Why do Students Avoid Each Other?

Investigating Positive and Negative Network Effects

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Why study avoidance?

- Negative ties can greatly influence positive network dynamics and beliefs and behavior (e.g., Labianca and Brass, 2006; Candollone et al., 2025)

- Many different types of negative ties: dislike, bullying, aggression, and avoidance

Broad literature on these (e.g., Huitsing et al., 2014, among others)

Less studied

- Avoidance is particularly interesting since it is often more frequent and less socially complex than bullying and aggression (Wójcik and Flak, 2019; Kros et al., 2021)

Previous classroom avoidance network studies

Using longitudinal network data from nine classes in two Dutch secondary schools:

(1) Compare antipathy (dislike), avoidance, and aggression networks (Kros et al., 2021)

- Avoidance tends to be reciprocated
- Students are more likely to avoid classmates of a different gender

(2) Coevolution of classroom friendship and avoidance networks (Toroslu and Jaspers, 2022)

- Students likely to avoid friends of those they avoided
- In at least one class, students agree with friends on who to avoid

Our contribution

We use 193 classroom networks to study:

(1) Structural dependencies in classroom avoidance networks

(2) How a student's tendency to avoid others and be avoided relates to their position in the classroom friendship network

We extend previous work in three ways:

(1) Account for global network properties in friendship networks (e.g., student connectedness)

(2) Control for lower-level, non-triadic structures between networks (e.g., tie overlap)

(3) Use a larger sample of classroom networks

Participants and procedures

Netherlands Wave 1: Children of Immigrants Longitudinal Survey in Four European Countries (CILS4EU)

- Primarily 14-year-old students (2010-2011)
- Questions on students' background and self-reported relationships with classmates

Removing classes with low survey participation (<50%) and small class sizes (<10 students):

98 schools → **193 classrooms** → **4,015 students**

Average class size: **21.1** students *(SD = 4.8)*

Network measures

Avoidance

"Which classmates would you not like to sit by?" ⟵ Nominate up to 5

Binary directed network $y^{(k)}$, where $y_{ij}^{(k)} = \begin{cases} 1 & \text{if student } i \text{ avoids classmate } j \\ 0 & \text{otherwise} \end{cases}$

Friendship

(1) "Which classmates are your best friends?" ⟵ Nominate up to 5

(2) "Which classmates do you often spend time with outside of school?"

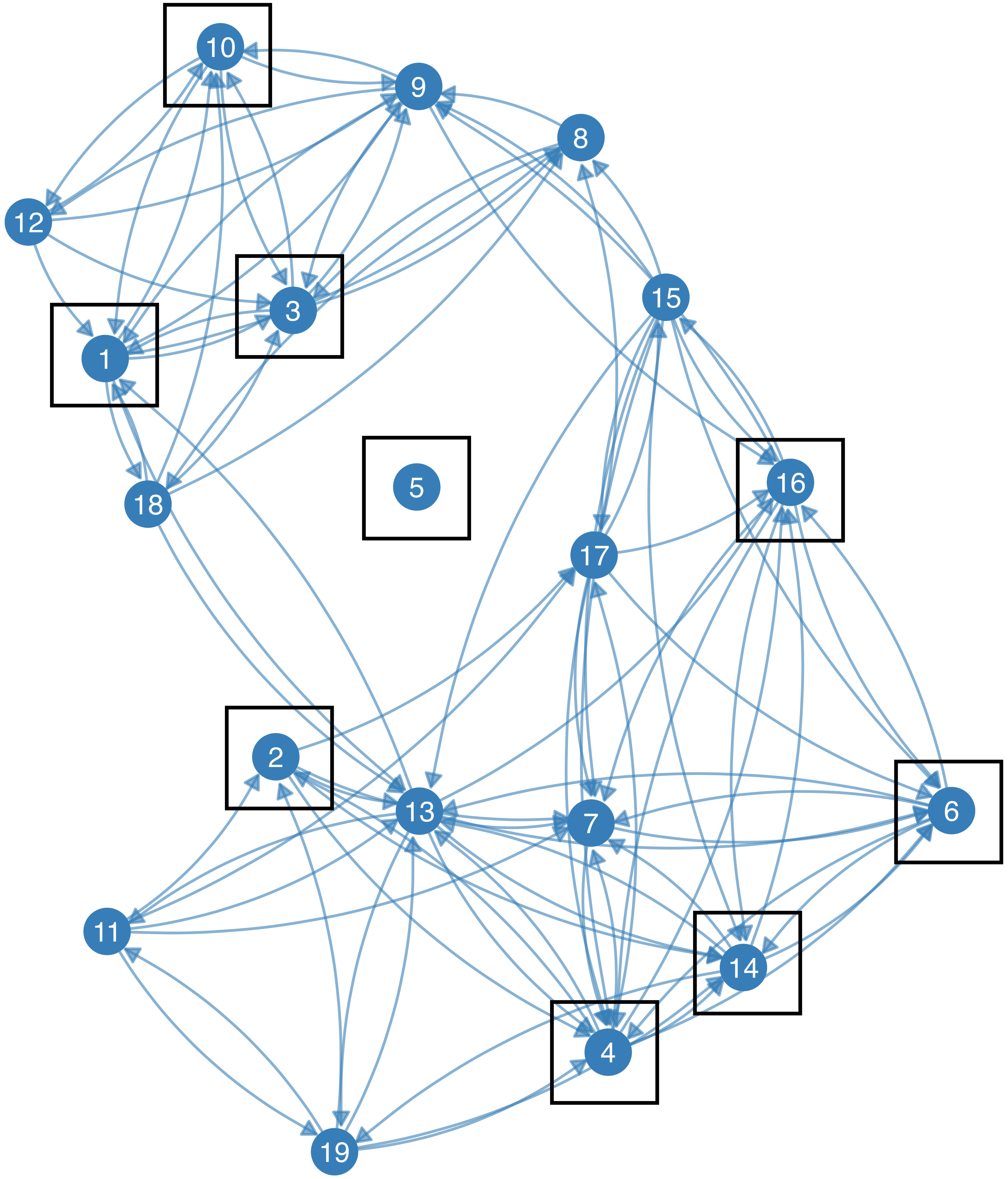
Student i nominates classmate j as a friend if they nominate them for (1) or (2)

