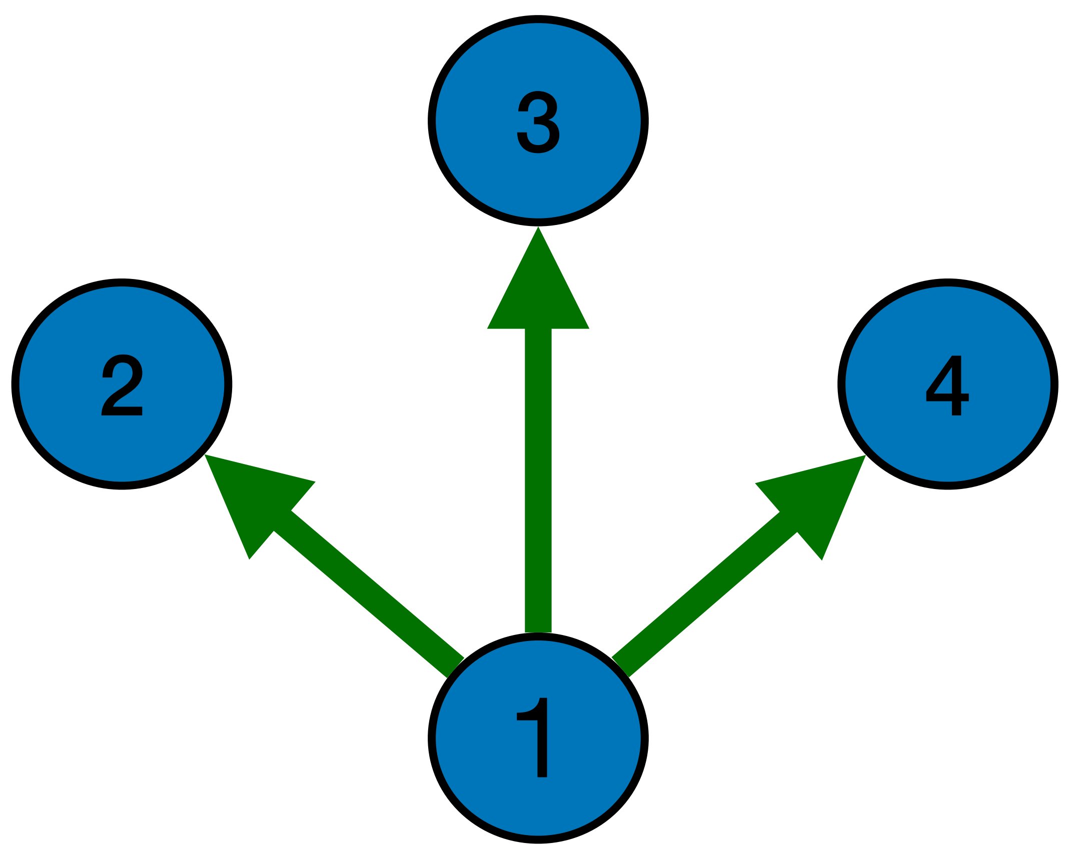


Building on shifting sands

No adoption



Adoption

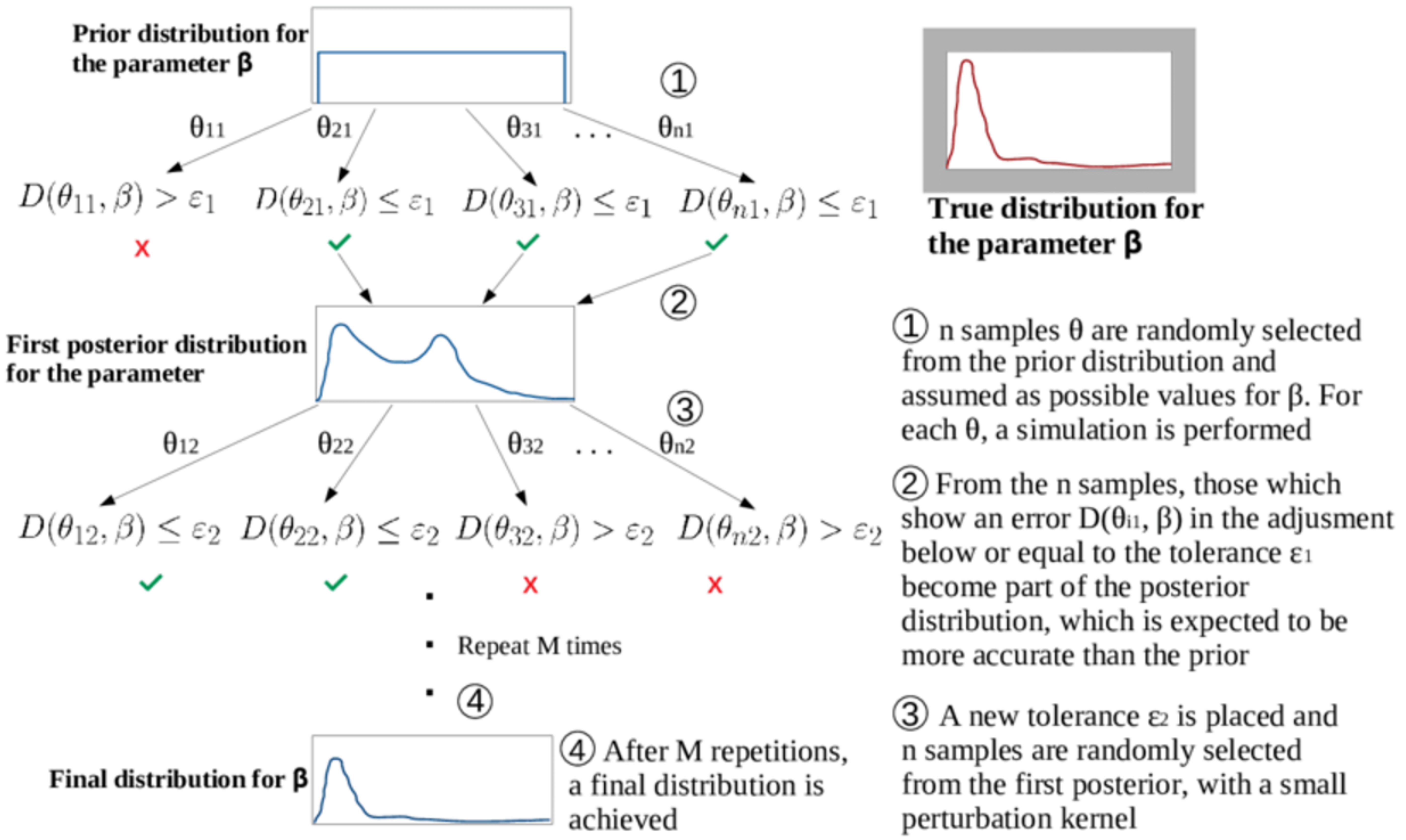


Estimation method

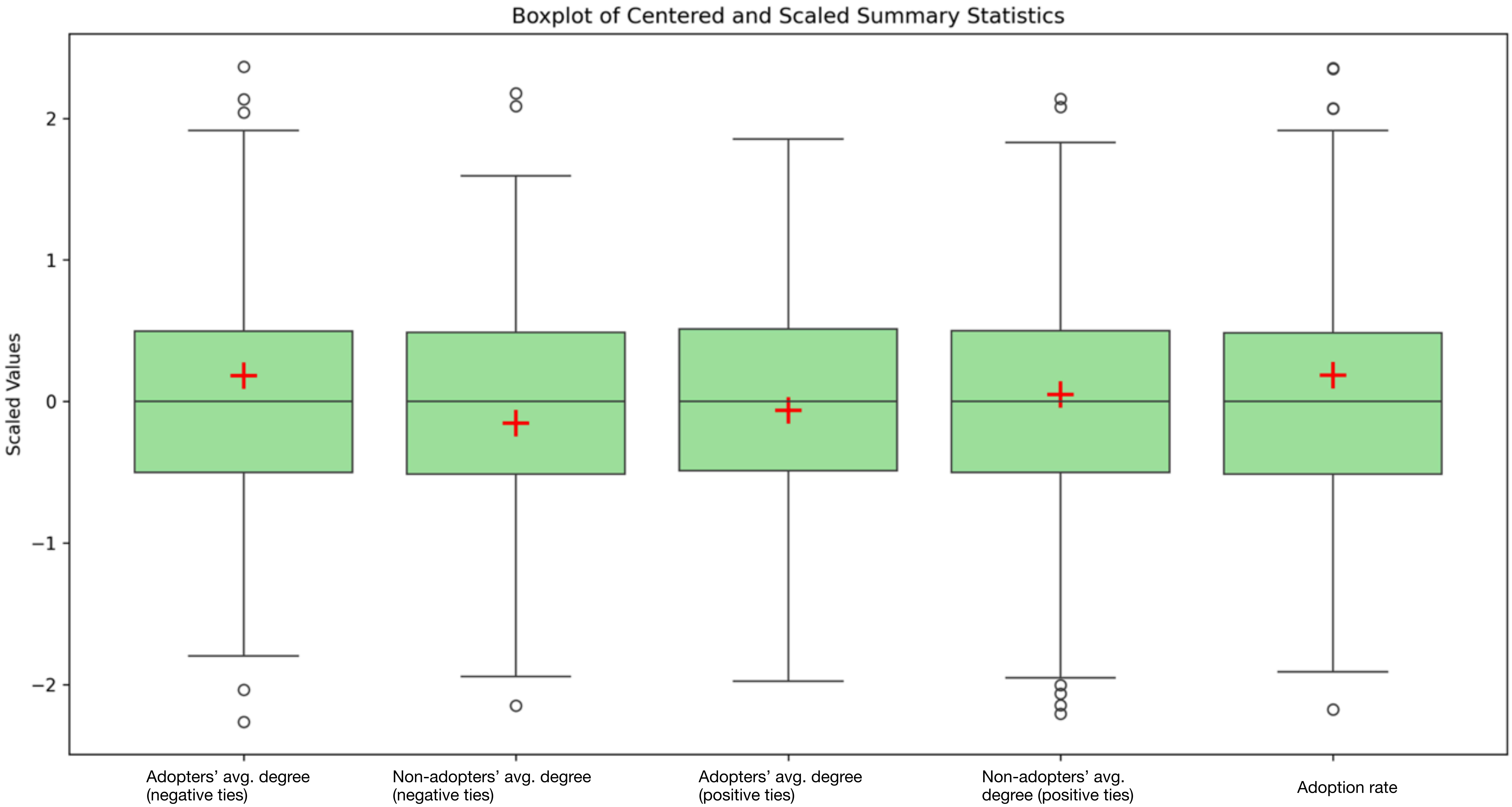
Approximate Bayesian Computation (Hartig et al., 2011)

Weakly informative priors (tested with predictive checks)

- Baseline: uniform [-3, 0]
- Threshold: {2, 3, 4, 5}
- Positive influence: uniform [0, 2.5]
- Negative influence: uniform [-2, 0]



