Empirical models of networks (and behaviour)

Explaining macro dynamics: On the use of empirically calibrated simulations in social sciences, Institute of Analytical Sociology, Athens, 3-5 December, 2023

Federico Bianchi

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

Empirical models of mechanisms

To test mechanism-based explanations we need models which are:

1. complex enough to model **social mechanisms**
2. **empirical data** to fit the model to (model selection through calibration/validation)

Problem 1 (model complexity)

- Model selection —> parameter estimation —> computing the likelihood of the model given the data —> counterfactual: what could have happened given what happened?
- simulation is needed because (complex) mechanism models' likelihood functions are usually mathematically untractable (Hartig et al., 2011)

Problem 2 (to what extent can we observe behaviour?)

- Models are collections of relationships between logical/numeric variables —> complex mechanism models are composed by sub-models of mechanism, including actors' behaviour (Macy & Flache, 2009: 'agents' in ABMs are models themselves)
- those relationships are sometimes un-observed (or un-observable? See Hedström, 2021)

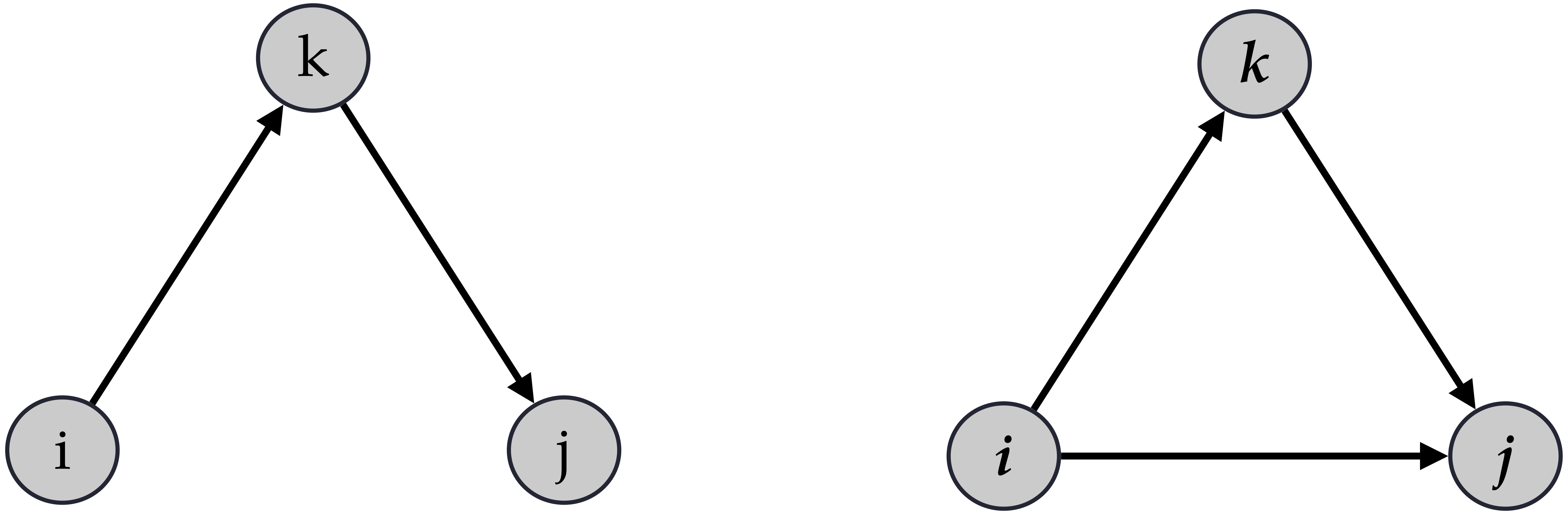
Network analysis needs empirical ABMs

Network processes vs. mechanisms

(Stadtfeld & Amati, 2021)

Reciprocation

- Complying to a norm prescribing reciprocation OR
- Instrumentally investing in a cooperative relationship to reap long-term benefits



Transitivity

- More likely to meet if we share a friend OR
- More likely to be similar if we share a friend OR
- Avoiding unpleasant emotions linked to imbalance

Statistical network models and behaviour

SAOMs (Stochastic Actor-Oriented Models) are a particular kind of ABMs (Snijders *et al.*, 2010), constrained by a set of assumptions on agents' decision-making and environmental constraints because

SAOM

- Agents optimize preferences based on expected utility at time $t + 1$
- Agents choose among an alternative set of options
- Agents have **information on the whole network**
- **Markov chain**: one change at a time
- Agents cannot coordinate (no collective action)

General ABM

- Broad range of behaviour, including learning, strategic forward-looking rationality, complex cognitive heuristics
- Agents can choose upon any kind of heuristics
- Agents can have **limited information**
- **Simultaneous events** are possible (critical events / threshold-like processes)
- Agents can coordinate (communicate, negotiate…)

Case 1:
Network formation

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Social Networks

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Status, cognitive overload, and incomplete information in advice-seeking networks: An agent-based model

Francesco Renzini *, Federico Bianchi, Flaminio Squazzoni

Department of Social and Political Sciences, University of Milan, Via Conservatorio 7, 20125 Milan, Italy