Some students did not complete all the self-reported social relationship questions

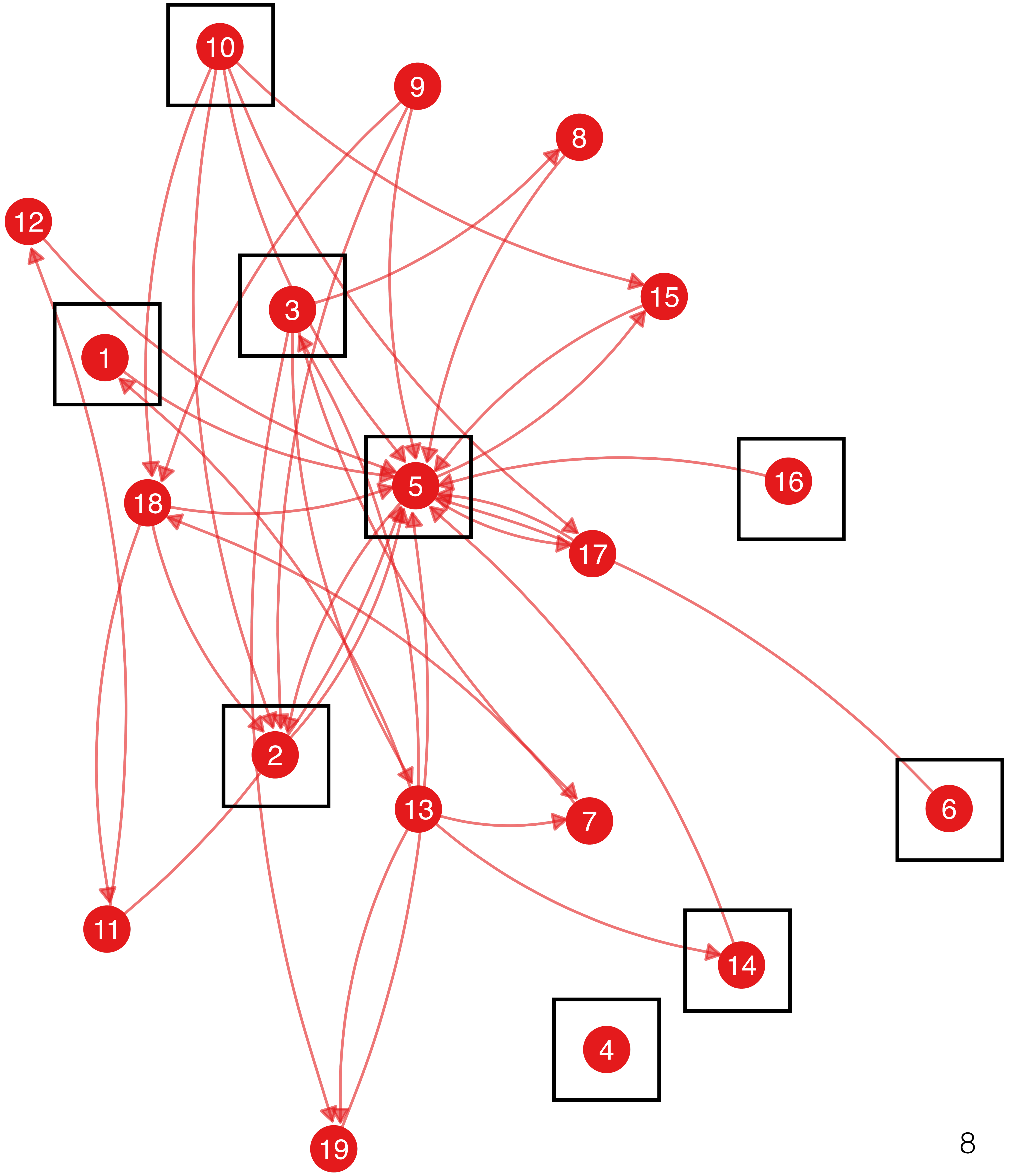
Question Type	Students Missing (%)
Not want to sit by	208 (5.1%)
Top 5 best friends	135 (3.3%)
Often spend time with outside of school	134 (3.3%)

We treat students who did not complete a given set of questions as having no nominations for that social relationship category