Model fit



0.05 0.06 2.39 2.42 14.96%

Conclusions - Example 1

- Adoption of collectively beneficial, yet stigmatized behaviour might be hindered by a combination of two pulling forces in one's personal network:
  - Need for **strong reinforcement** (high threshold-based **prevalence** of the behaviour among trusted people)
  - High sensitivity to **negative influence**
- **Difficult to estimate threshold values with no ABM**

Between solidarity and expediency: Uncovering framing-based mechanisms of prosocial behaviour through an empirical agent-based model

Federico Bianchi & Francesco Renzini
Behave Lab, Department of Social and Political Sciences, University of Milan, Italy

Prosocial behaviour and framing

- Prosocial behaviour is driven by a mix of **instrumental expediency** and **normative** compliance with **solidaristic** obligations towards others (Simpson & Willer, 2015), which are **time-varying** and **context-dependent** (Lindenberg, 1998, 2006; Kroneberg, 2014; Esser & Kroneberg, 2015) according to actors' **framing of the relationship as solidary or instrumental** (Fiske, 1991)
- *Ego*'s framing of their relationship with *alter* may vary over time as a **macro-micro feedback** of certain contextual features, such as the connectivity of the wider social network (Marwell et al., 1988; Coleman, 1988, 1991)
- Advice-seeking networks are usually found to be driven by direct reciprocation and transitive closure (e.g., Agneessens & Wittek, 2012)

One relational process - two different mechanisms

$t = 0$

1. Complying to a solidarity norm (Lindenberg, 2015)

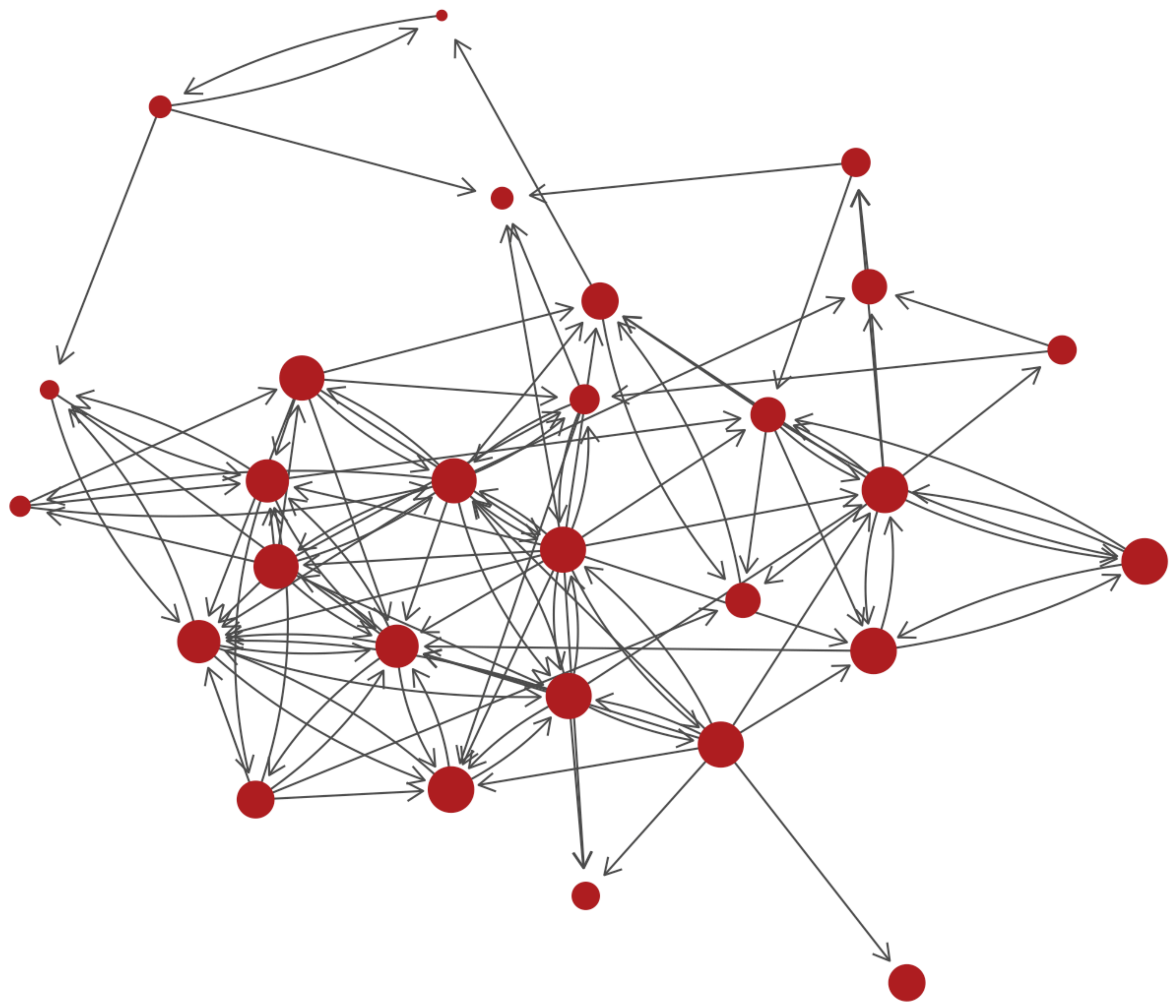
2. Strategically investing in a long-term relationship (Coleman, 1991)