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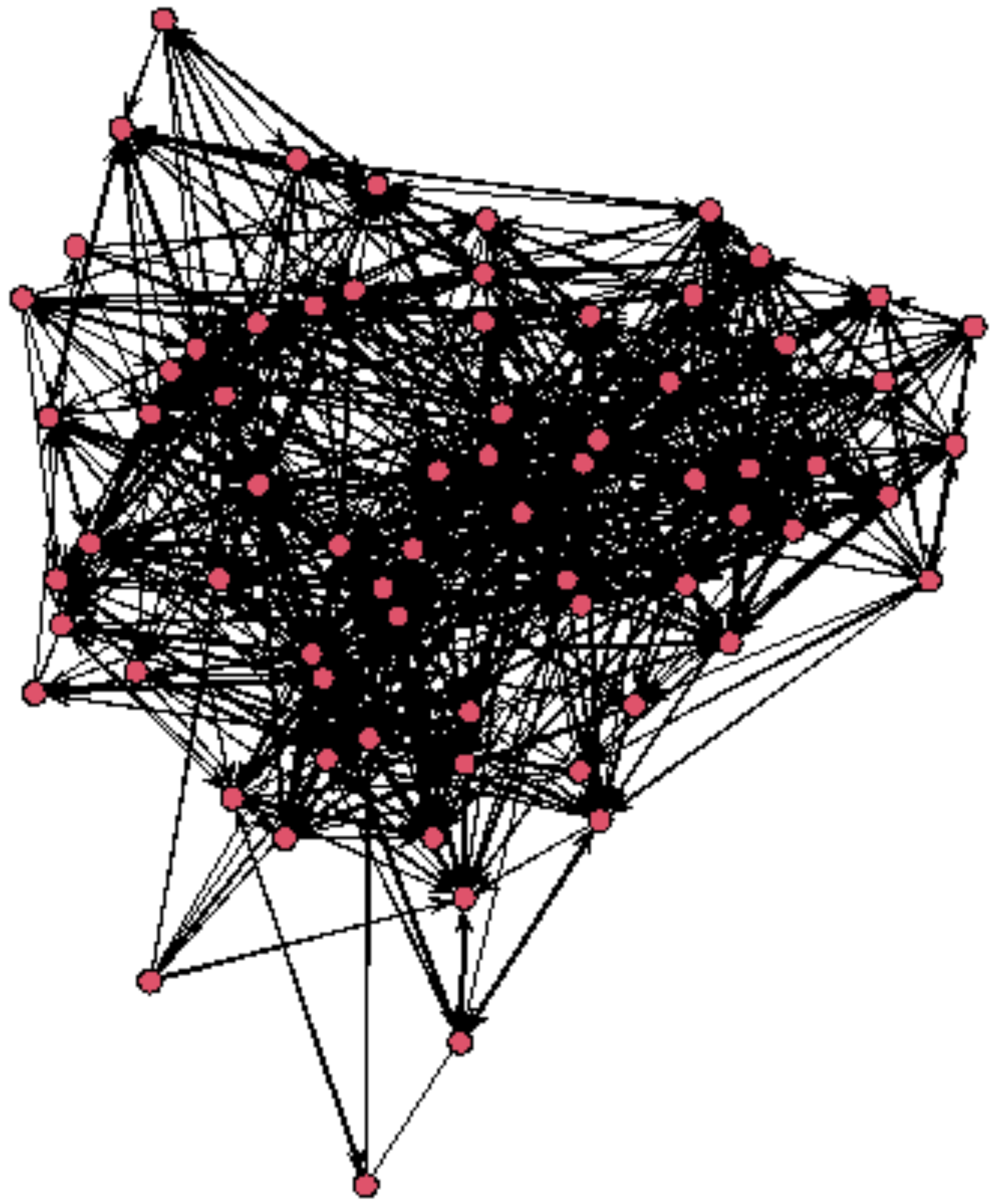
ABSTRACT

Advice-seeking typically occurs across organizational boundaries through informal connections. By using Stochastic Actor-Oriented Models (SAOM), previous research has tried to identify the micro-level mechanisms behind these informal connections. Unfortunately, these models assume perfect network information, require agents to perform too cognitively demanding decisions, and do not account for threshold-based critical events, such as simultaneous tie changes. In the context of knowledge-intensive organizations, the shortage of high-skilled professionals could determine complex network effects given that many less-skilled professionals would seek advice from a few easily overloaded, selective high-skilled, who are also sensitive to status demotion. To capture these context-specific organizational features, we have elaborated on SAOM with an agent-based model that assumes local information, status-based tie selection, and simultaneous re-direction of multiple ties. By fitting our simulated networks to Lazega's advice network used in previous research, we reproduced the same set of macro-level network metrics with a parsimonious model based on more empirically plausible assumptions than previous research. Our findings show the advantage of exploring multiple generative paths of network formation with different models.

