NETWORKS 2021

Micro-macro analysis with empirically calibrated social simulations in RSiena

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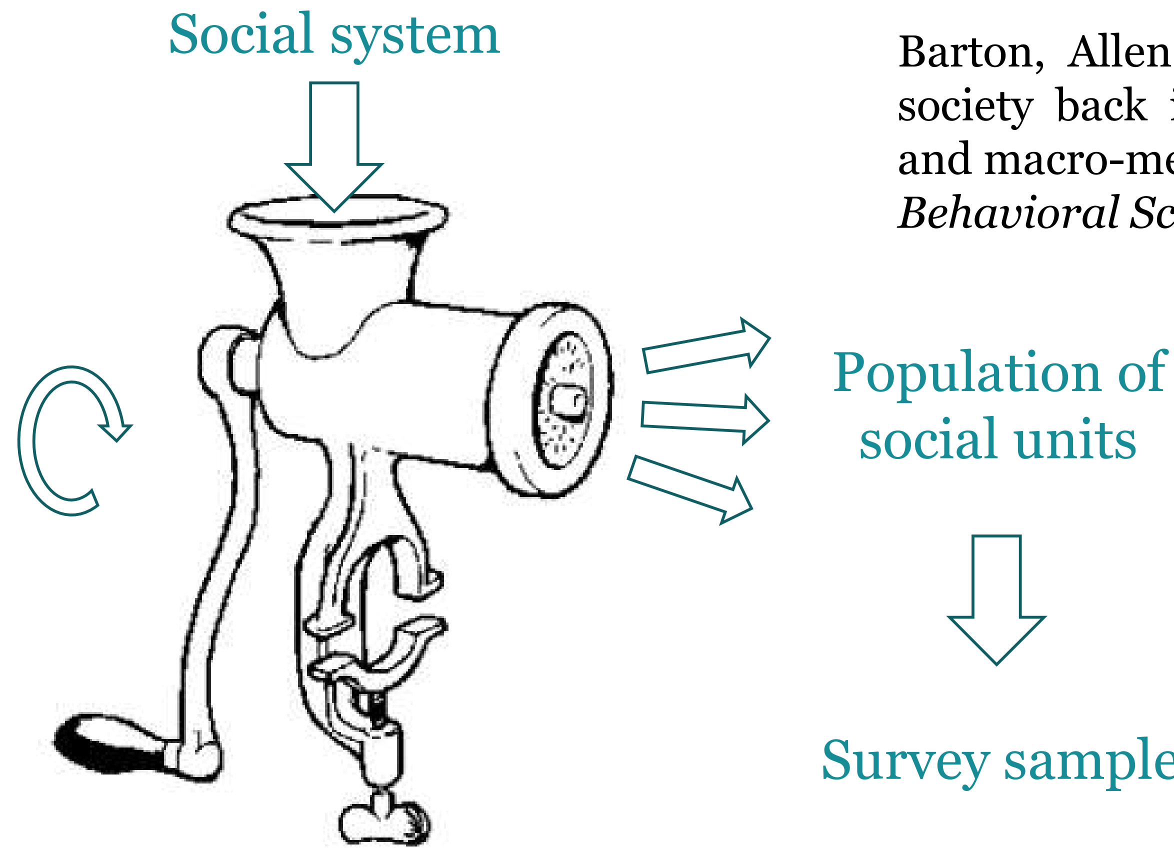
Background: Allen Barton’s meat grinder (1968) and the role of networks in explaining societal phenomena

Survey methodology cannot possibly reveal anything about how social systems work.

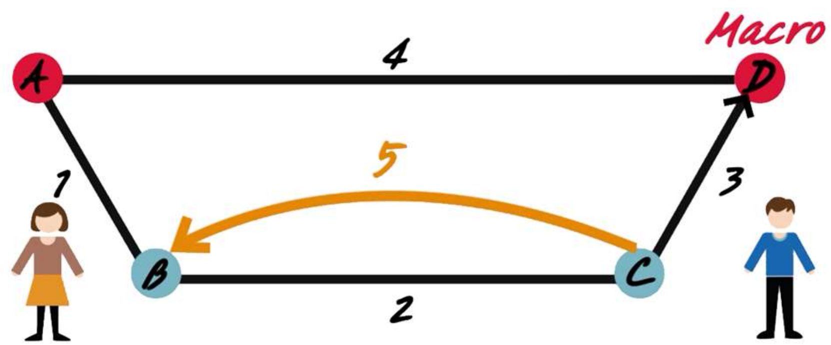
Barton, Allen (1968). Bringing society back in: Survey research and macro-methodology. *American Behavioral Scientist* 12:1–9.



Arguably, network methodology can!

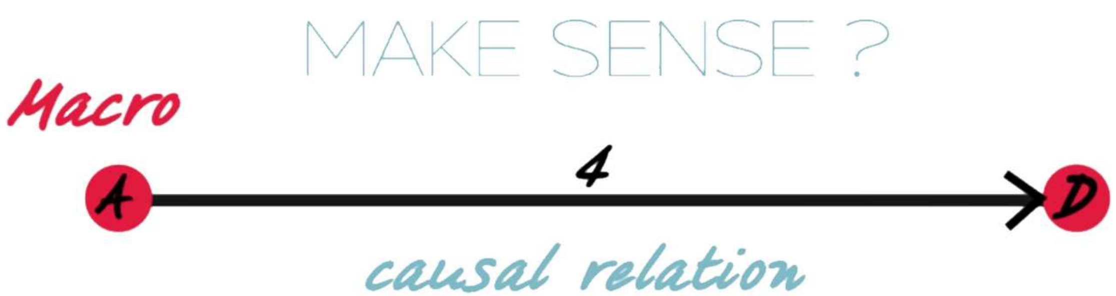
1. The micro-macro problem

- Individuals as drivers for societal change
- Coleman boat as tool for thinking

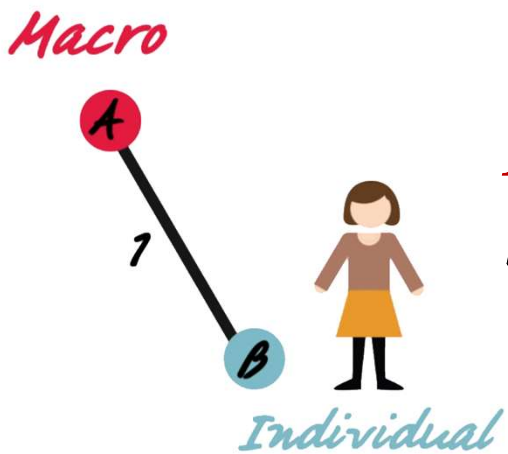


An examplary macro level research question ...

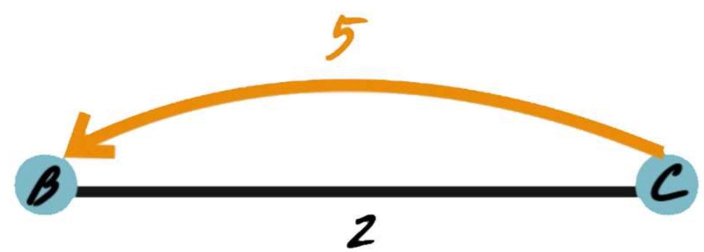
Does bilingual education foster minority integration?



… and a possible micro level network explanation

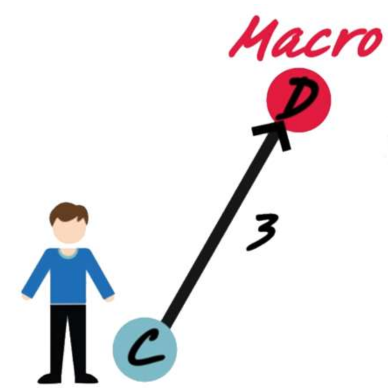


Bilingual education reduces status differences between host and migrant language students.



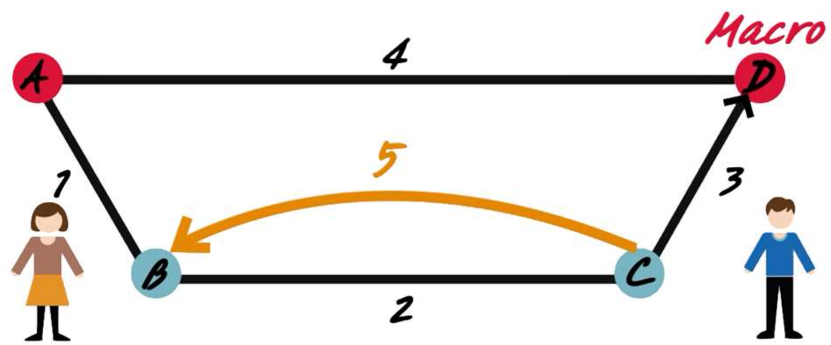
Students' social interactions reflect existing status differences.