$t = 1$

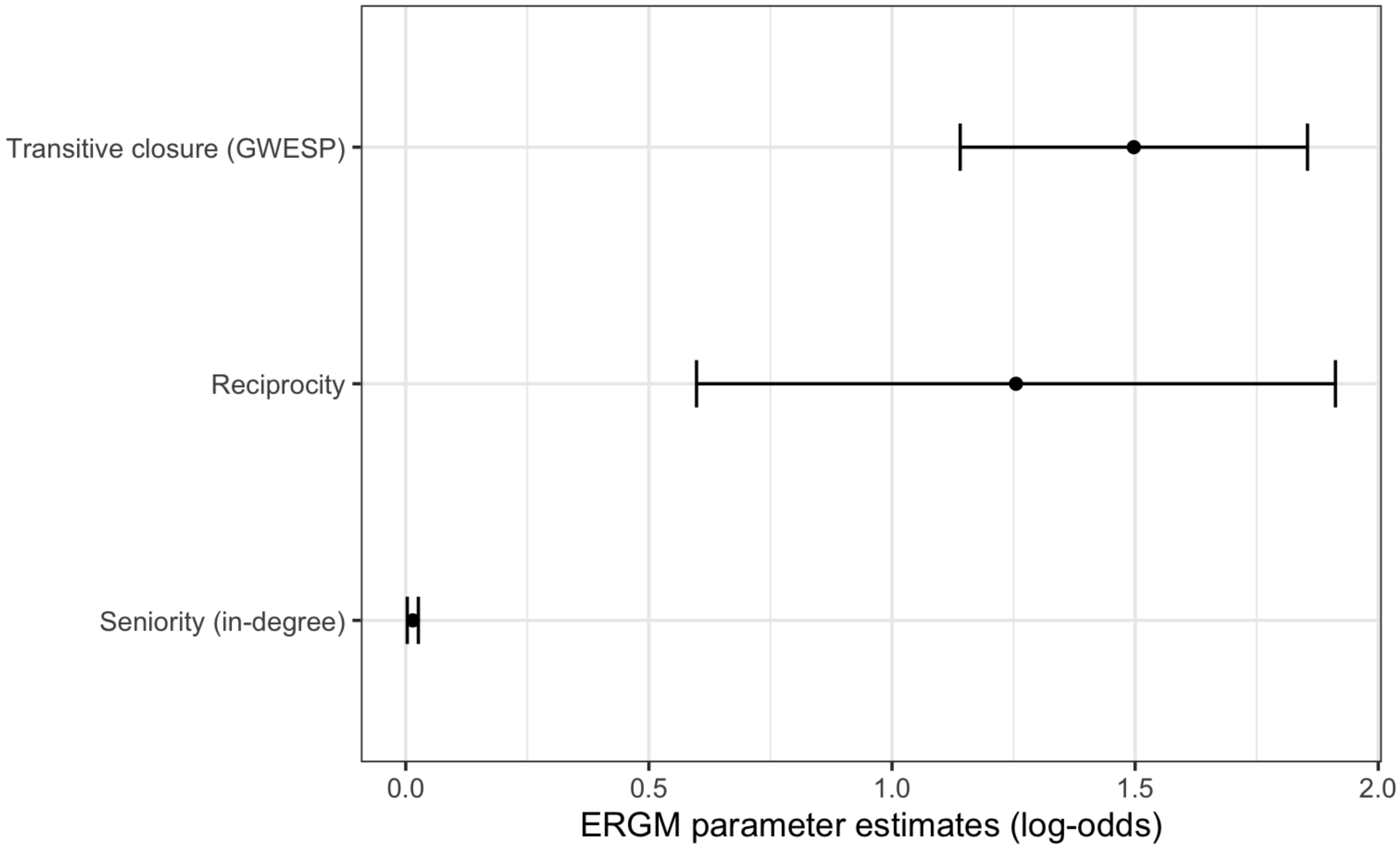
Data

- **Data collection**: 2016 face-to-face questionnaire administration
- **Context**: freelance workers sharing a coworking space in Brescia, Italy (no shared collective identity, frequent business collaborations —> see Bianchi et al., 2018)
- **Advice giving**: Who do you usually turn to for advice? (Reversed edges)
- Individual attributes: **seniority**