Overload cycles in advice-seeking networks

- Lazega's classic advice-seeking network (Lazega, 2001)
- Context: law firm in '90s New England (n = 71)
- High internal competition for status: different preferences based on status (**unobserved**)
- Lazega (2006, 2014): "cognitive overload" (time is valuable) (**unobserved**)
- No generalized triadic/popularity processes because information is limited (competition)



Mechanism model doesn't suit stat models' assumptions

(Snijders & Steglich, 2015)

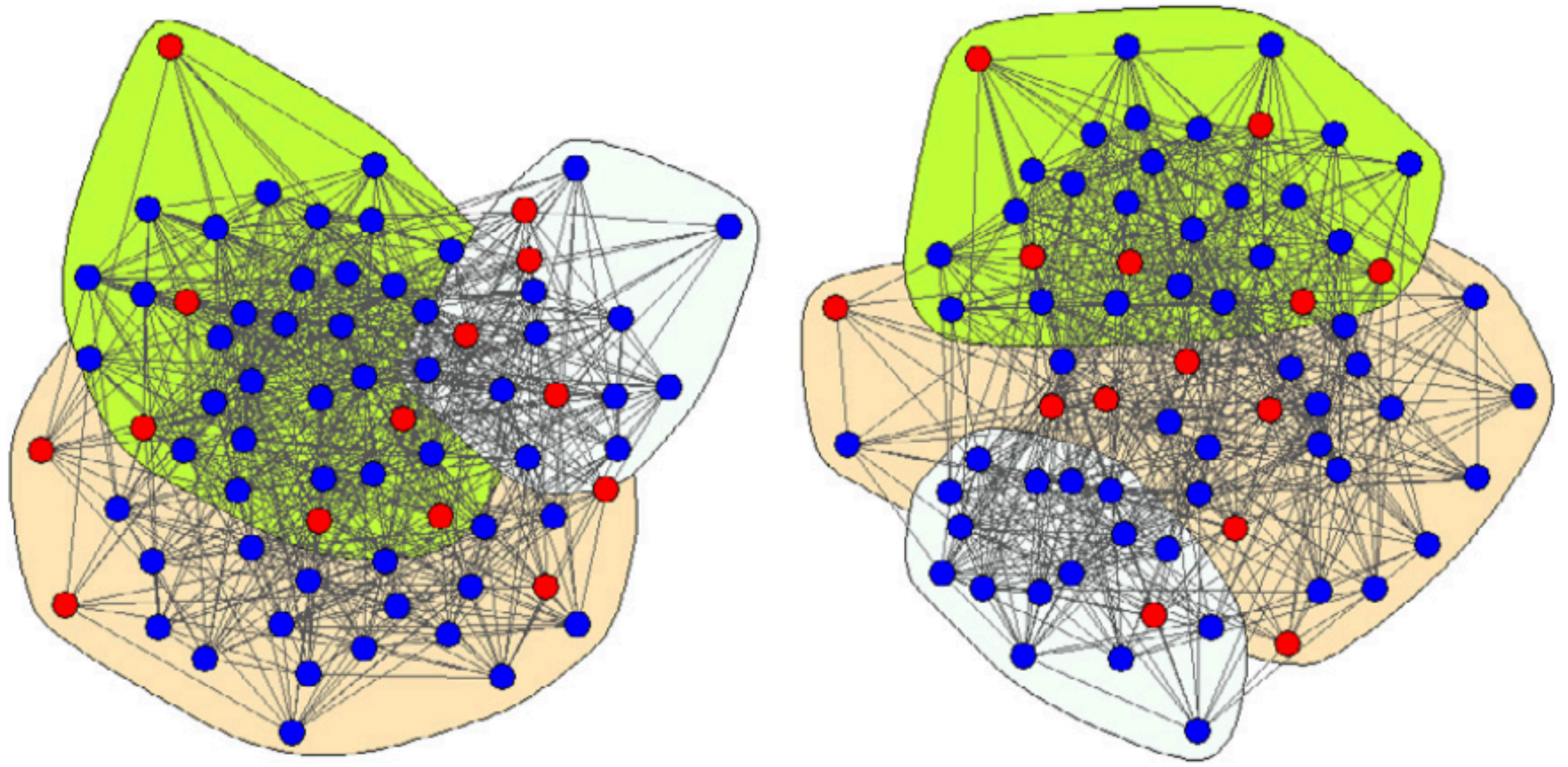
Our mechanism model

- If number of requesting agents meets a threshold, lower-status ties reallocate their requests simultaneously
- In case of reallocation, lower-status choose according to simple heuristics of exploitation (reciprocation) and exploration (transitivity)

SAOM

- No simultaneous events
- Information is not limited
- Model with a large set of network processes

Calibration/validation



$$f_i^l(\boldsymbol{\beta}, X) = \beta_0^l \sum_{j \neq i} x_{ij} + \mathbb{1}\{Indeg_h < \tau\}(\beta_{attract}^l \sum_{j \neq i} x_{ij} T_j) +$$
$$(1 - \mathbb{1}\{Indeg_h < \tau\})(\beta_{EL}^l \sum_{j \in L} x_{ij} x_{ji} + \beta_{ER}^l \sum_{j,k \in L} x_{ij} x_{jk} x_{ik}) + \epsilon$$