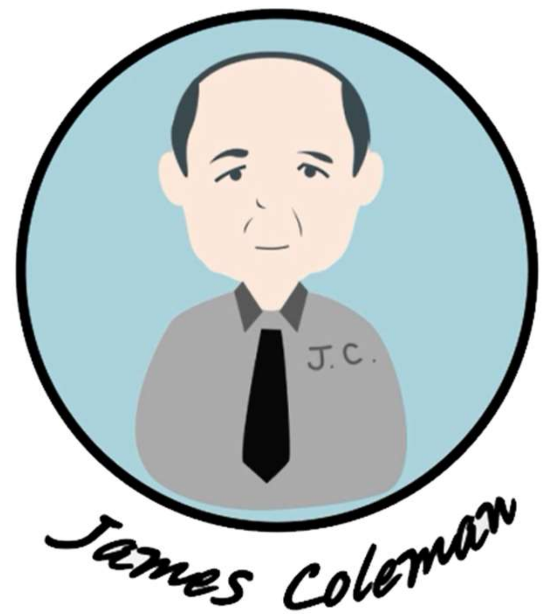
Social interactions result in a friendship network.



The micro-macro problem

- Individuals as drivers for societal change
- Coleman boat as tool for thinking





- In practice, often only one social system is studied.

¿ Can we say something about macro level properties of this system on the basis of statistical results on the micro level ?

With stochastic network models we can!

Developed for *testing* micro level behavioural theories:

- Exponential Random Graph Models,
- Stochastic Actor-oriented Models.

Complex, dependent data requires *simulation-based inference* for estimating model parameters.

- *Generative models*, they make distributions of networks.

Simulation engine can be *re-purposed for micro-macro studies* (as in agent-based modelling / social simulation) .

Macro outcomes ≈ network level indices

Network structure / topology

- small world: *clustering* & *short distances*
- *hierarchy*
- hub formation: *scale-free* property

Network structure & actor attributes

- *autocorrelation:* segregation & polarisation

Structure of multiple networks / multiplexity

- role algebras, e.g., *structural balance*
- *entrainment*

Explanation ≈ micro level mechanisms

Understood in view of some micro behaviour theory

local condition → local outcome

In complex, interdependent systems *intransparently* related to macro outcome of interest

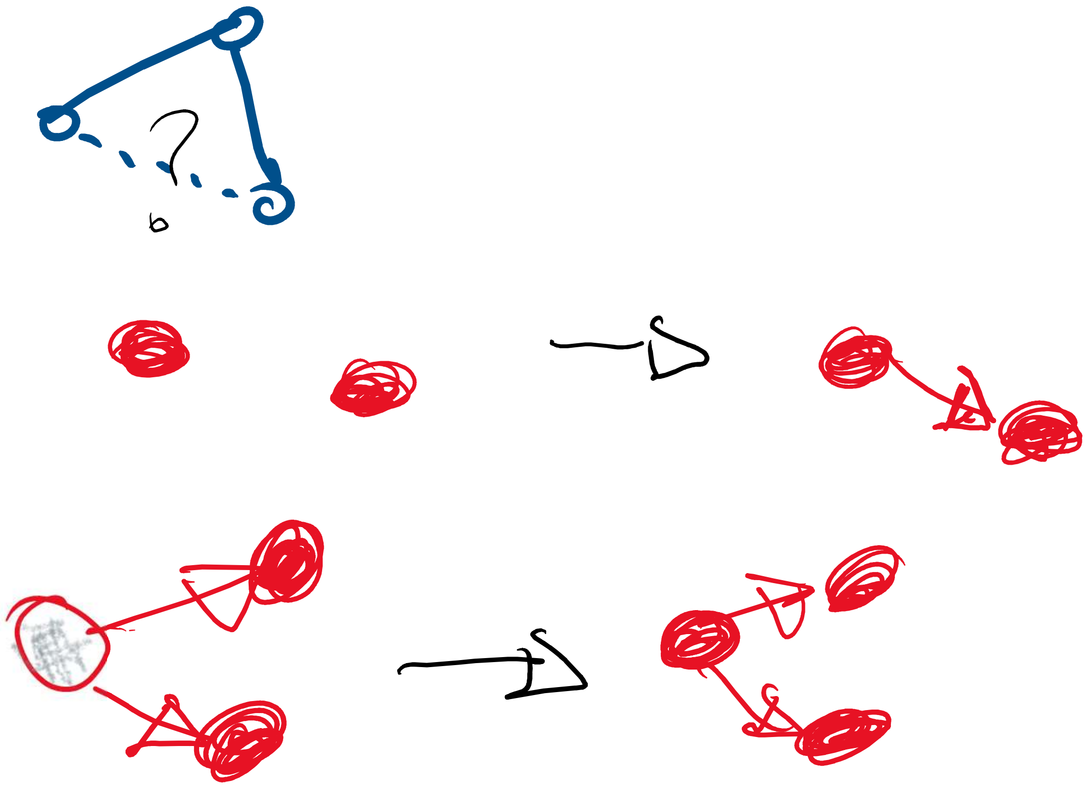
Twin tasks of empirical analysis:

1. *Does the mechanism operate* at the micro level ? — Part 1
2. To what degree *is it responsible for macro outcome* ? — Part 2

Stochastic network models (ERGM, SAOM)

Purpose: empirical testing of micro-level mechanisms

- Structure of networks
- Dynamics of networks
- Dynamics on (dynamic) networks



Models require simulation-based inference

Reason: complex data & intractable likelihood

- Exists since the early 1950s:

A STOCHASTIC APPROXIMATION METHOD[1]

By Herbert Robbins and Sutton Monro

University of North Carolina

Equation of State Calculations by Fast Computing Machines

Nicholas Metropolis, Arianna W. Rosenbluth, Marshall N. Rosenbluth, and Augusta H. Teller,
Los Alamos Scientific Laboratory, Los Alamos, New Mexico

and

Edward Teller,* *Department of Physics, University of Chicago, Chicago, Illinois*
(Received March 6, 1953)

Illustration with two parameters on the following slides...

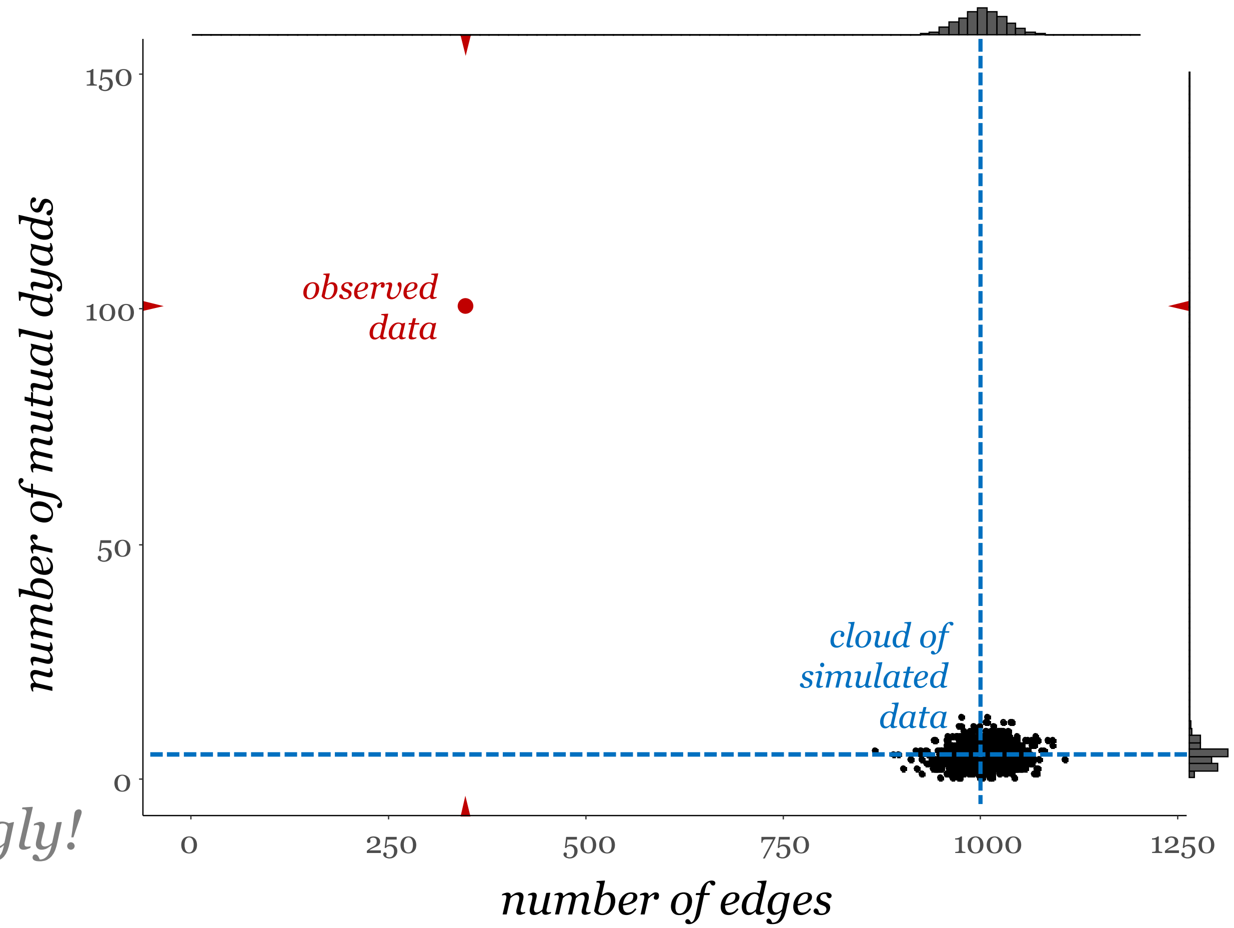
Initial simulations can be way off!