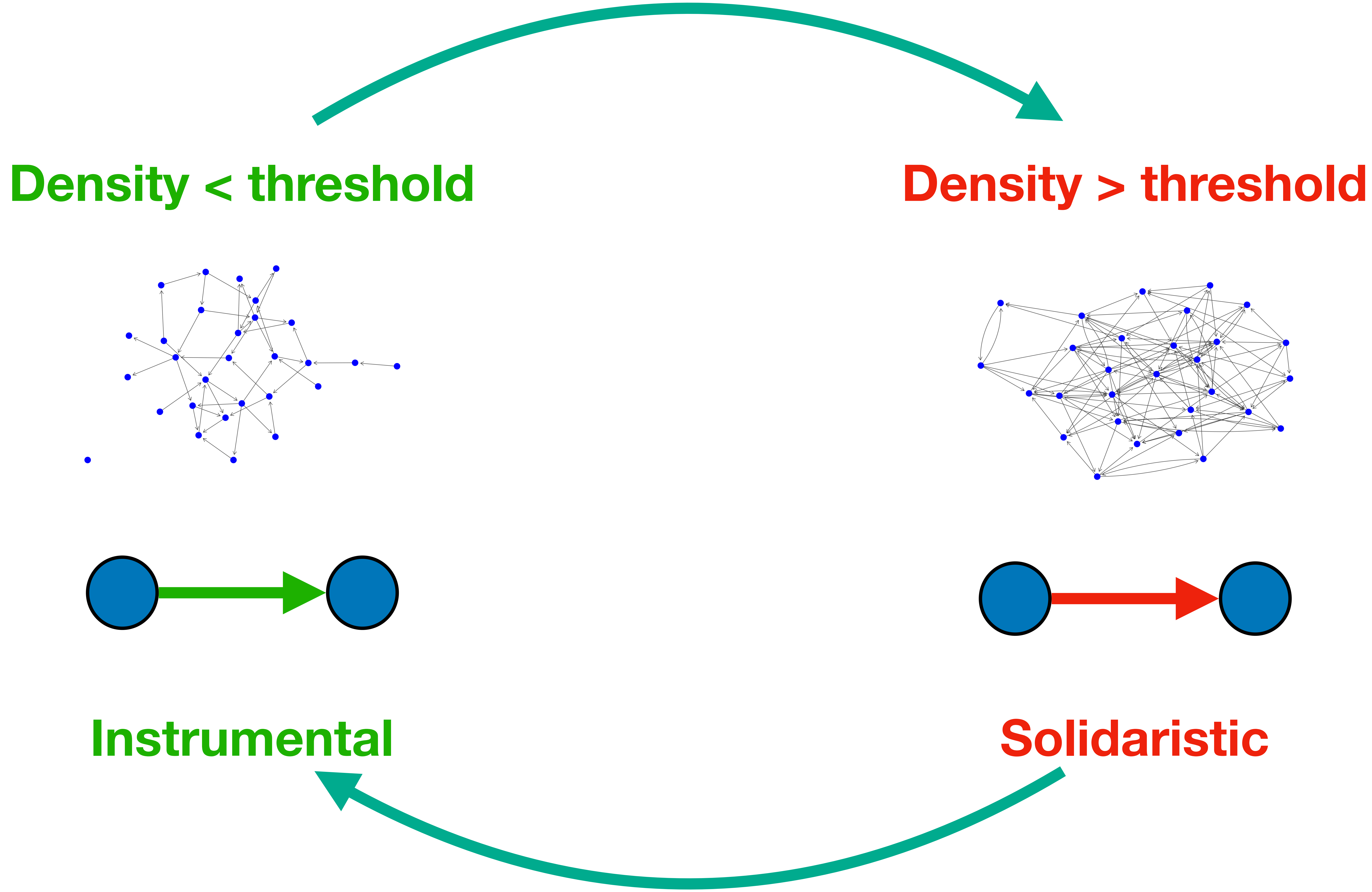
- # individuals (nodes) = 29
- # ties = 120
- density = 0.15
- avg. degree = 4.10 (SD = 3.57)
- avg. seniority (months) = 29.34 (SD 14.26)



Evidence of reciprocation - what mechanism?



Frame switching



Instrumental framing

IF

High salience of costs: *Ego* will help (costly transfer of resources) *alter* ($x_{ij} = 1$) if perceived costs (i.e., # of currently helped people) do not exceed a certain individual threshold

$$c_{i,t} \leq \tau_i, \quad \tau_i = \text{max outdegree}_i$$

AND

Conditional cooperation: *Ego* does not help an *alter* who belongs to *ego*'s "black books" (i.e., *alter* has refusde to help *ego* in the past) (*shadow of the future*: Axelrod, 1984; *credit slip theory*: Coleman, 1991)

$$j \notin B_{i,t}$$

THEN

$$\rightarrow x_{ij} = 1$$

Solidaristic framing

IF

Low salience of costs: *Ego* will help (costly transfer of resources) *alter* ($x_{ij} = 1$) if perceived costs (i.e., # of currently helped people) do not exceed a certain individual threshold

$c_{i,t} \leq \boxed{s_i \cdot} \tau_i, \quad \tau_i = \text{max outdegree}_i$

AND

Sanction of opportunism: *Ego* does not help an *alter* who belongs to *ego*'s "black books" (i.e., *alter* has refused to help *ego* in the past) (*shadow of the future*: Axelrod, 1984; *credit slip theory*: Coleman, 1991)