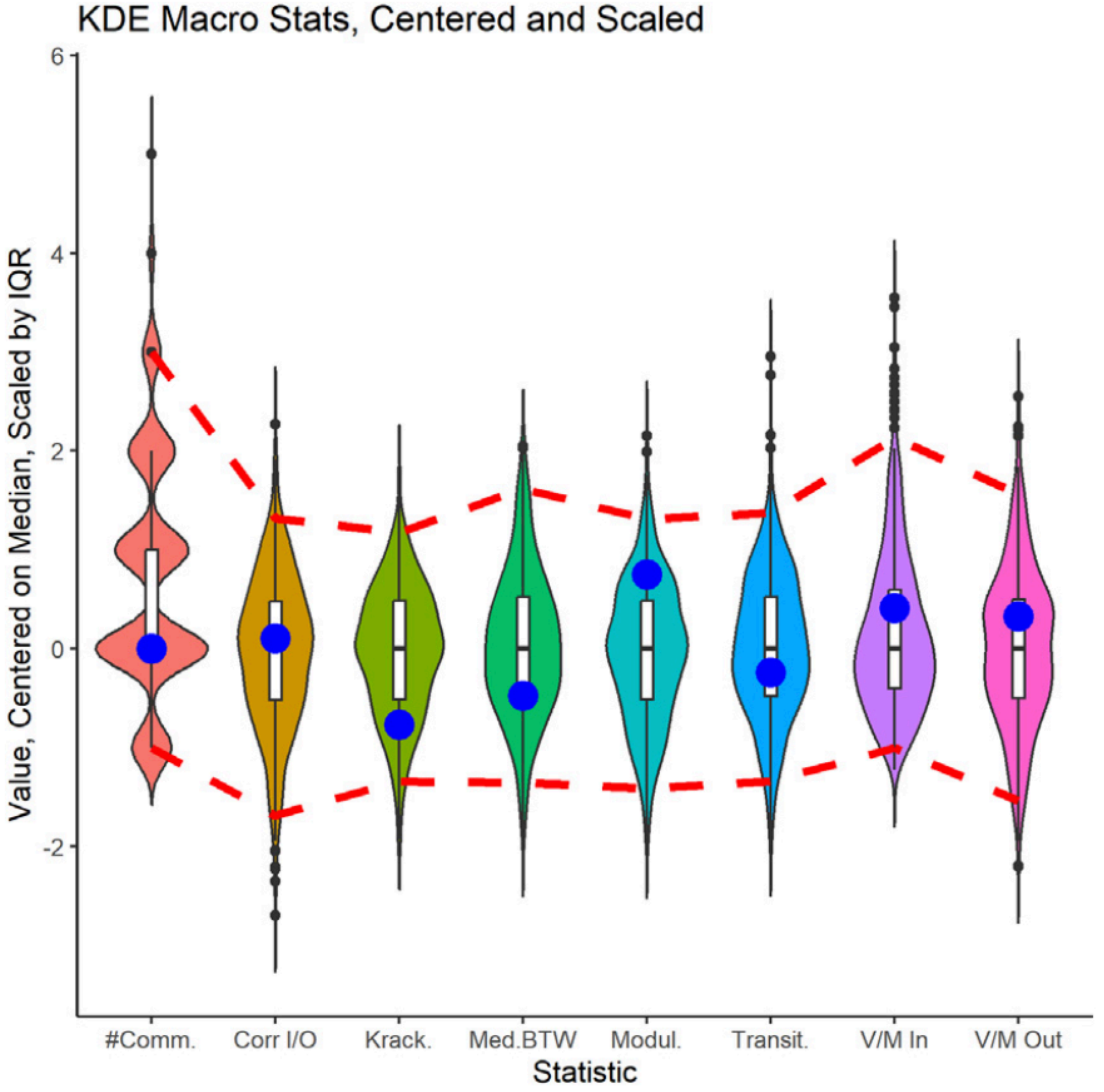


Table 4
Parameters of good-fitting models.