A *first guess* for the parameter values is needed for starting the simulation engine.

Usually these initial parameter values give simulated data that look very different from the data set we want to model.

Here: too many edges, but too few of them reciprocated.

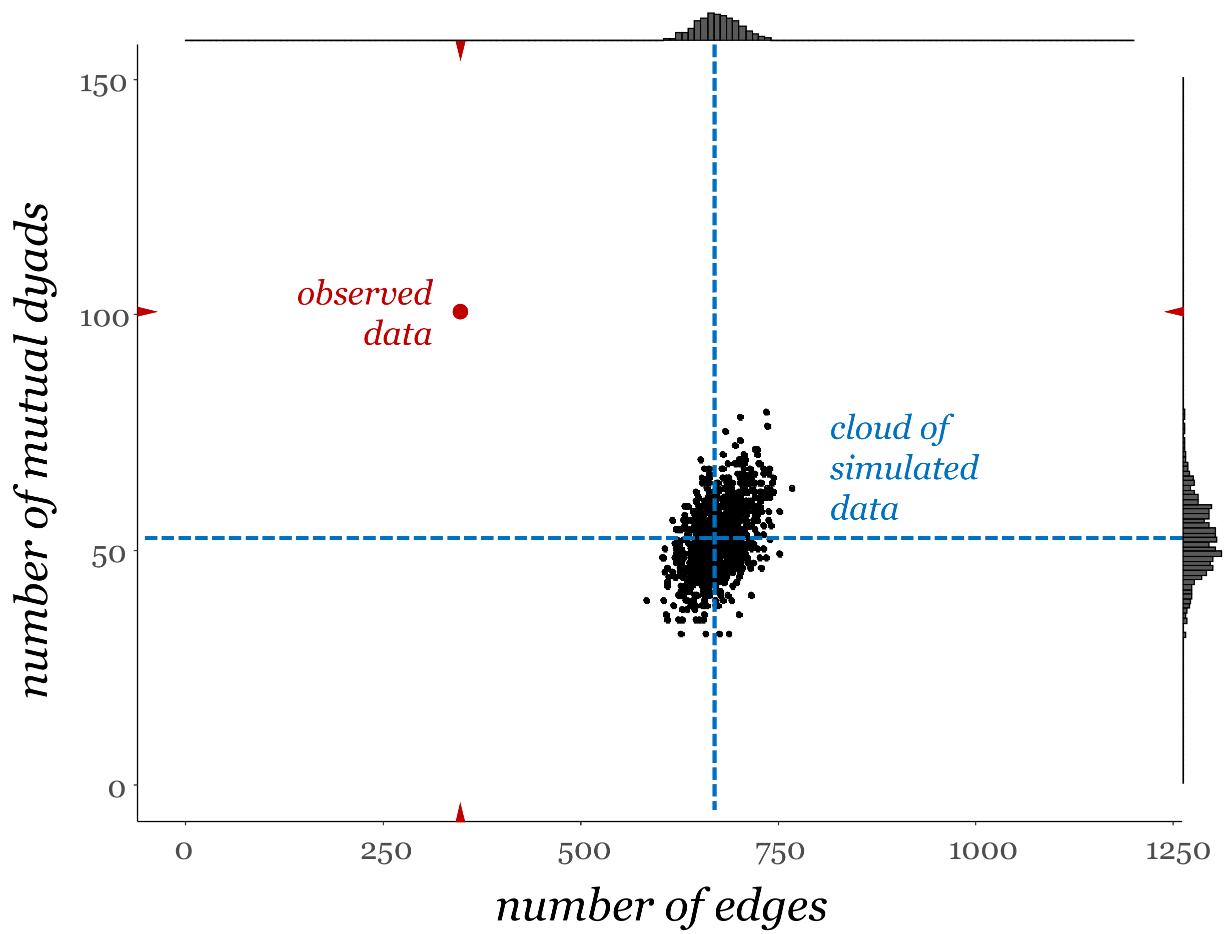
$\Rightarrow$ *adjust parameters accordingly!*



After improving parameters

A smaller edges parameter and a larger reciprocity (mutual) parameter will give simulated data that look a bit more like the data set we want to model.

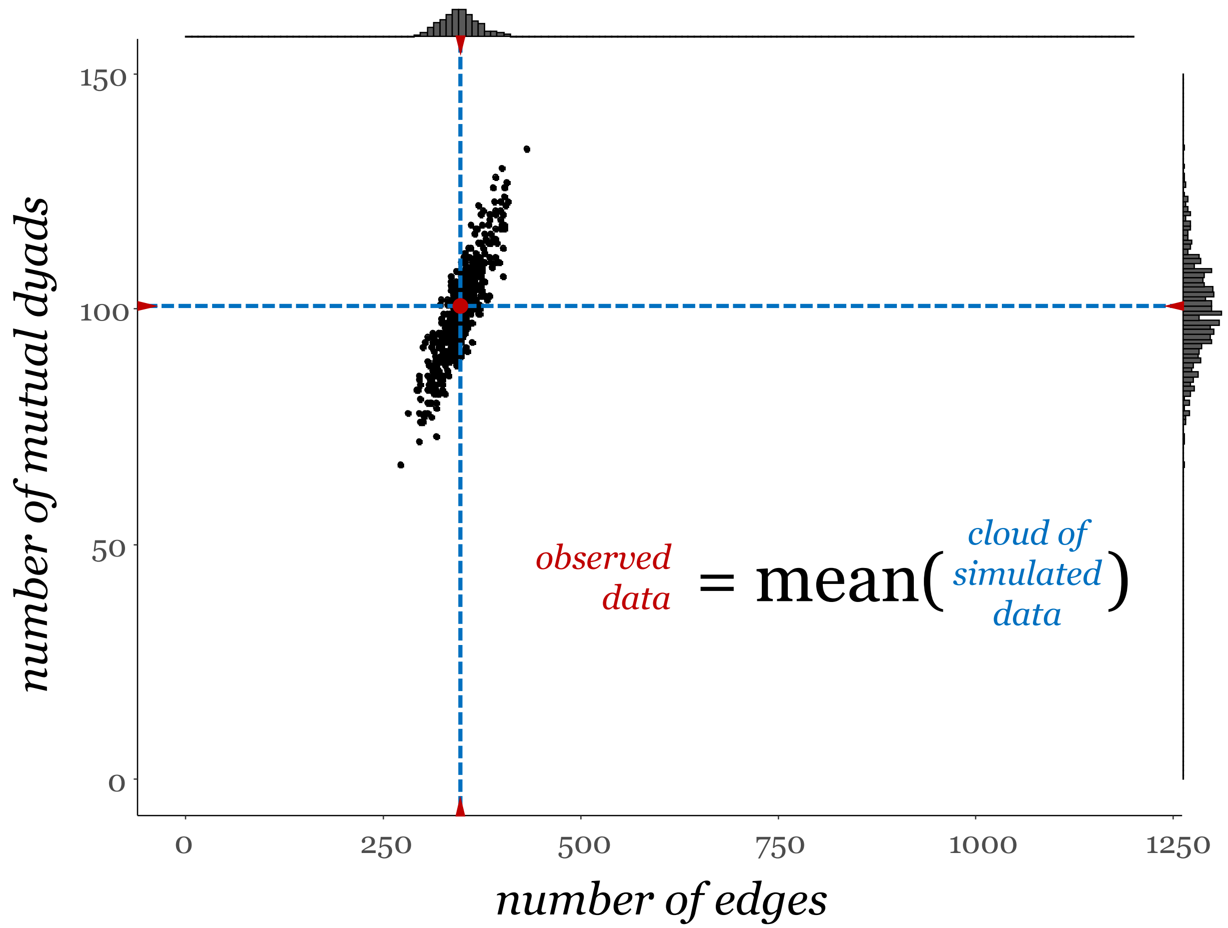
The estimation algorithm iterates between parameter updating, simulating new data, and comparing these to the observed data.



After convergence (successful calibration)

If the estimation algorithm converges, statistical inference about the parameter values becomes possible.

Unfortunately, convergence is not guaranteed for all data sets and all model specifications (keyword: model *degeneracy*).