Friendship

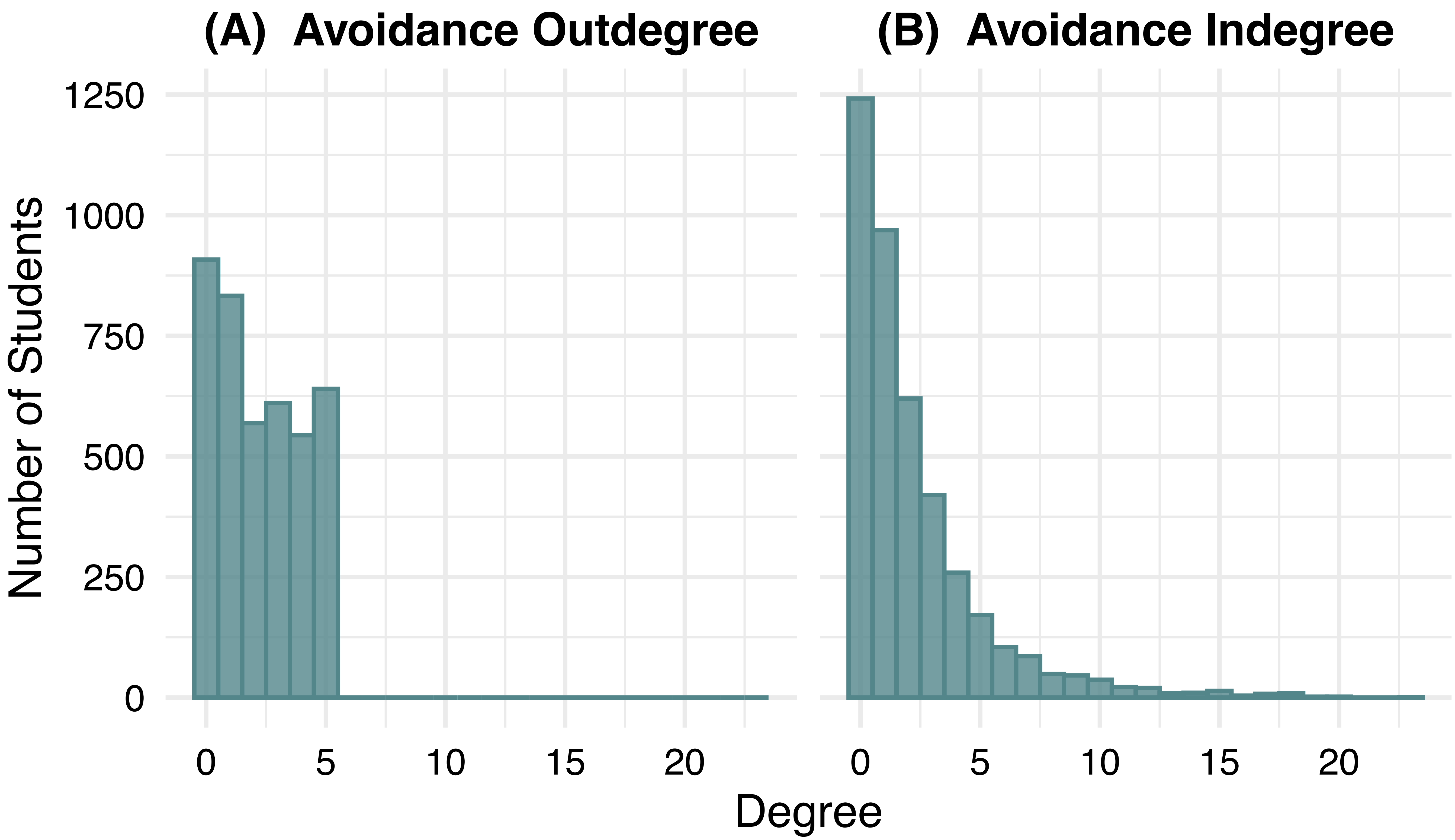


Avoidance



Degree-related descriptives

- Students avoid **2.4** *(SD = 1.7)* classmates and consider **3.7** *(SD = 1.7)* classmates their friends, on average
- **19.1%** of avoidance ties are reciprocated in a classroom, on average
- **7.4%** of students neither avoid nor are avoided by any of their classmates, on average



There is little overlap between friendship and avoidance

	Mean Jaccard Index	**SD Jaccard Index**
Avoidance and Friendship	0.023	0.029
Avoidance and Transposed Friendship	0.027	0.026

Transposed Friendship:

If classmate j considers student i a friend $\Rightarrow$ tie from student i to classmate j

Exponential Random Graph Models (ERGMs)

- Observed network is a single realization of a random network among a set of actors
- Observed network structure emerges from a series of local tendencies

Reciprocity: tendency for ties to be mutual between actors

Homophily: tendency for actors with the similar characteristics to form ties

- Outcome can be represented as the log-odds that actor i sends a tie to actor j, holding the other ties in the network fixed

Exponential Random Graph Models (ERGMs)

Observed network y is a realization of a random network $\mathbf{Y}$ with n actors

Conditional probability of observing y follows an exponential family distribution:

$$\mathbb{P}_{\theta,\mathcal{Y}}(\mathbf{Y} = y \mid \mathbf{X}) = \frac{\exp(\theta' g(y, \mathbf{X}))}{\kappa(\theta, \mathcal{Y})}$$

- $\mathbf{X}$: covariate matrix
- $g(y, \mathbf{X})$: sufficient statistic vector
- θ: coefficient vector for $g(y, \mathbf{X})$
- $\kappa(\theta, \mathcal{Y})$: normalizing constant computed over sample space of possible networks $\mathcal{Y}$

Contains counts of network configurations or a function of these counts within y and covariates in $\mathbf{X}$

e.g, reciprocity: $\frac{1}{2}\sum_i \sum_j y_{ij} y_{ji}$

Tie-level ERGM formulation

Outcome is the conditional log-odds of i sending a tie to j:

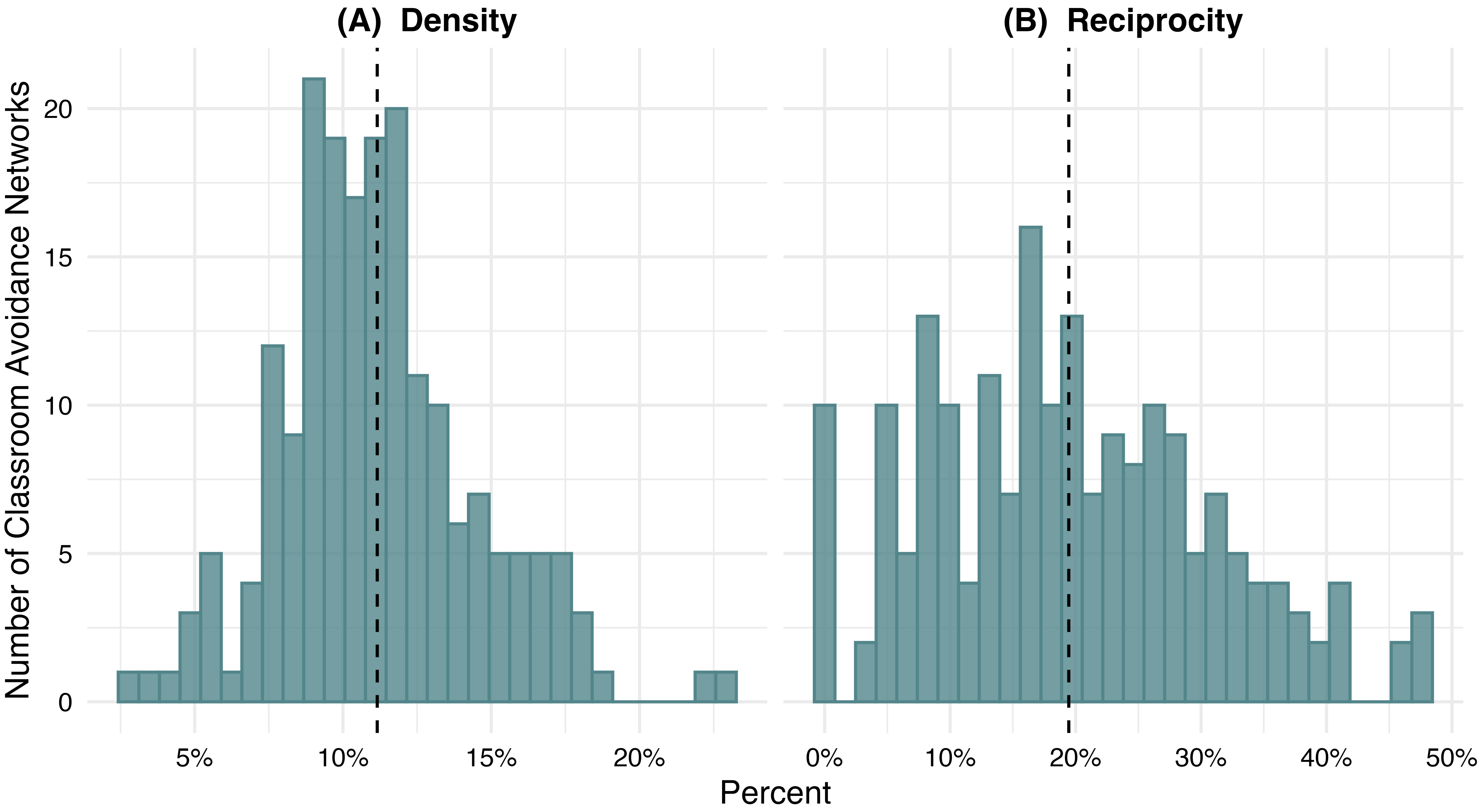
$$\log\left(\frac{\mathbb{P}(Y_{ij}=1 \mid \mathbf{X}, Y_{-ij})}{\mathbb{P}(Y_{ij}=0 \mid \mathbf{X}, Y_{-ij})}\right) = \theta' \delta_{ij}^{+}(y, \mathbf{X})$$

- Y_{ij}: tie from i to j
- Y_{-ij}: all other ties in the network besides Y_{ij}
- $\delta_{ij}^{+}(y, \mathbf{X})$: change statistic vector

Measures change in sufficient statistic vector when $y_{ij} = 1$ vs. when $y_{ij} = 0$

ERGM coefficients: change in the conditional log-odds of a tie associated with a one-unit increase in the given statistic

Heterogeneity in classroom avoidance networks



Hierarchical ERGMs

Extends the ERGM framework to a sample of networks:

- Allows the effects of the local tendencies on the network structure to vary across the sample

⟶ Results in network-specific random effects

- Assumes the network-specific random effects come from a common population distribution

⟶ "Borrows strength" across networks to estimate the network-specific random effects

Hierarchical ERGM setup

Let $y^{(1)}, y^{(2)}, \ldots, y^{(193)}$ denote our sample of classroom avoidance networks, where:

- $n^{(k)}$: number of students in the avoidance network for classroom k
- $\mathbf{X}^{(k)}$: exogenous covariates for classroom k

Student-level attributes
(e.g., student i's gender)

Dyad-level attributes *(e.g., whether student i is friends with classmate j)*

Hierarchical ERGM formulation

Classroom avoidance network $y^{(k)}$ is a realization of a random network $\mathbf{Y}^{(k)}$ with $n^{(k)}$ actors

Conditional probability of observing $y^{(k)}$ follows an exponential-family distribution:

$$\mathbb{P}_{\mathscr{Y}^{(k)}}(\mathbf{Y}^{(k)} = y^{(k)} \mid \mathbf{X}^{(k)}, \theta^{(k)}) = \frac{\exp\{(\theta^{(k)})^\top g(y^{(k)}, \mathbf{X}^{(k)})\}}{\kappa(\theta^{(k)}, \mathscr{Y}^{(k)})}$$