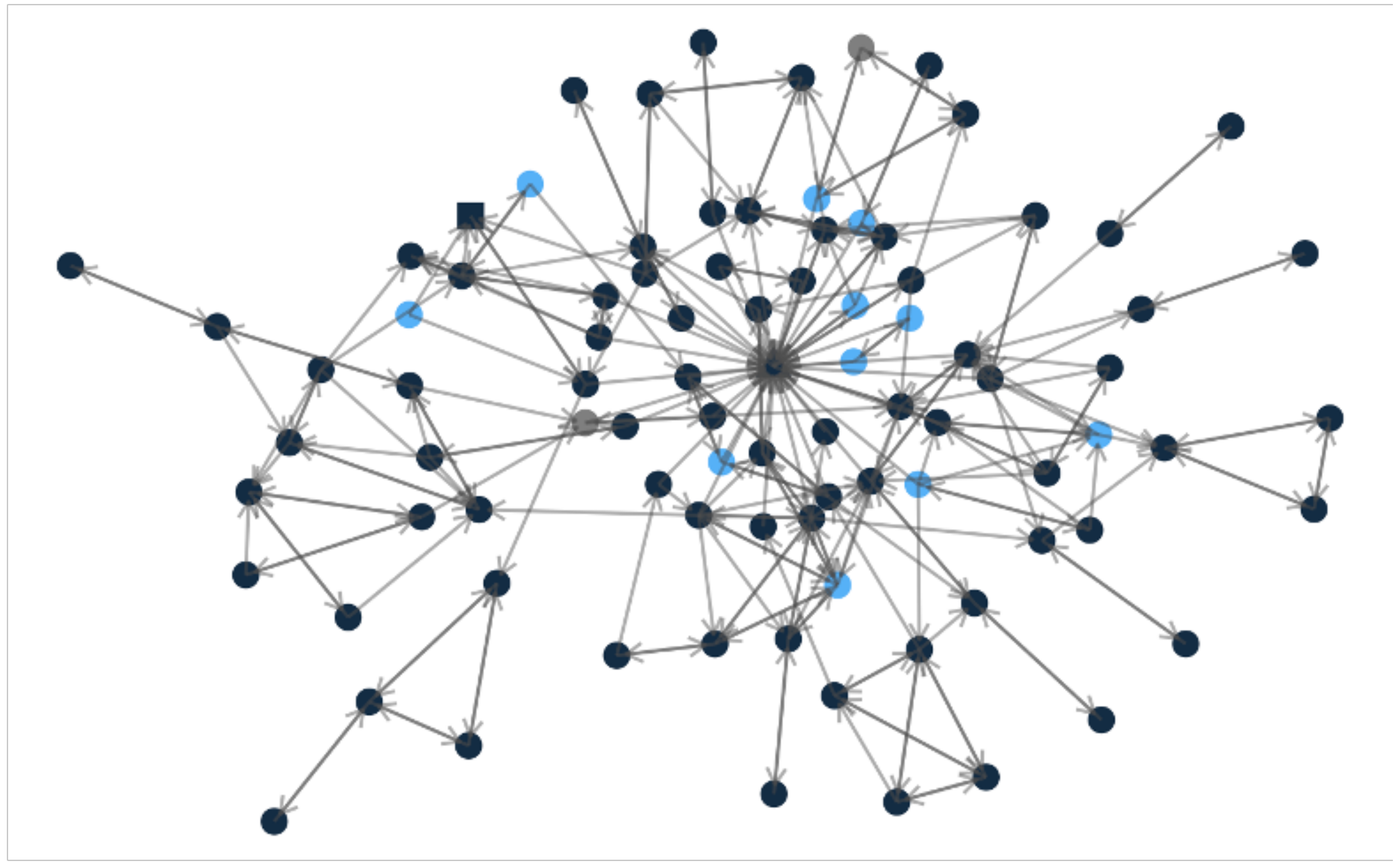
Parameter	Value
Both cases	
Baseline propensity low-skilled (β_0^l)	−0.4
Baseline propensity high-skilled (β_0^h)	−3
Attractiveness towards high-skilled for both types ($\beta_{attract}$)	2.3
Reported tuple (β_{EL}^l, β_{ER}^l) for **case 1**	
(β_{EL}^l, β_{ER}^l)	(0.5, 0.25)
Reported tuple (β_{EL}^l, β_{ER}^l) for **case 2**	
(β_{EL}^l, β_{ER}^l)	(0.25, 0.5)