We get a lot more than test results!

Stadtfeld, C. (2018). The Micro–Macro Link in Social Networks. *Emerging Trends in the Social and Behavioral Sciences*, 1-15.

These models *instantiate* micro level behavioural theories.

They can be used for *generating* macro level outcomes[†], given their assumptions, parameters, and the data.

- Manipulation of these dimensions allows to make statements about the manipulation's consequences.
- Requires *other parameters* or *other data* than available.
- Can in part be linked to *counterfactual*[‡] causality concepts.

† Robins, G., Pattison, P., & Woolcock, J. (2005). Small and other worlds: Global network structures from local processes. *American Journal of Sociology*, *110*(4), 894-936.

‡ Pearl, J., & Mackenzie, D. (2018). *The Book of Why: The New Science of Cause and Effect*. Basic Books.

Studying emergence with stoch. network models

Emergence always is *conditional on a model specification*.

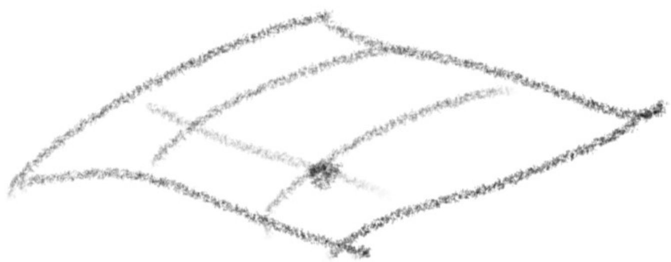
- Transitivity can *emerge* if a model specification does not contain an explicit transitivity term (but, e.g., homophily terms).
- Transitivity does *not emerge* (but is modelled) if the model specification does contain such an explicit transitivity term.

Questions to ask before running an empirically calibrated, counterfactual simulation study:

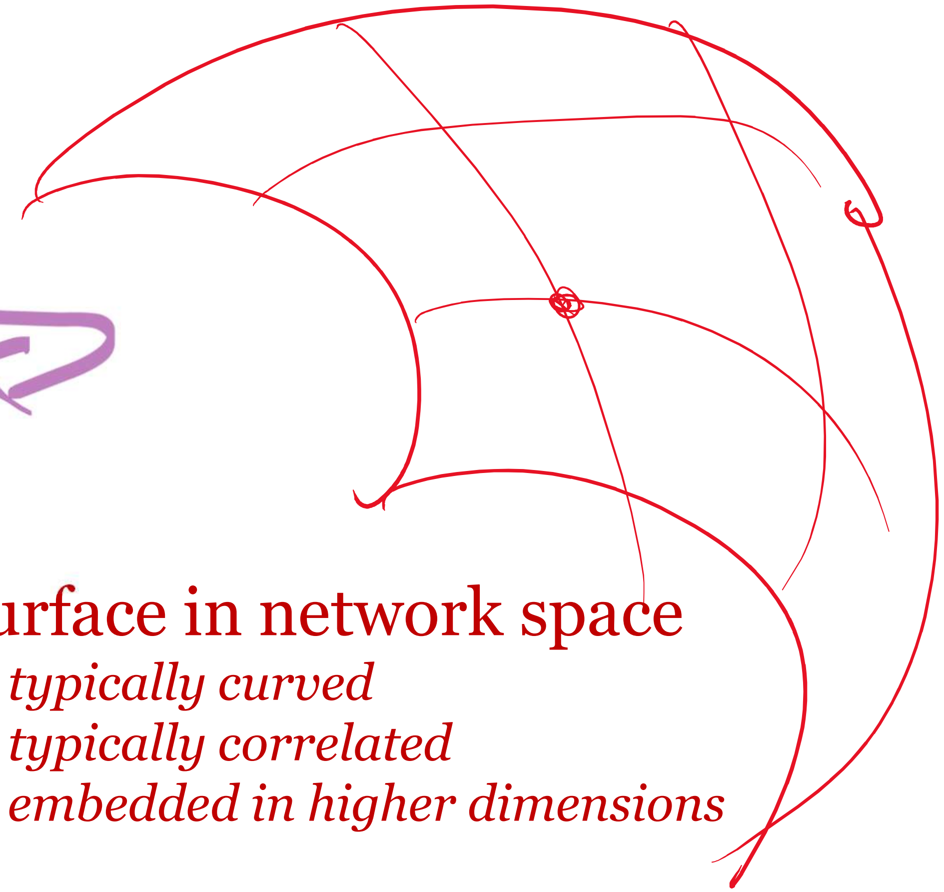
- What network-level outcomes do we want to study?
- How do we best deal with emergence?

Mapping the space of network features

Parameter space
- *seemingly flat*
- *seemingly orthogonal*
- *of dimensionality we choose*



expectation-over-simulations establishes one-to-one correspondence



Surface in network space
- *typically curved*
- *typically correlated*
- *embedded in higher dimensions*

Mapping the space of network features

Param

- seemi
- seemi
- of dim

Related terminology in exponential random graph modelling (and exponential families in general):

- *Natural parametrization* (in parameter space)
- *Mean value parametrization* (in space of subgraph counts, which is a subspace of the overall network space)

Both are available in the R-package `ergm` and used, e.g., in these papers:

Handcock, Mark S. (2003). Assessing degeneracy in statistical models of social networks. *Working Paper no. 39, Center for Statistics and the Social Sciences, University of Washington, Seattle*

van Duijn, Marijtje A.J., Krista J. Gile, Mark S. Handcock (2009). A framework for the comparison of maximum pseudo-likelihood and maximum likelihood estimation of exponential family random graph models. *Social Networks 31(1), 52-62.*

Three types of empirically calibrated simulations

First type: Manipulations of estimated parameters, see what changes

- Requires strong belief in the model and details of its parametrisation. Same as in agent-based simulations.
- Everything not explicitly manipulated is treated as *potentially emergent*

Second type: Manipulations of estimated parameters *plus model adjustment* such that simulations account for observed features on control dimensions

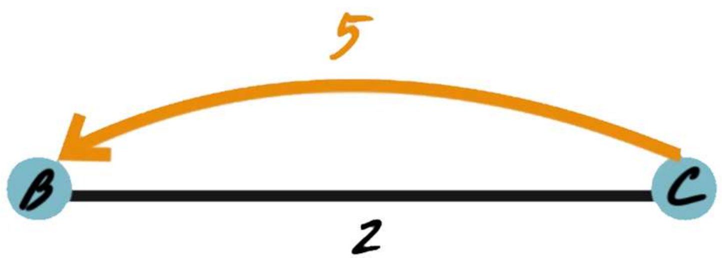
- Belief in data regularities overrides belief in the model, on control dimensions.

Third type: Manipulations of *input data* keeping everything else as estimated.

First type: simple parameter manipulations

1. Estimate a model.
2. Make model variants by manipulating parameter(s) of interest.
3. Simulate networks from the model variants.
4. See what the model variants predict on the macro feature of interest.

In the Coleman boat, this corresponds to counterfactual scenarios on the micro level (Arrows 2+5).



Example for a Type 1 Micro-Macro study

How does intergroup integration depend on the relative strength of homophily?

Simulation design:

1. Calibrate network model with homophily term to available data set.
2. Counterfactually change homophily parameter (in steps).
3. Generate outcome networks from all models.
4. Compare them on the number of intergroup ties.

Initial results from lab exercise "Type 1"

	Estimate	Standard Error	Convergence t-ratio
basic rate parameter friendship	3.1566	(0.5849)	-0.0019
outdegree (density)	-2.5656	(0.4473)	0.0037
reciprocity	1.0812	(0.5246)	-0.0042
transitive triplets	0.4239	(0.1474)	0.0329
transitive recipr. triplets	-0.3594	(0.2300)	0.0395
primary	1.0901	(0.4531)	0.0076
same sex.M	**1.1301**	**(0.4848)**	**0.0190**

Overall maximum convergence ratio: 0.0971

manipulate with factor multiplication

Probably better model for simulating: `simX` instead of `sameX`

	Estimate	Standard Error	Convergence t-ratio
basic rate parameter friendship	3.1456	(0.5359)	-0.0368
outdegree (density)	-2.0222	(0.3030)	0.0114
reciprocity	1.1221	(0.5356)	0.0107
transitive triplets	0.4349	(0.1547)	0.0353
transitive recipr. triplets	-0.3771	(0.2415)	0.0254
primary	1.1062	(0.4358)	0.0659
sex.M similarity	**1.1024**	**(0.4644)**	**0.0158**

Overall maximum convergence ratio: 0.1062

manipulate with factor multiplication

Why "probably better"? Is there any difference?