Can contain counts of network configurations and exogenous covariates

e.g. reciprocity: $\frac{1}{2}\sum_i \sum_j y_{ij}^{(k)} y_{ji}^{(k)}$

- $g(y^{(k)}, \mathbf{X}^{(k)})$: sufficient statistic vector for classroom k
- $\theta^{(k)}$: ERGM parameters <u>specific</u> to classroom k
- $\kappa(\theta^{(k)}, \mathscr{Y}^{(k)})$: normalizing constant for classroom k computed over sample space of possible networks $\mathscr{Y}^{(k)}$

Hierarchical ERGM formulation

While $\theta^{(k)}$ are specific to classroom k, we assume that for all $k \in \{1,\ldots,193\}$:

$$\theta^{(k)} \sim \text{Normal}(\mu, \Sigma) \quad \longleftarrow \text{hierarchical part}$$

Thus,

- μ represents the <u>average</u> effect across our 193 classroom avoidance networks
- Main diagonal of Σ gives the <u>variance</u> of each effect across our 193 classroom avoidance networks

We focus most of our interpretations on μ and its variance (on main diagonal of Σ)

Model specification

In our hierarchical ERGM, we include:

(1) Friendship-related effects

(2) Endogenous network effects (e.g., reciprocity, degree-related controls)

(3) Gender controls (Kros et al., 2021)

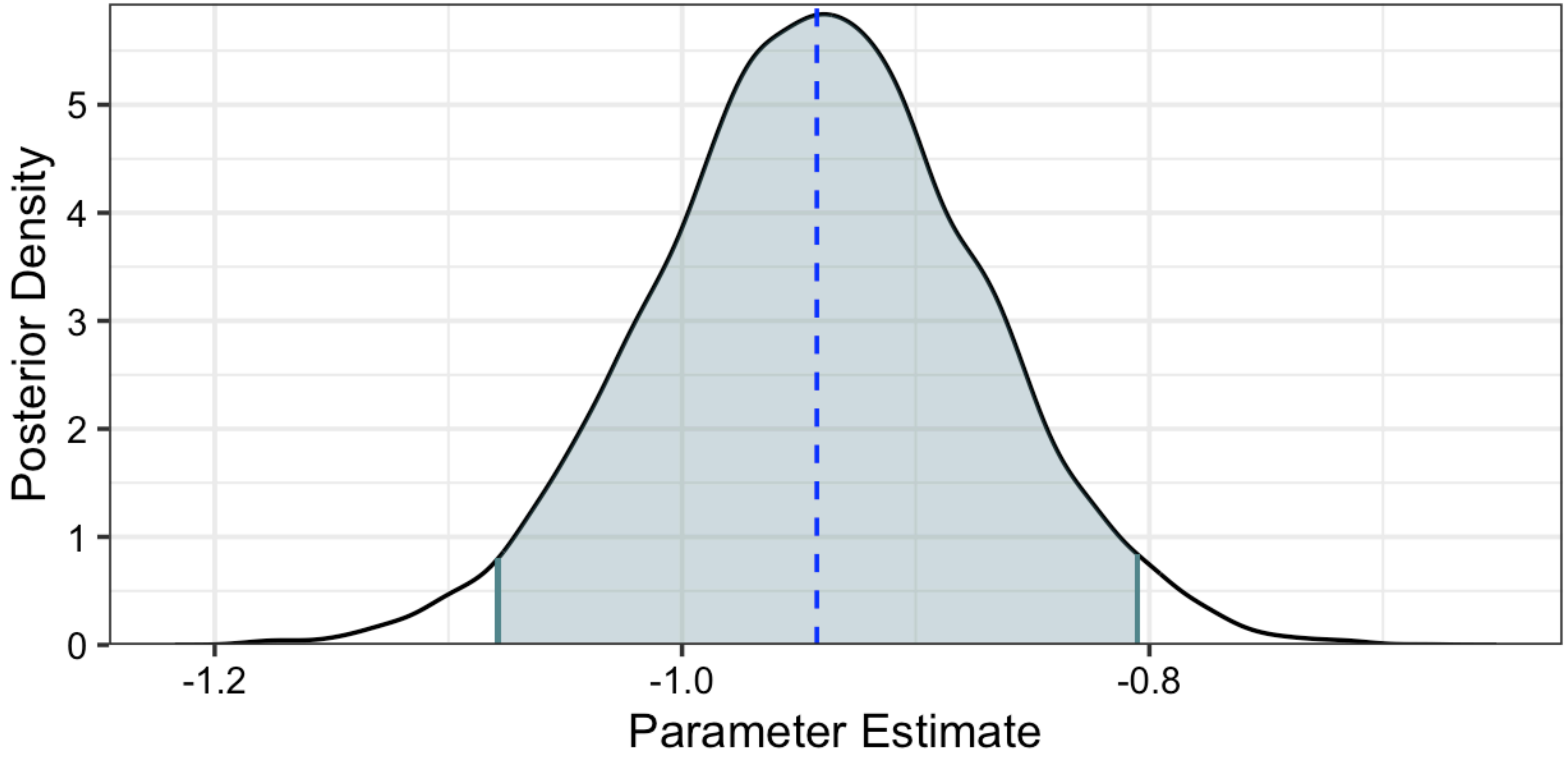
Use Bayesian framework to estimate our parameters (Agneessens et al., 2024)*