$j \notin B_{i,t}$

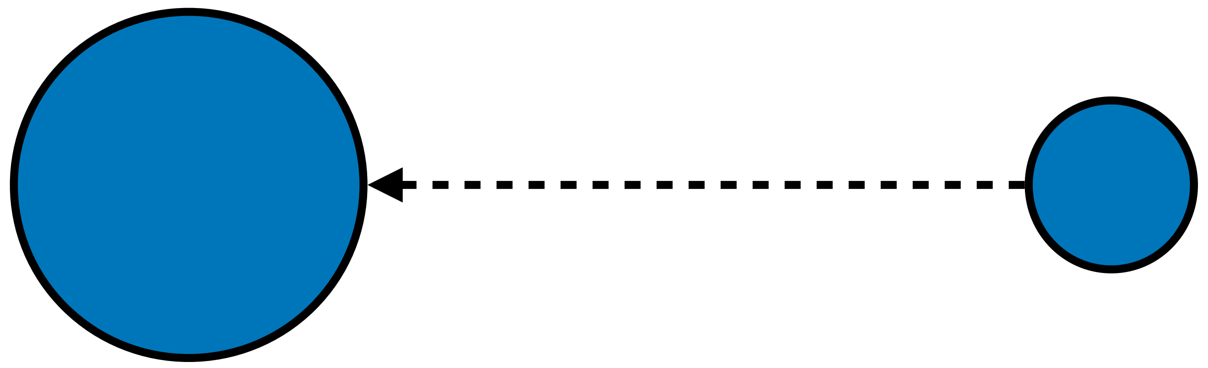
THEN

$\rightarrow x_{ij} = 1$

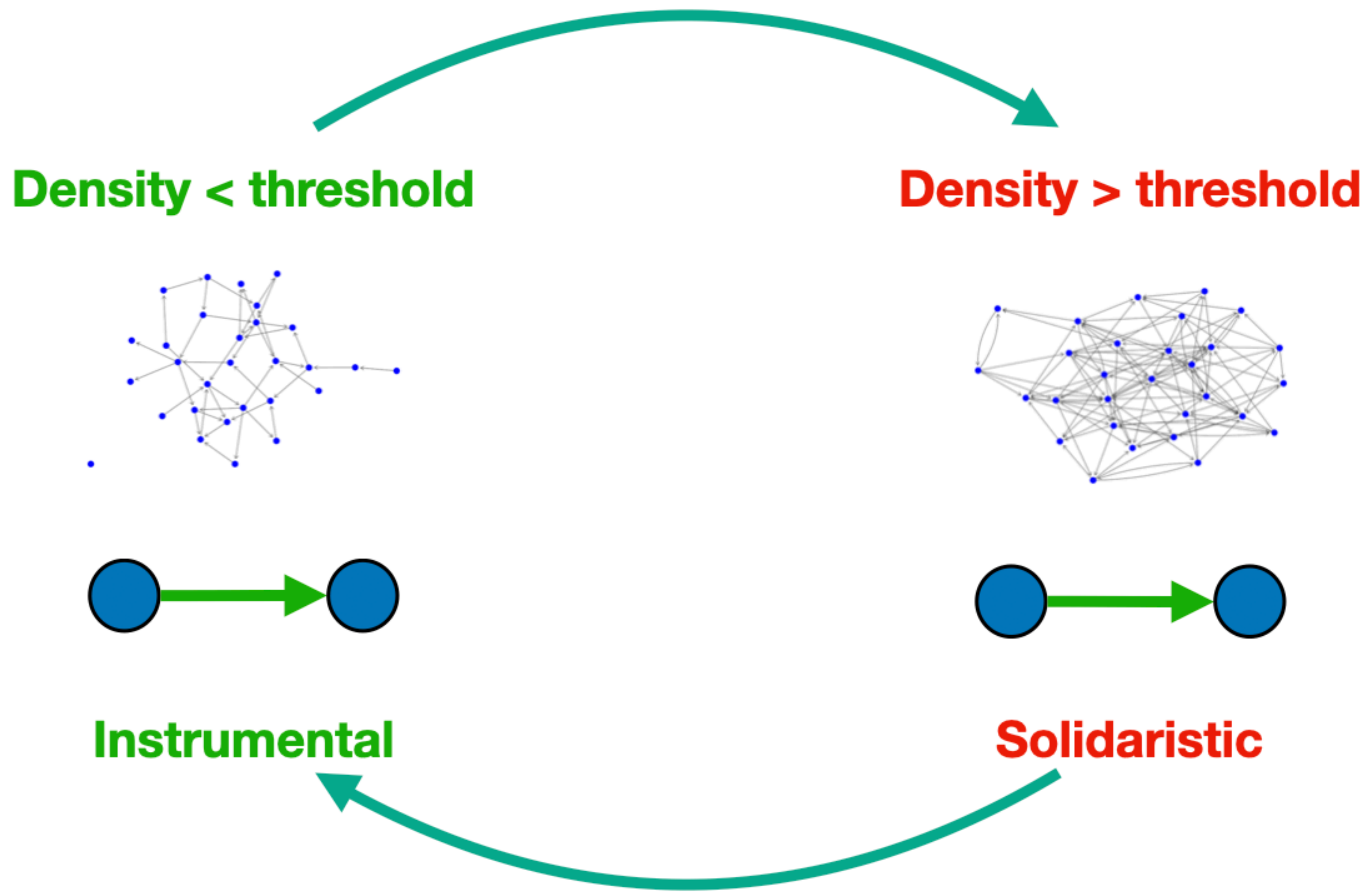
Agent-based model of network formation

- ABM of the network formation (Bianchi, 2023; Bianchi & Renzini, *forthcoming*)
- **Model** of coworkers' advice exchange:
  - **Selection**: *ego*'s probability of **being asked** for advice by *alter* as a function of *ego*'s seniority
  - **Exchange**: *ego* sends an advice tie to *alter* according to their framing of the relationship
- **Estimating**:
  - **Change in cost perception**
  - Density threshold for frame switching
- **Fitting:** Set of summary statistics