- For empirical inference, the two specifications and the results are fully equivalent.
- Note that intercept estimates `outdegree (density)` differ:

  `-2.57 (0.45)` initial model (`sameX`)

  `-2.02 (0.30)` maybe better model (`simX`)
- Specification difference is in *centering* (`simX` is, `sameX` is not):

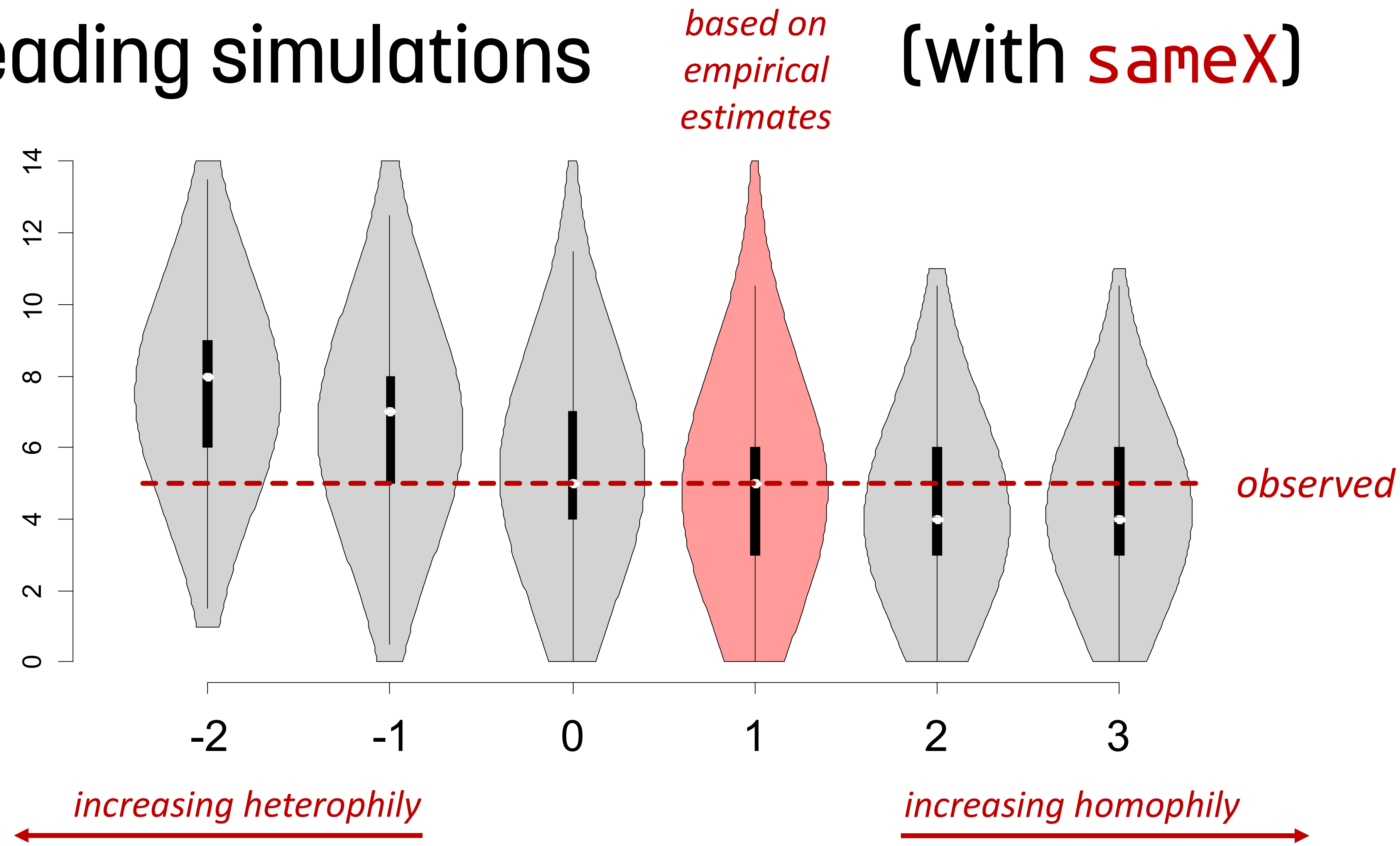
  → Manipulation of non-centered effect also affects number of ties!

  → If you do not want this, use centered effect – or (better yet) "Type 2"

Maybe misleading simulations (with sameX)

vertical axis:
number of cross-gender friendships

horizontal axis:
multiplication factor for empirical gender homophily estimate



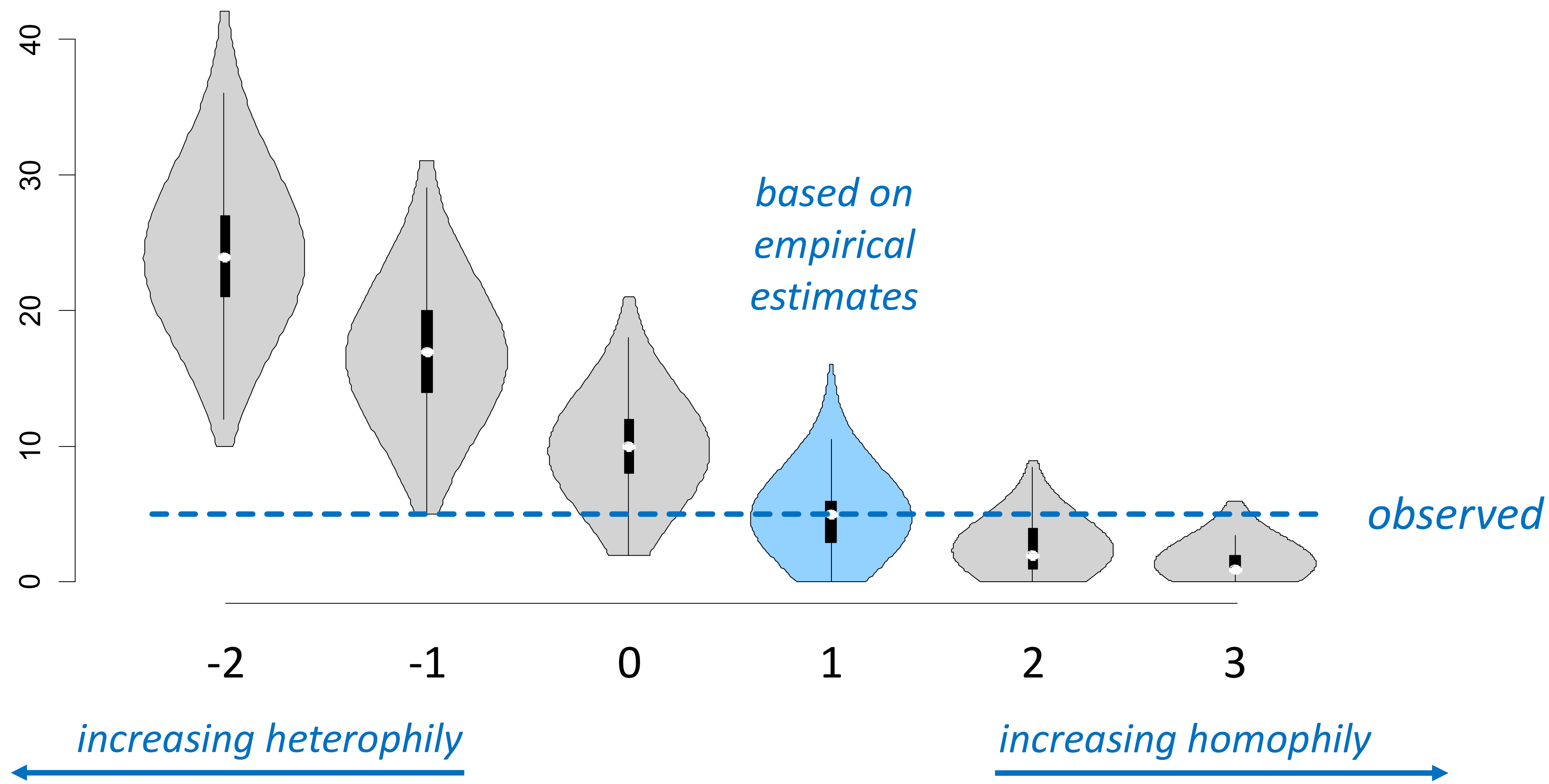
Maybe more useful simulations (using `simX`)

vertical axis:

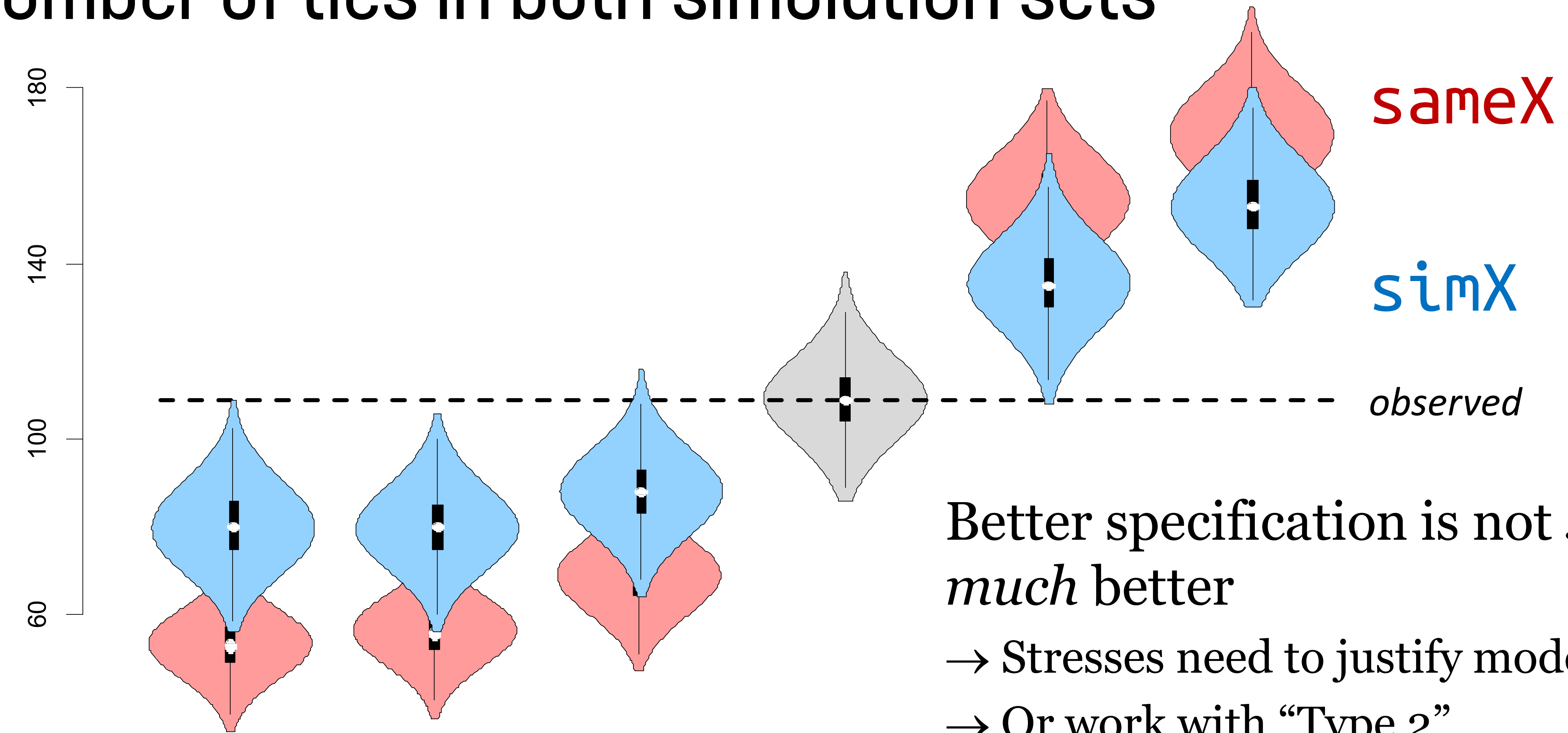
number of cross-gender friendships

horizontal axis:

multiplication factor for empirical gender homophily estimate



Number of ties in both simulation sets



Better specification is not *so much* better

→ Stresses need to justify model!

→ Or work with "Type 2"

Examples of published Type 1 studies

Cynthia M. Lakon, John R. Hipp, Cheng Wang, Carter T. Butts, and Rupa Jose (2015). Simulating Dynamic Network Models and Adolescent Smoking: The Impact of Varying Peer Influence and Peer Selection. *American Journal of Public Health*, 105, 2438-2448.

David R. Schaefer, jimi adams, and Steven A. Haas (2013). Social Networks and Smoking: Exploring the Effects of Peer Influence and Smoker Popularity Through Simulations. *Health Education and Behavior*, 40, no. 1, 24S-32S.

Second type: (re-)calibration of control parameters

- Idea is the same as for first type, BUT it is made sure that the simulated data look like the real data on desired control dimensions.
- For this purpose, after parameter manipulation, the control parameters are re-fitted to the data by another estimation run, conditional on the values of the counterfactually manipulated parameters.
- Basically, the manipulation is done in the *mean value parametrisation / network subgraph count space*.

Example above extended to Type 2 study

How does intergroup integration depend on the relative strength of homophily?

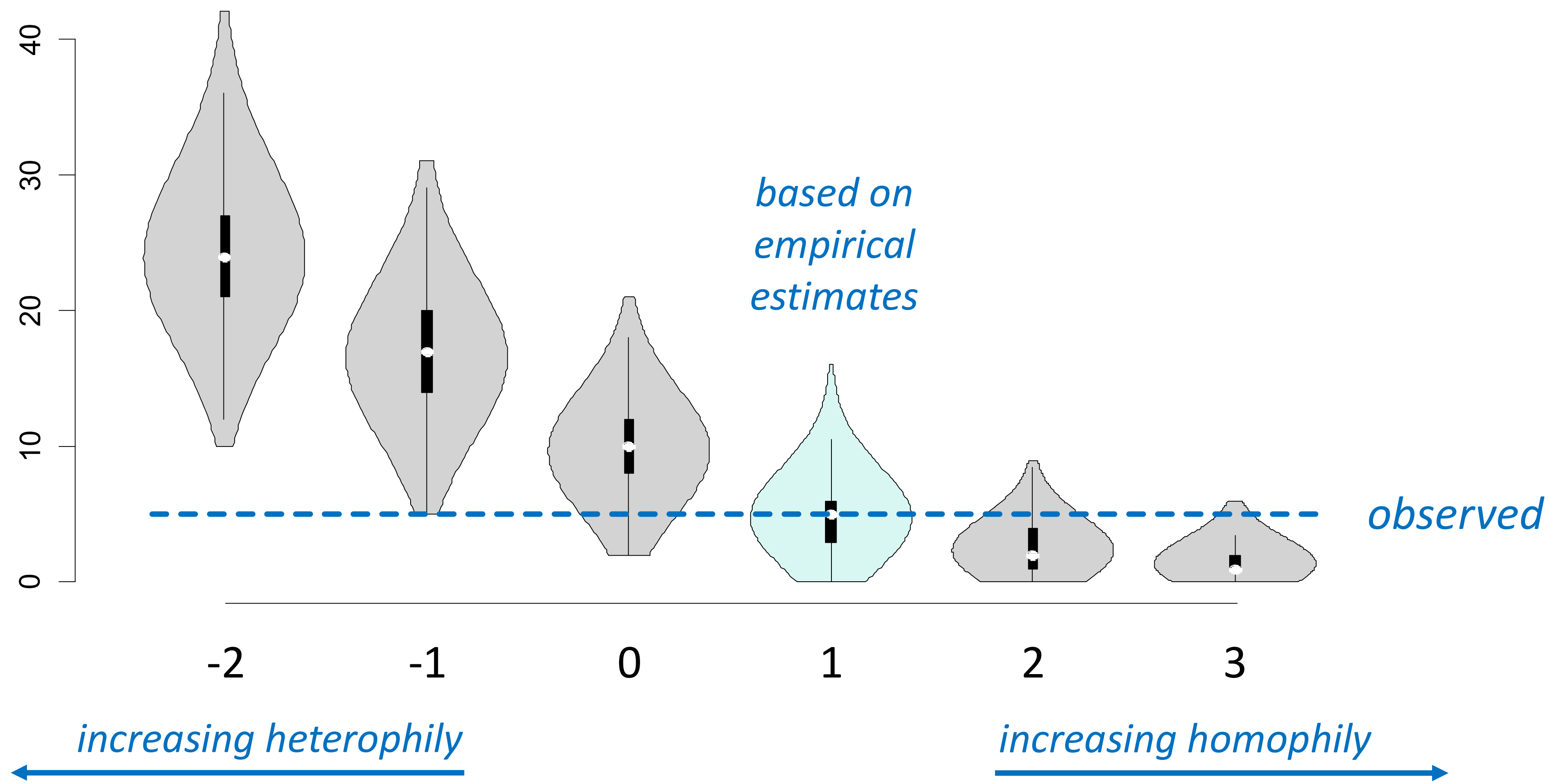
Simulation design:

1. Calibrate network model with homophily term to available data set.
2. Counterfactually change homophily parameter (in steps).
3. Re-calibrate all non-manipulated parameters to the data. ←NEW !!
4. Generate outcome networks from all models.
5. Compare them on the number of intergroup ties.