*https://github.com/johankoskinen/BayesERGM

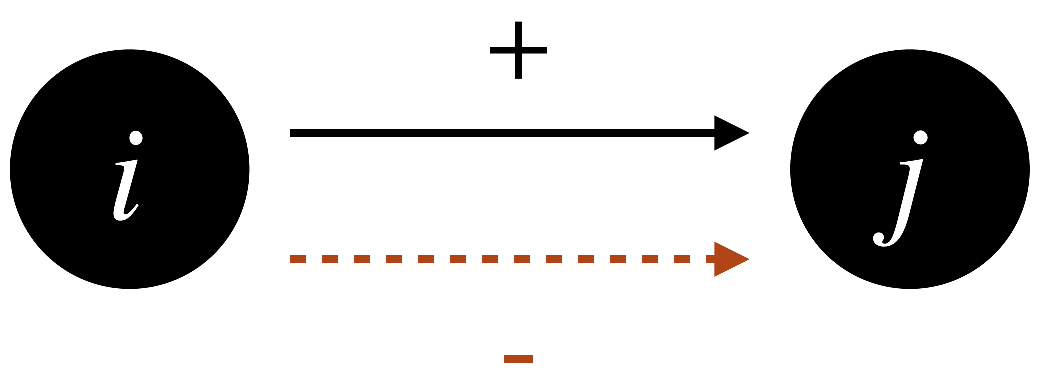
Hierarchical ERGM estimation

(1) Obtain posterior distribution for each of our parameters

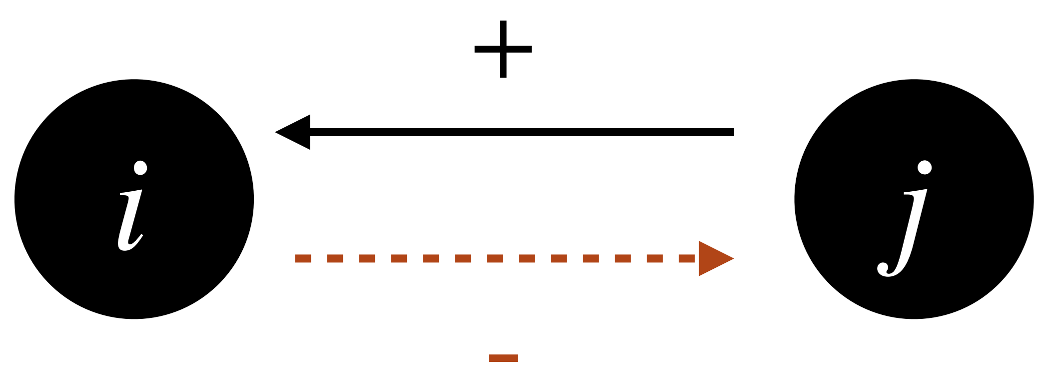
(2) Extract each parameter's posterior mean and 95% credible interval (CI)



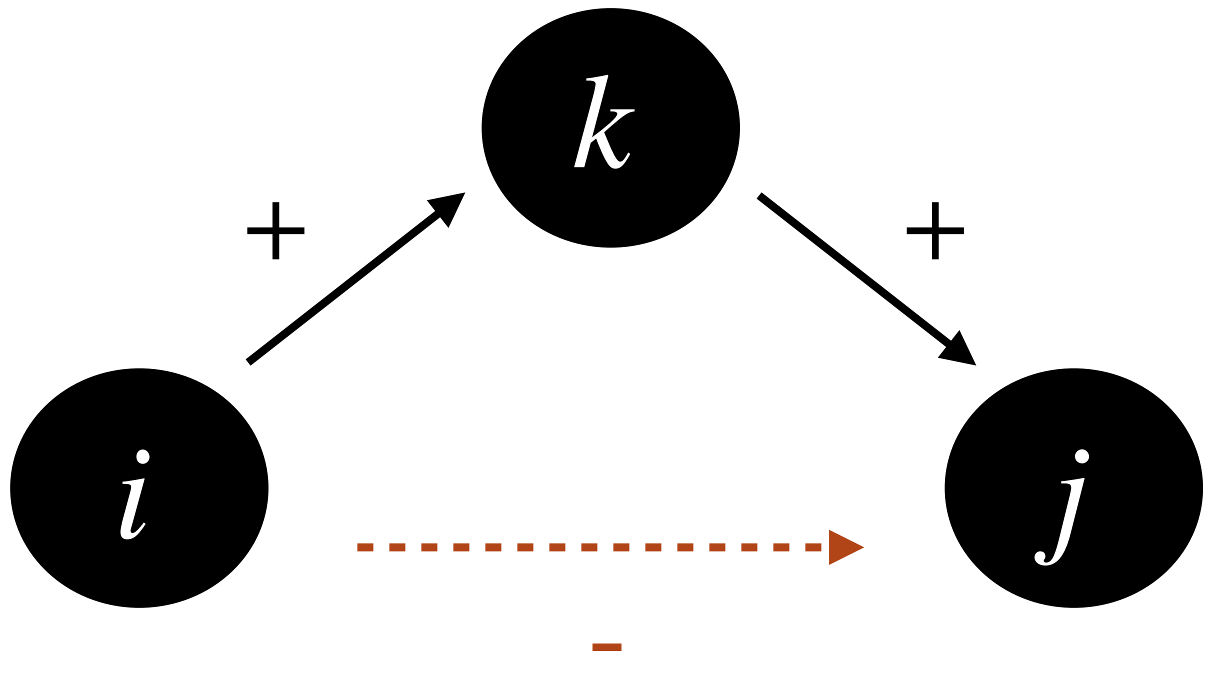
On average, avoidance networks are highly associated with friendship networks



Students tend <u>not</u> to avoid classmates they consider a friend (OR = 0.37, 95% CI [0.32, 0.44])