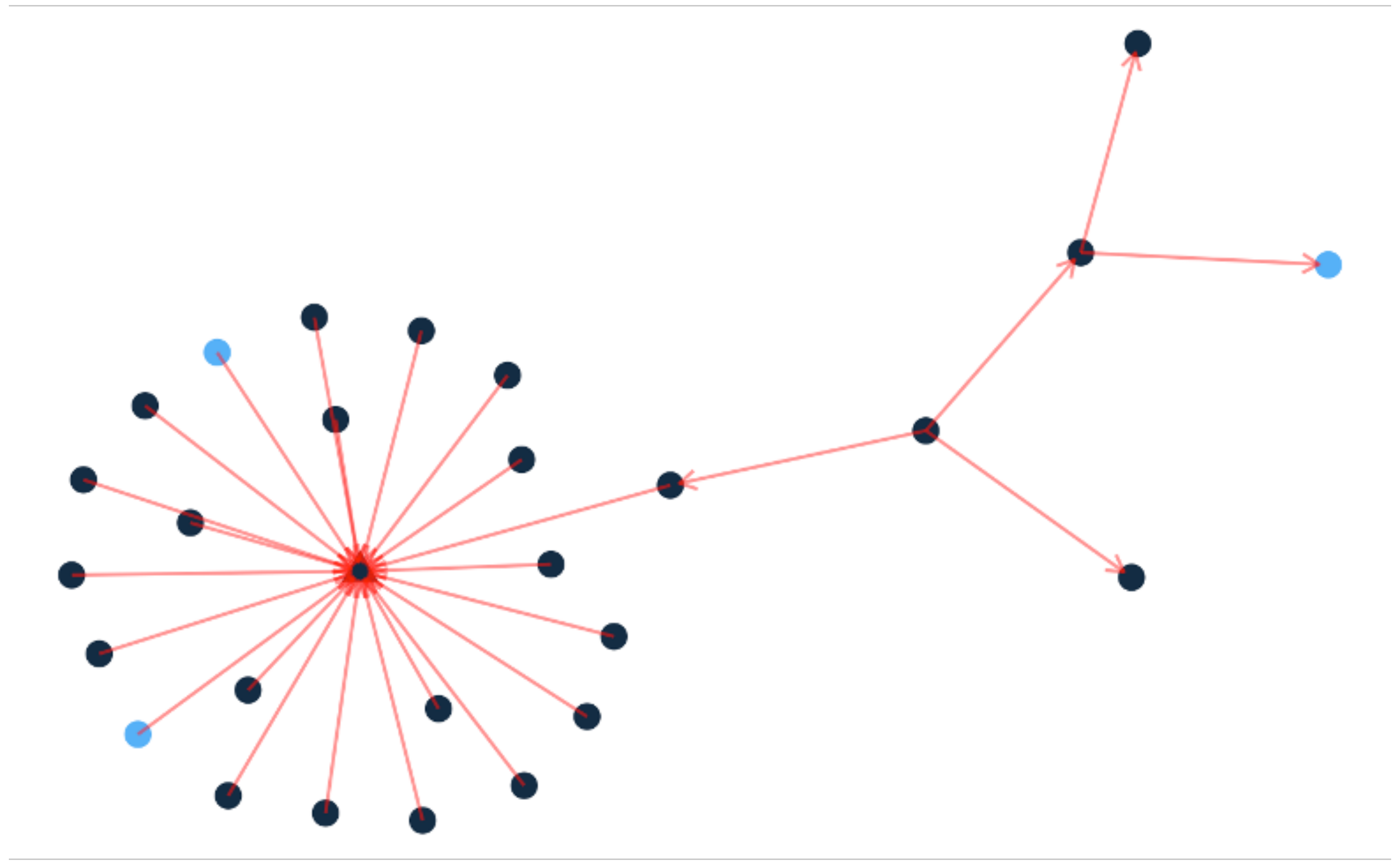
Case 2:
Networks affecting behaviour

Complex contagion and diffusion of health practices (with Elisa Bellotti)

- Despite governmental interventions, only ~12% of villagers take up anti-malaria prevemptive practices (10 villages in Meghalaya, India)

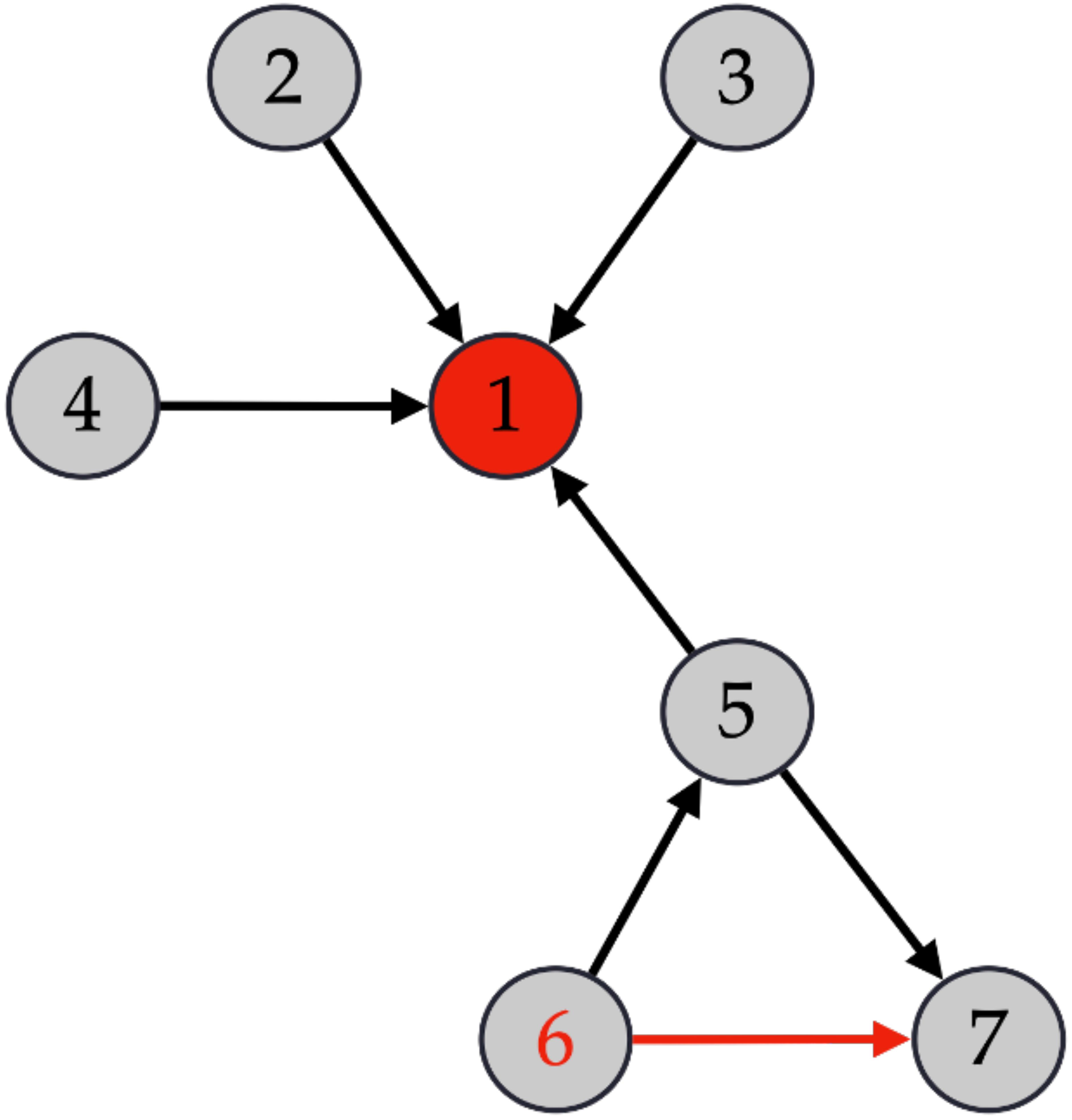
- Any threshold-based contagion influence through positive and negative ties? (**unobserved**)