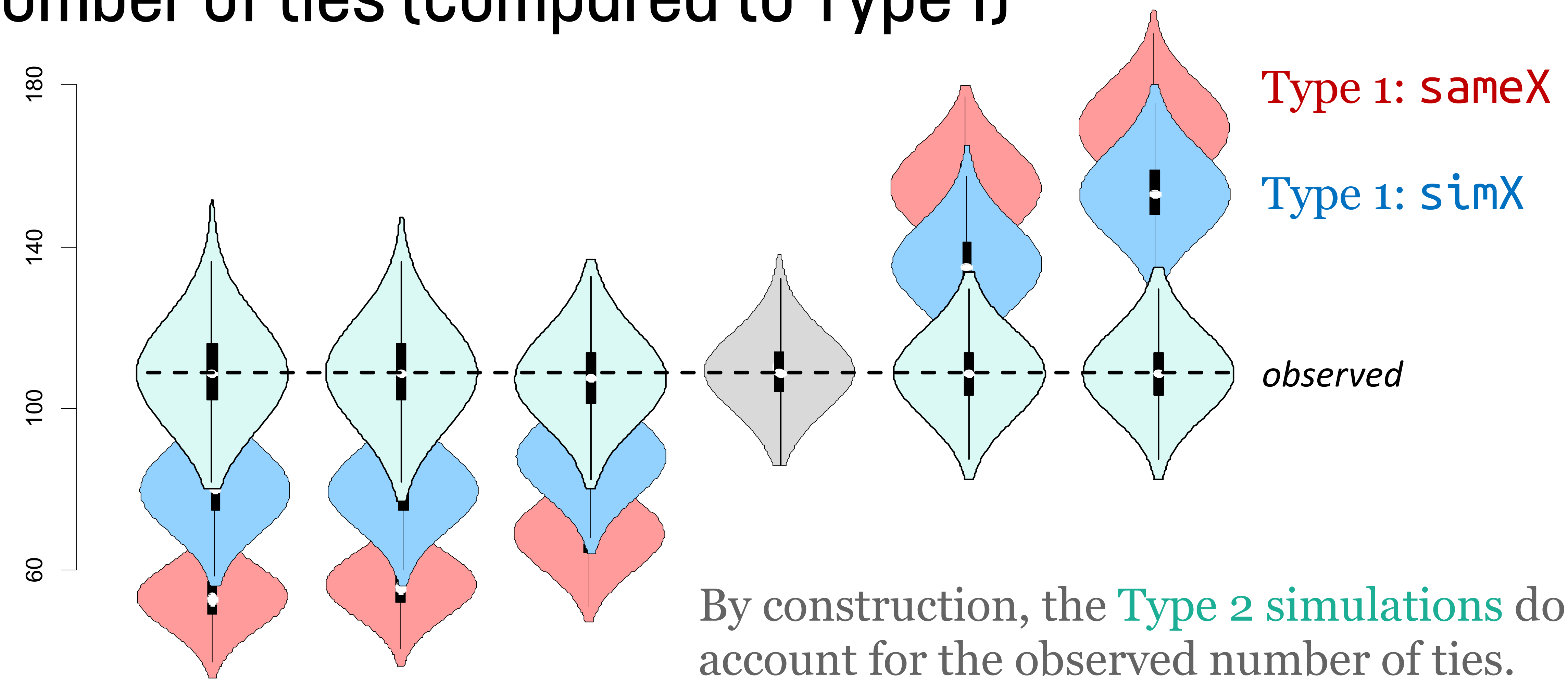
Results on cross-gender ties

vertical axis:
number of cross-gender friendships

horizontal axis:
multiplication factor for empirical gender homophily estimate



Number of ties (compared to Type 1)



By construction, the Type 2 simulations do account for the observed number of ties.

Examples of published Type 2 studies

Fujimoto, K., Snijders, T. A., & Valente, T. W. (2018). Multivariate dynamics of one-mode and two-mode networks: Explaining similarity in sports participation among friends. *Network Science*, *6*(3), 370-395.

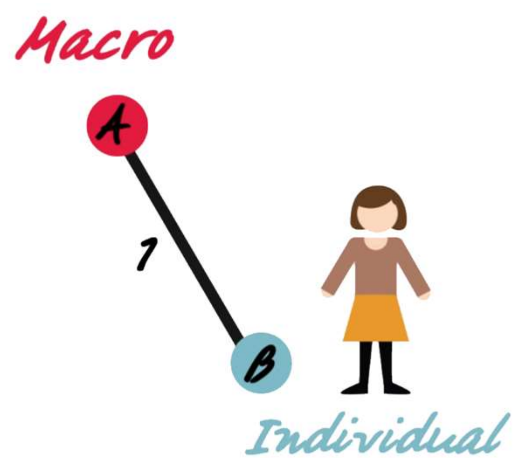
Snijders, T. A., & Steglich, C. E. (2015). Representing micro–macro linkages by actor-based dynamic network models. *Sociological Methods & Research*, *44*(2), 222-271.

Steglich, C. (2007). Closure, constraint and homophily: Joint determinants of network segregation. *Presentation at the XXVII Sunbelt Social Networks conference*.

Steglich, C., Snijders, T. A., & Pearson, M. (2010). 8. Dynamic Networks and Behavior: Separating Selection from Influence. *Sociological Methodology*, *40*(1), 329-393.

Third type: sensitivity to input data

- Stochastic actor-based model generates output networks
  - conditional on parameters, but also
  - conditional on initial network.
- In fully empirical studies, this initial network is usually the *first observation* of the analysed sequence.
- But it can also be used as something to be manipulated!
- In the Coleman boat, this corresponds to counterfactual scenarios on Arrow 1.



Example for a "Type 3" Macro-Micro-Macro study

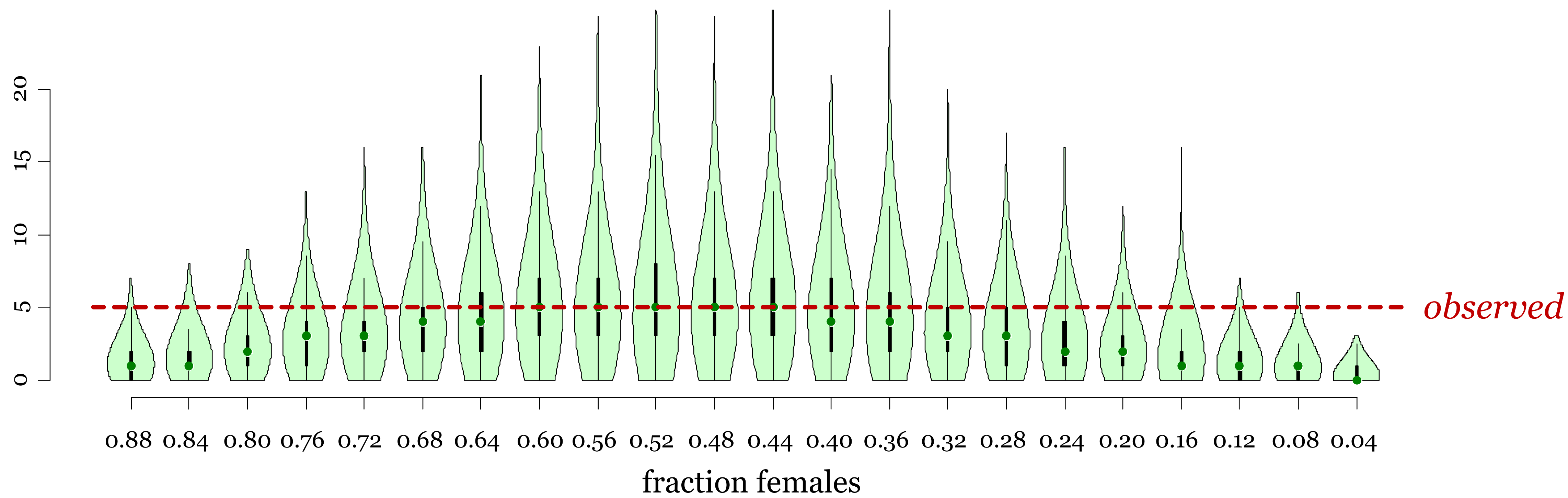
How does opportunity structure in school classes affect intergroup relations?