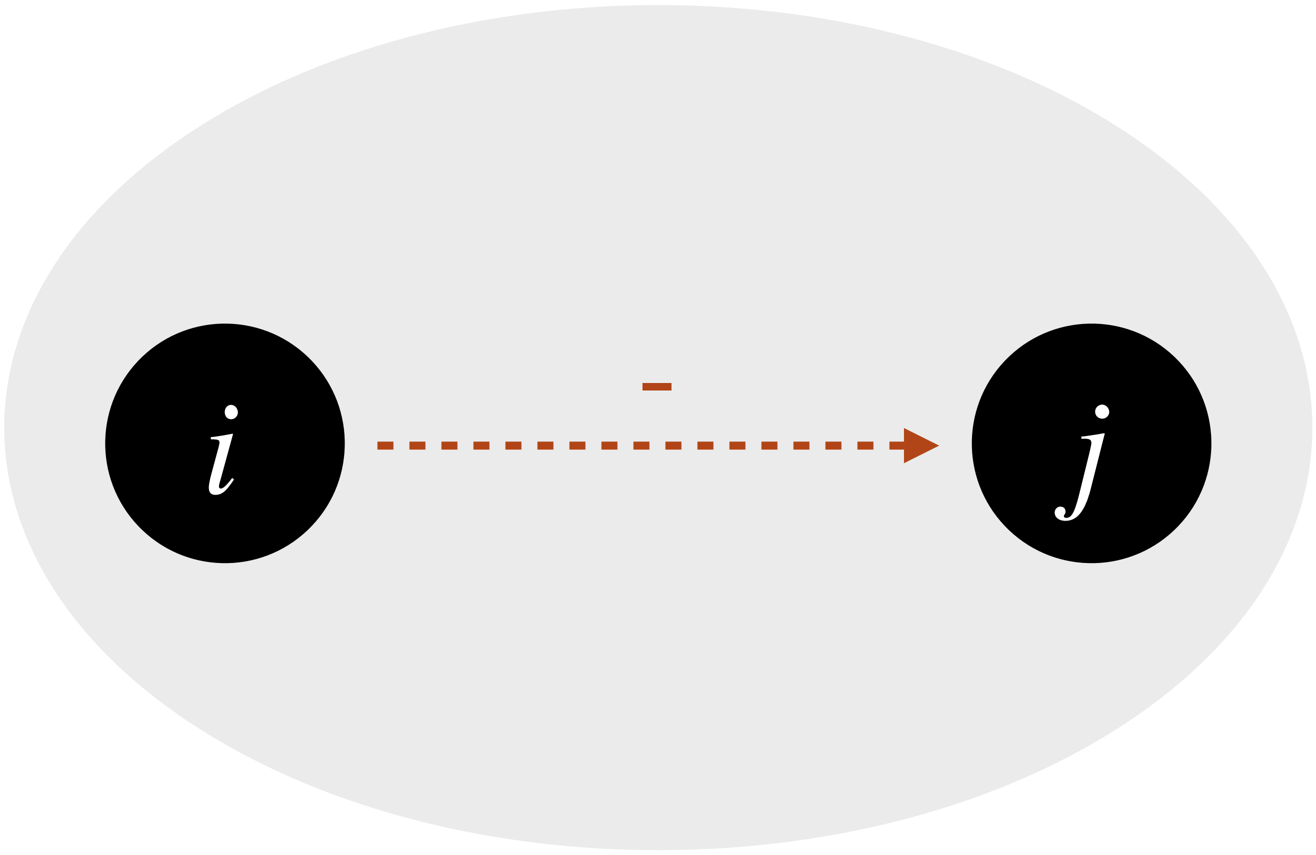


Students tend <u>not</u> to avoid classmates who consider them a friend (OR = 0.48, 95% CI [0.45, 0.53])