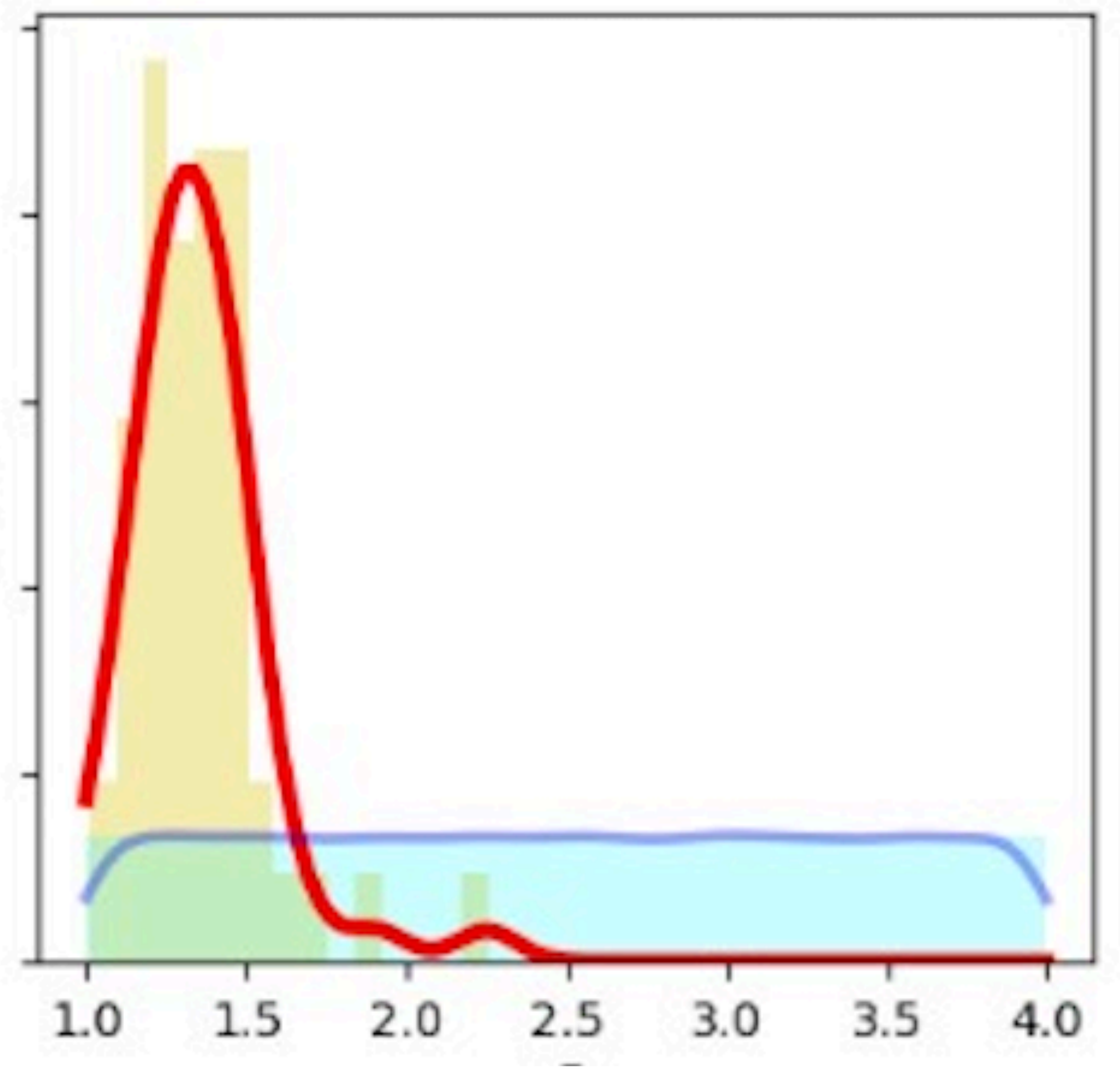
Selection



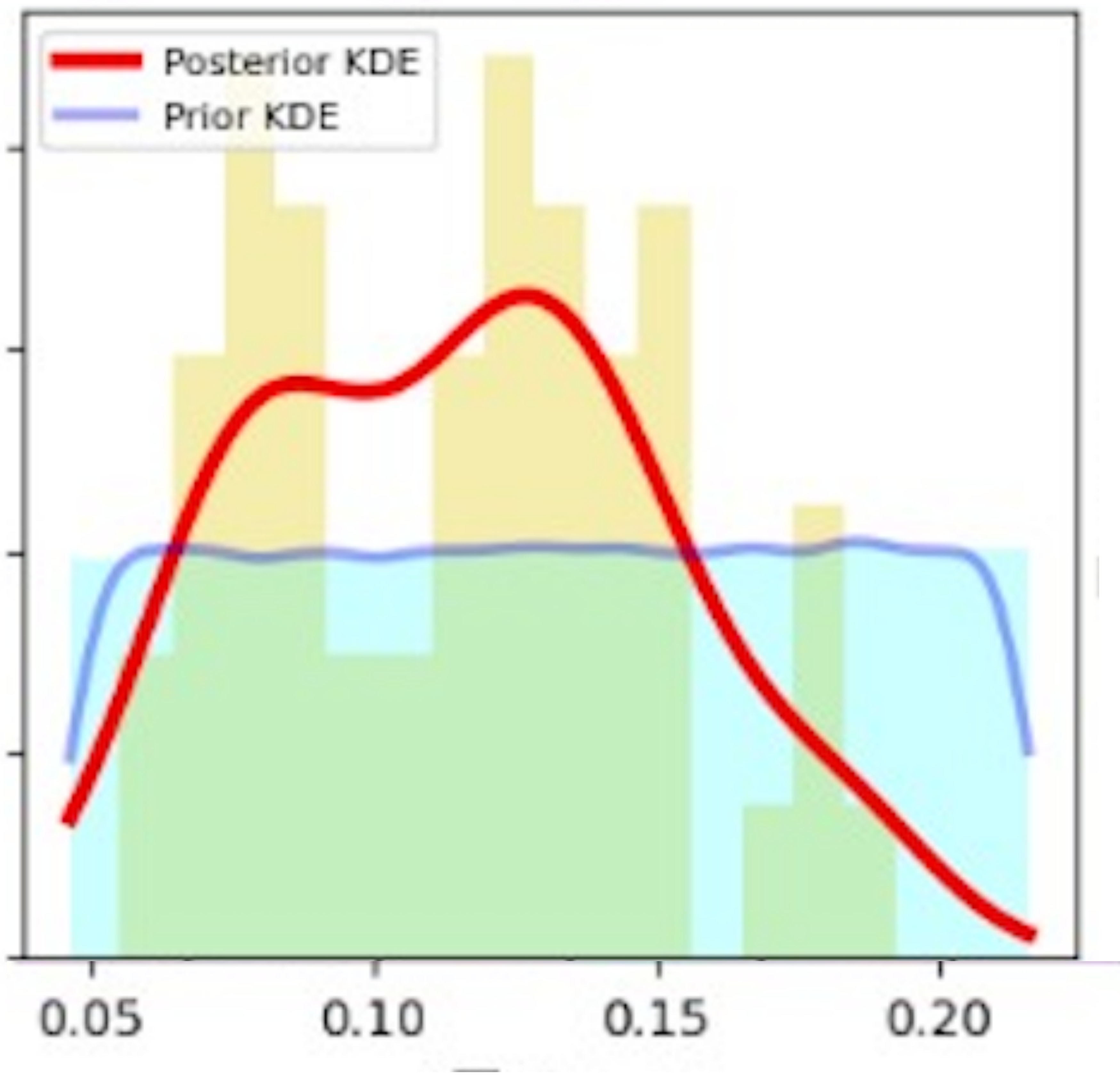
Exchange



Results:
prior vs. posterior parameter distributions

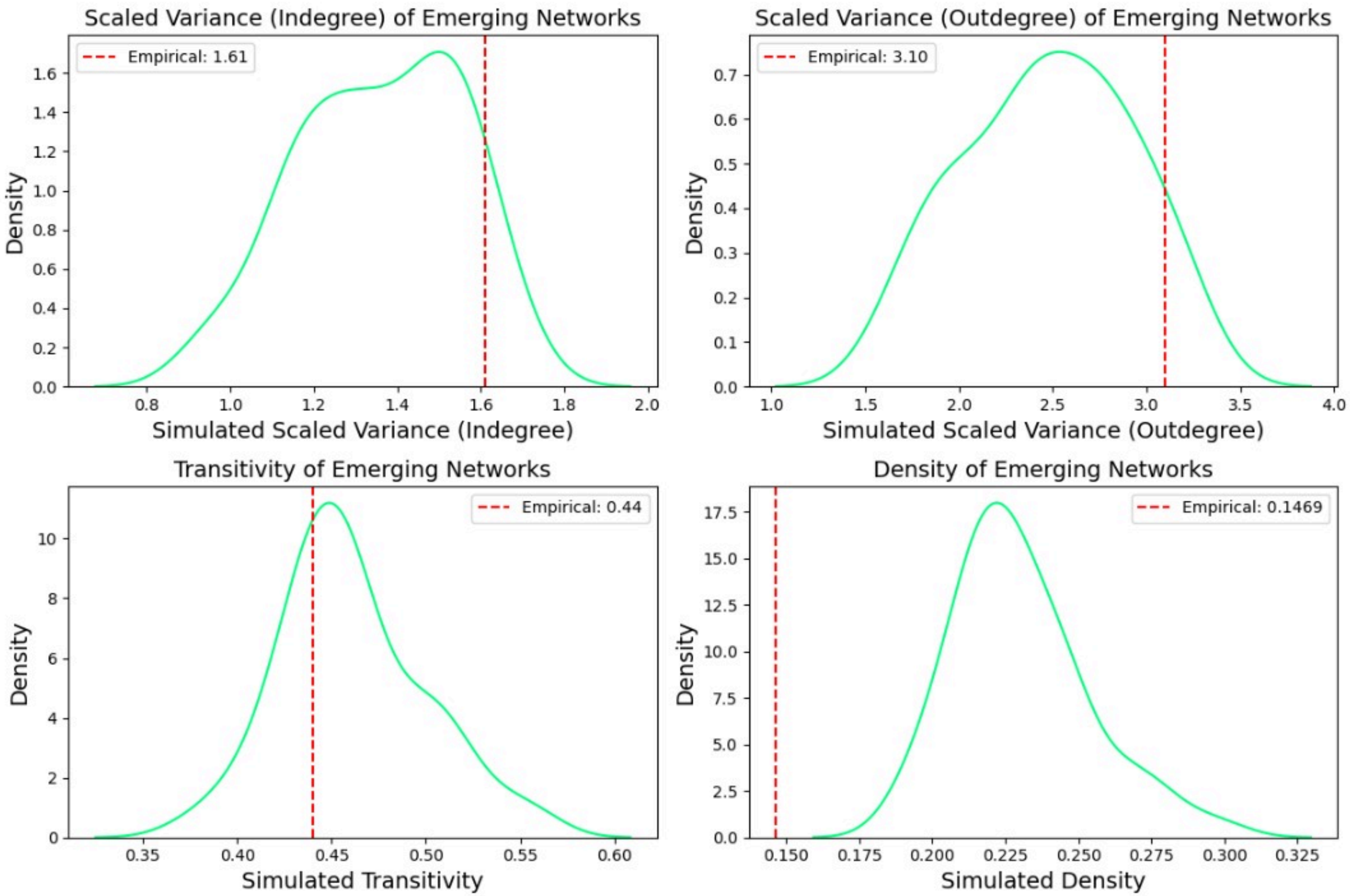


Cost threshold



Density threshold for frame switching

Model fit



Scaled Variance (Indegree) of Emerging Networks
Empirical: 1.61
Density
Simulated Scaled Variance (Indegree)
Scaled Variance (Outdegree) of Emerging Networks
Empirical: 3.10
Density
Simulated Scaled Variance (Outdegree)
Transitivity of Emerging Networks
Empirical: 0.44
Density
Simulated Transitivity
Density of Emerging Networks
Empirical: 0.1469
Density
Simulated Density

Conclusions - Example 2

- Preliminary evidence for **within-individual, time-varying framing** dynamics in explaining **prosocial behaviour** in a small social system
- **Cognition matters**! Mechanism models ignoring context-dependent motives underlying behaviour might fail to adequately explain cooperation

Conclusions on ABM and social networks

- ABMs can model more granular causal mechanisms of social network formation and influence
- Unobserved components of mechanisms can be modelled and their impact empirically estimated
- Accounting for cognition and behaviour in social network models

Website	https://federico-bianchi.github.io/
Mail	federico.bianchi1@unimi.it
BlueSky	@federicobianchi.bsky.social
X	@federico_fb

Predictive checks