Simulation design:

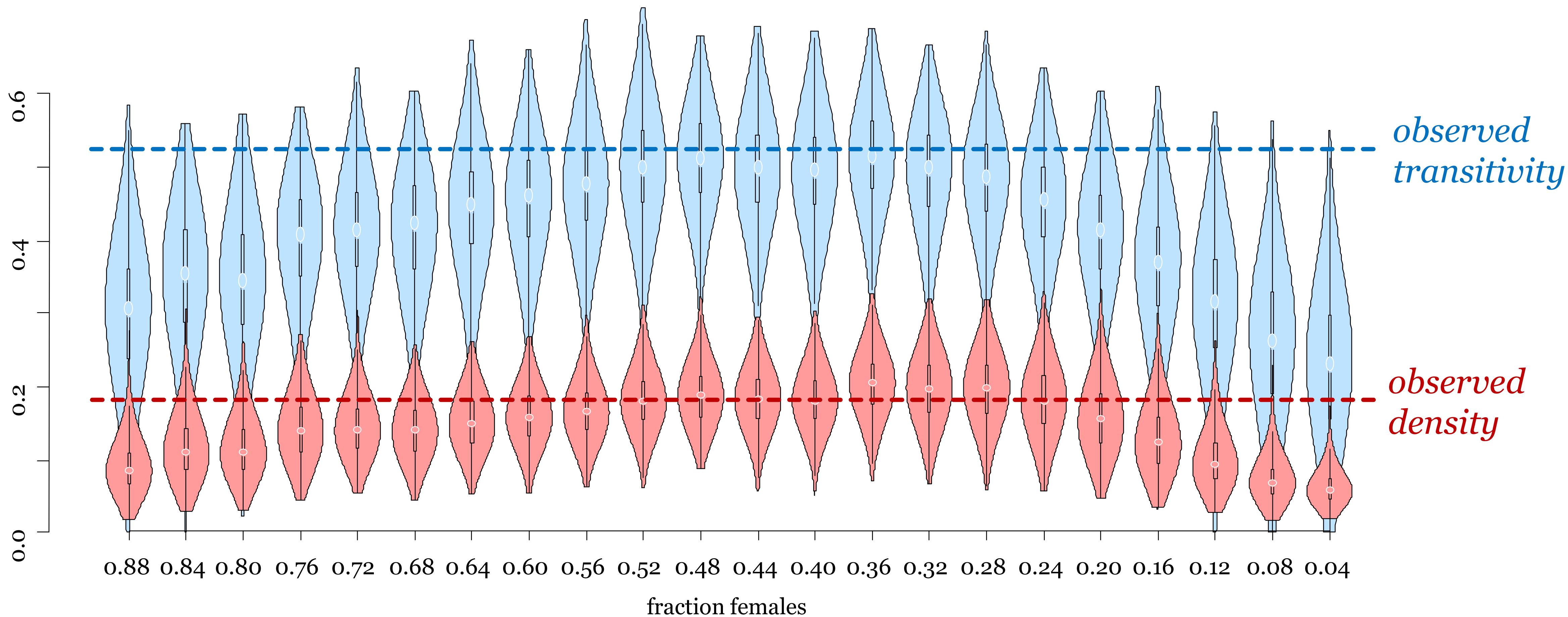
1. Calibrate gender homophily model to available data set.
2. Use estimated parameters but vary input data by changing its gender distribution, then generate outcome networks.
3. Investigate sensitivity of intergroup relations (e.g., a count of them) to this variation.

Outcome: Number of cross-gender friendships

As could be expected: the more the gender groups differ in size, the less opportunities for cross-gender ties there are, and the lower their number.



Other outcomes: transitivity and density



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What the above shows

Also here the question is:

> *Are we willing to interpret the results on transitivity or density as* emergent *phenomena?*

A published example combining Types 1 and 3

jimi adams & David R. Schaefer. 2016. How Initial Prevalence Moderates Network-Based Smoking Change: Estimating Contextual Effects with Stochastic Actor Based Models. *Journal of Health & Social Behavior* 57(1):22-38.

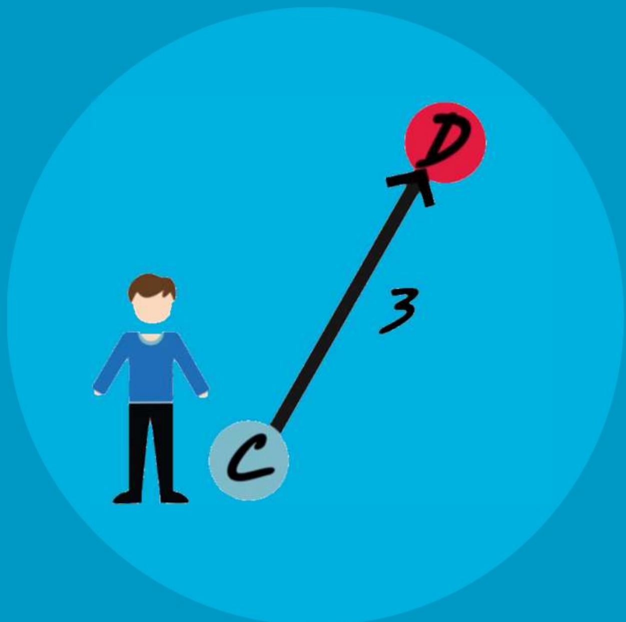
We use an empirically grounded simulation model to examine how initial smoking prevalence moderates the effectiveness of potential interventions designed to change adolescent smoking behavior. Our model *investigates the differences that result when manipulating peer influence and smoker popularity as* intervention levers. We demonstrate how a simulation-based approach allows us to estimate outcomes that arise (1) when intervention effects could plausibly alter peer influence and/or smoker popularity effects and (2) across a sample of schools that match the range of initial conditions of smoking prevalence in U.S. schools. We show how these different initial conditions combined with the exact same intervention effects can produce substantially different outcomes—for example, effects that produce smoking declines in some settings can actually increase smoking in others. We explore the form and magnitude of these differences. Our model also provides a template to evaluate the potential effects of alternative intervention scenarios.

Take-home messages?

Maybe these two.

- Be aware of potential model artefacts (such as *omitting a non-centered effect will lead to overall less ties*, with everything that this implies in turn).
- Think enough about emergence and calibration issues: is calibration needed, or not? For which parameters?
- Prepare to defend your beliefs.

Coleman boat graphics
with kind permission
of Petri Ylikoski



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A note on the word "counterfactual"

Causal inference by way of *counterfactuals* rests on "what if"-scenarios:

What	would my job status be today would my arrival time have been would segregation look like	*if*	I had received that grant I had taken the other road we admitted more minority students	*?*

These scenarios are about "alternate facts" (*third type* of study above).

Studies of first and second type above are not always interpretable as counterFACTual! (Sometimes yes, sometimes not – depends on details.)

Another example for Type 2 study: Steglich et al. 2010

How much is observed network autocorrelation determined by mechanisms of selection, influence, or others?

Simulation design:

1. Calibrate selection and influence model to available data set.
2. Calibrate also simpler (mis-specified, counterfactual) models with parameters of interest fixed (e.g., selection has zero effect) to the same data.
3. Generate outcome networks from all models and compare them on network autocorrelation.

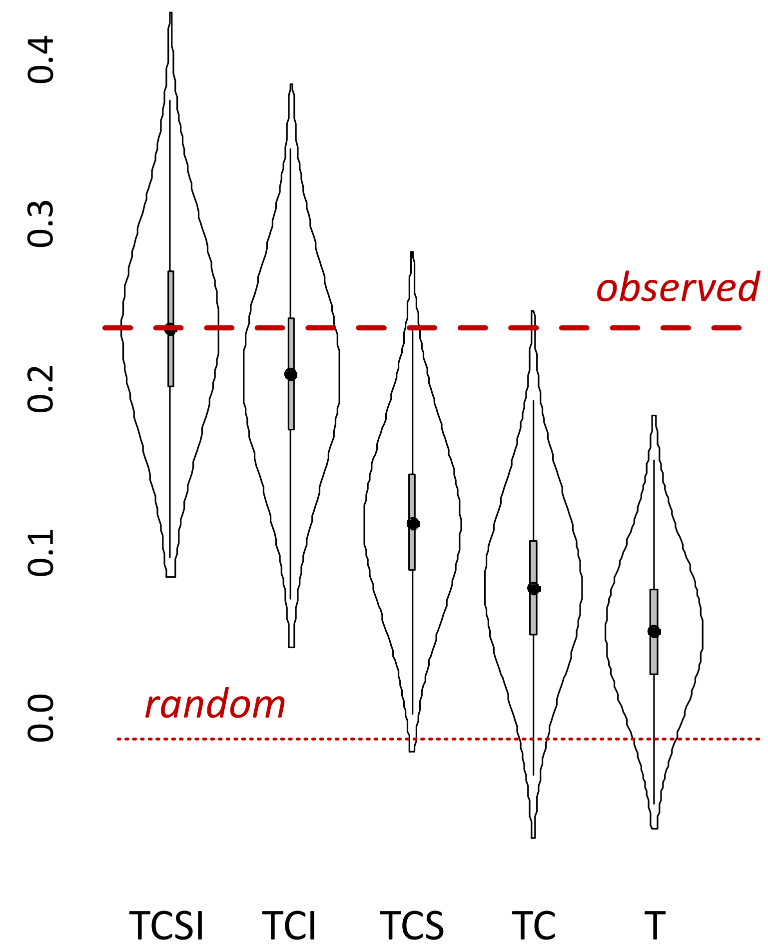
Results from such a study

To what degree are performance of advice giver and advice recipient associated?

- Indicator Moran's autocorrelation:

$$I = \frac{n\sum_{ij} x_{ij}(z_i - \overline{z})(z_j - \overline{z})}{\left(\sum_{ij} x_{ij}\right)\left(\sum_{i}(z_i - \overline{z})^2\right)}$$

- Compared are (partially) nested models including these components:
  T rend (rewiring, performance drift, etc.)
  C ontrol (gender, experience, etc.)
  S election (homophily, etc.)
  I nfluence (assimilation, etc.)



RSiena architecture