Mechanism model

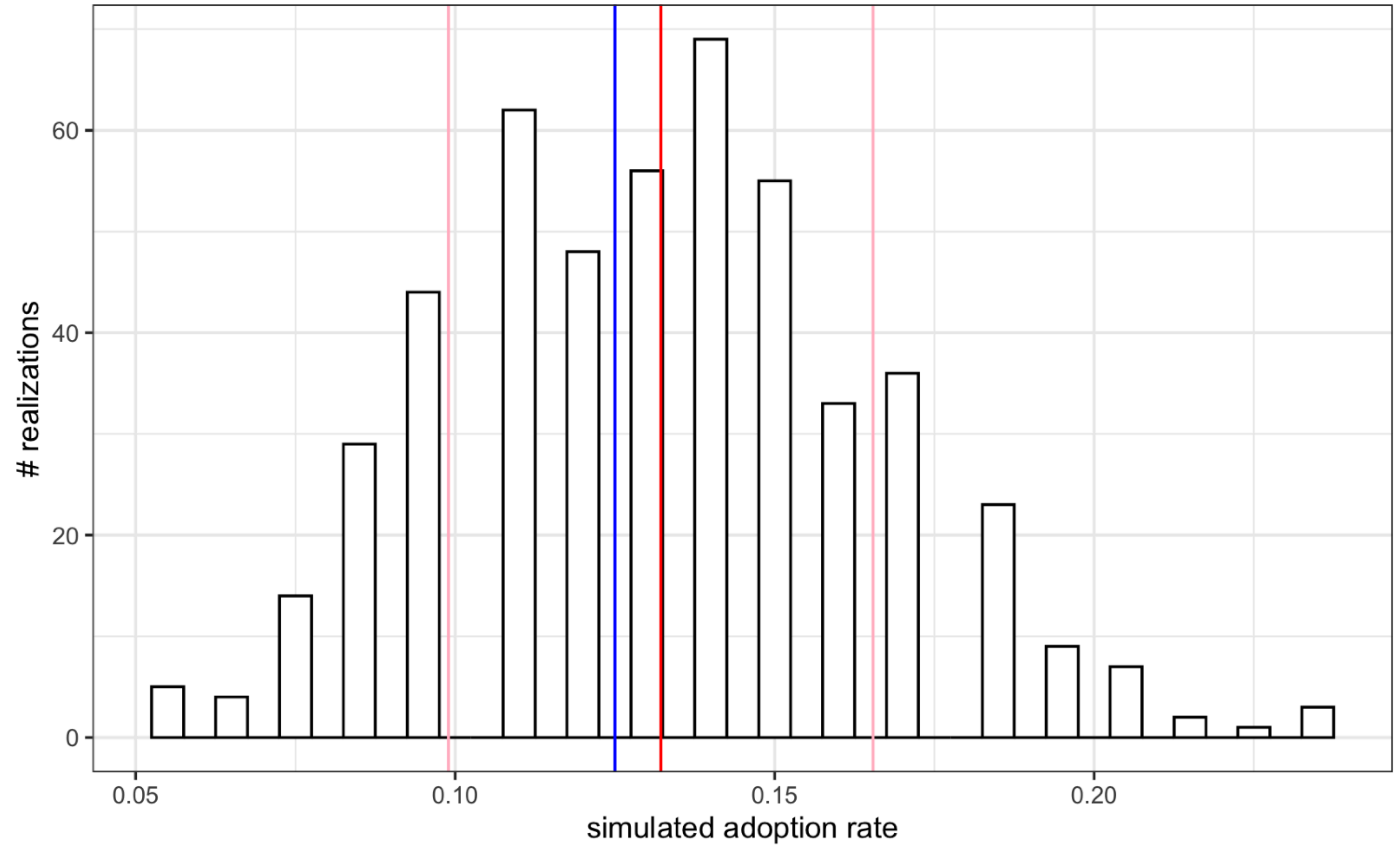
- Individuals adopt preventive measure (binary choice) as a logistic objective function of local network properties
- Parameters to be estimated:
  - threshold levels (positive ties) for adoption contagion
  - impact of negative influence (= adoption by negative contacts)
- Assuming:
  - positive impact of within-household adoption
  - ‘zealots’ and stubborn agents

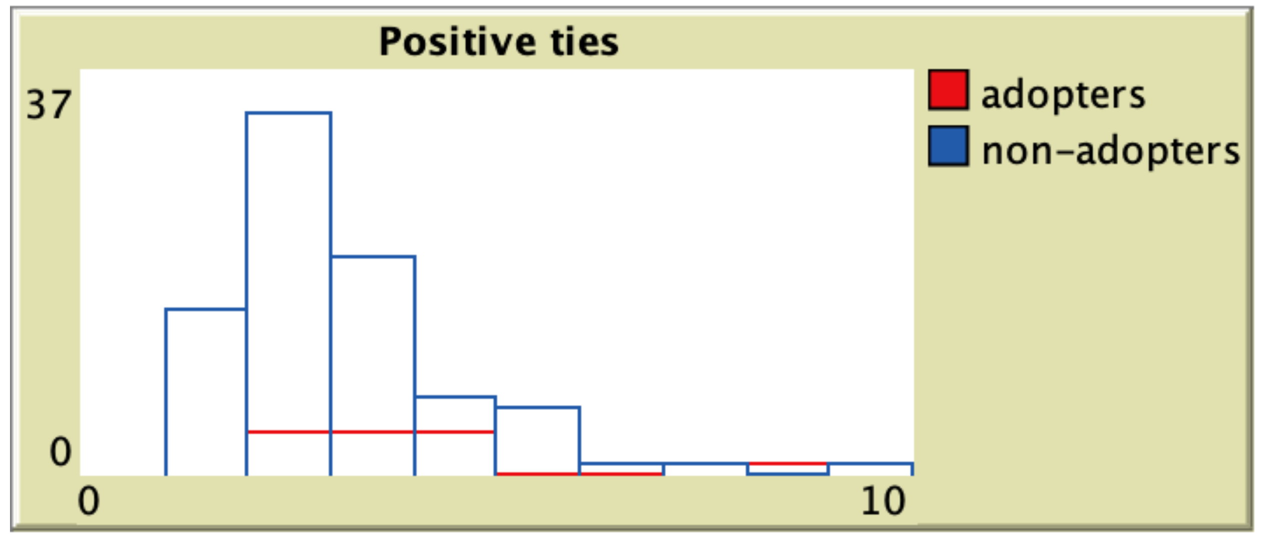


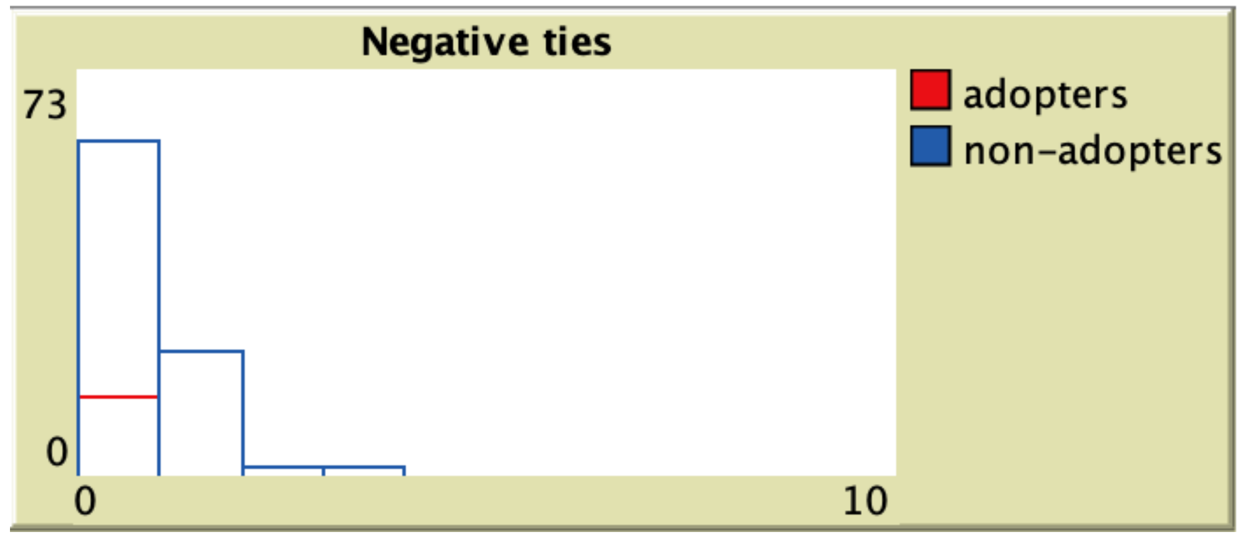
Calibration/validation

Baseline	-2.79
Adoption by most household members	0.70
Threshold for contagion	**3**
Threshold-based contagion	**0.81**
Negative influence	-1.18

Genetic algorithm minimizing distance between empirical and simulated SS







Behave Summer School on ABM

- Week 2 is on:
  - Calibration through maximization, optimization, minimization
  - Validation
  - Parameter estimation
  - Model selection

Behave Summer School on ABM

Discussion (?)

- We need empirical models (calibration/validation) because we want to identify mechanisms as precise as they can account for possible change (policy). What room for theoretical models?
- We do not want our empirical models to reproduce highly idiosyncratic phenomena. Mechanisms pertain to the realm of social reality, all we can do is to come up with mechanism models which can be activated by certain empirical conditions —> stochasticity
- Cognitive aspects of mechanisms tend to be unobservable. Should we give up on them? No, unless we give up on useful empirical models.
    - Estimate behavioural parameters
    - Calibrate behaviour via experiments

Mail: federico.bianchi1@unimi.it

X: @federico_fb @BehaveLab_unimi

Bsky: @federicobianchi.bsky.social

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