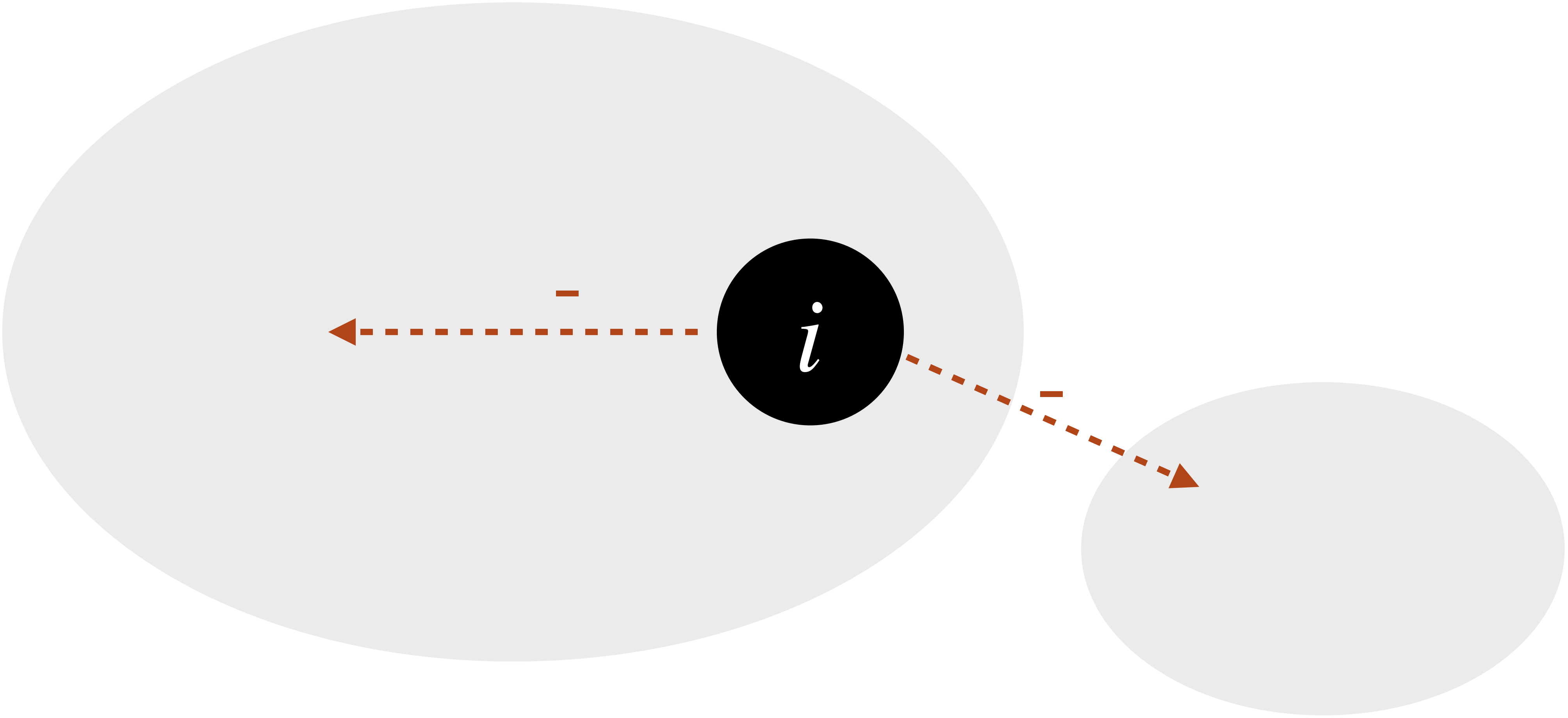


Students tend <u>not</u> to avoid classmates who are "friends-of-friends" (OR = 0.75, 95% CI [0.72, 0.79])

On average, avoidance networks are highly associated with friendship networks

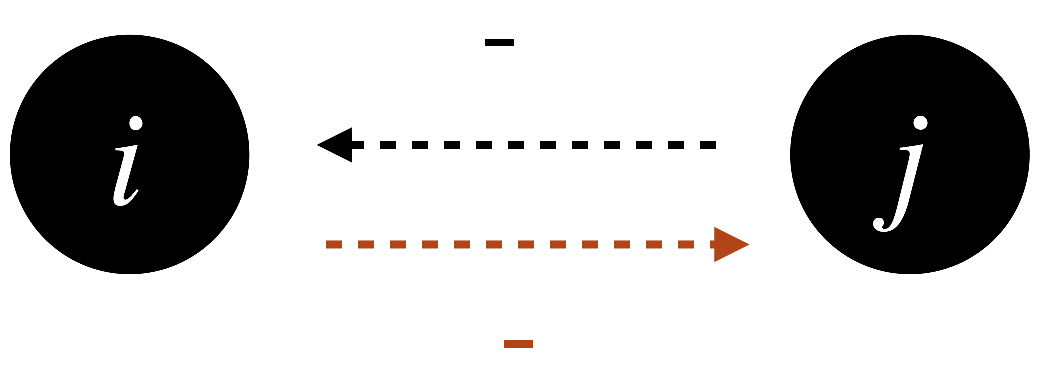


Students tend <u>not</u> to avoid classmates they are weakly connected to in the friendship network (OR = 0.69, 95% CI [0.63, 0.77])

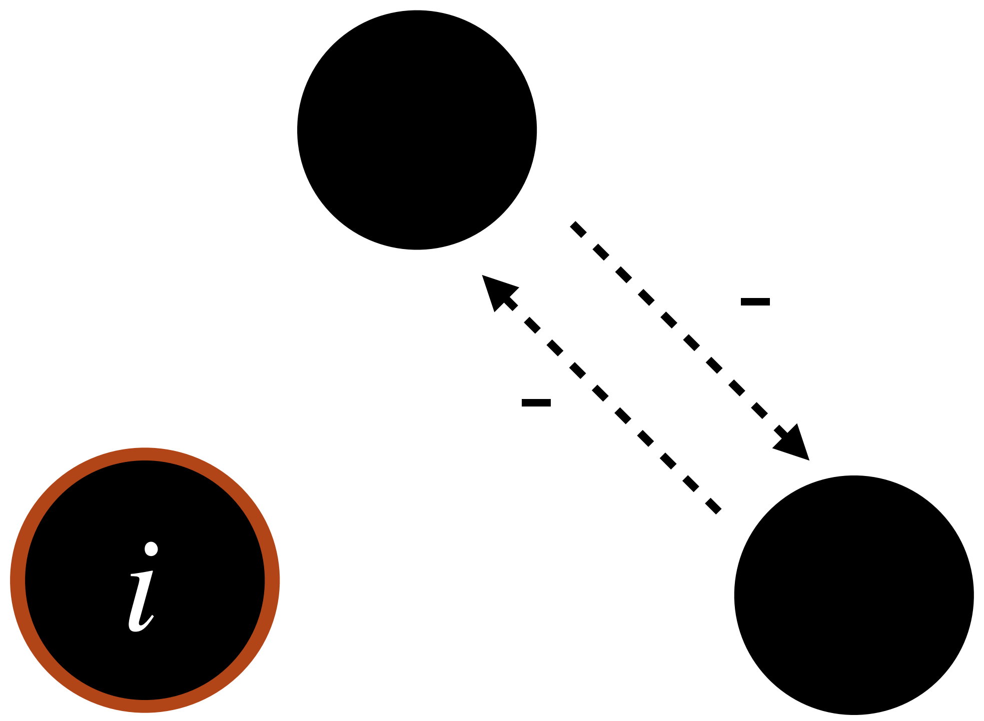


Students in the largest weakly connected component of the friendship network are <u>more</u> likely to avoid others (OR = 1.21, 95% CI [1.09, 1.33])

There are strong average reciprocity and degree-related endogenous effects in avoidance networks

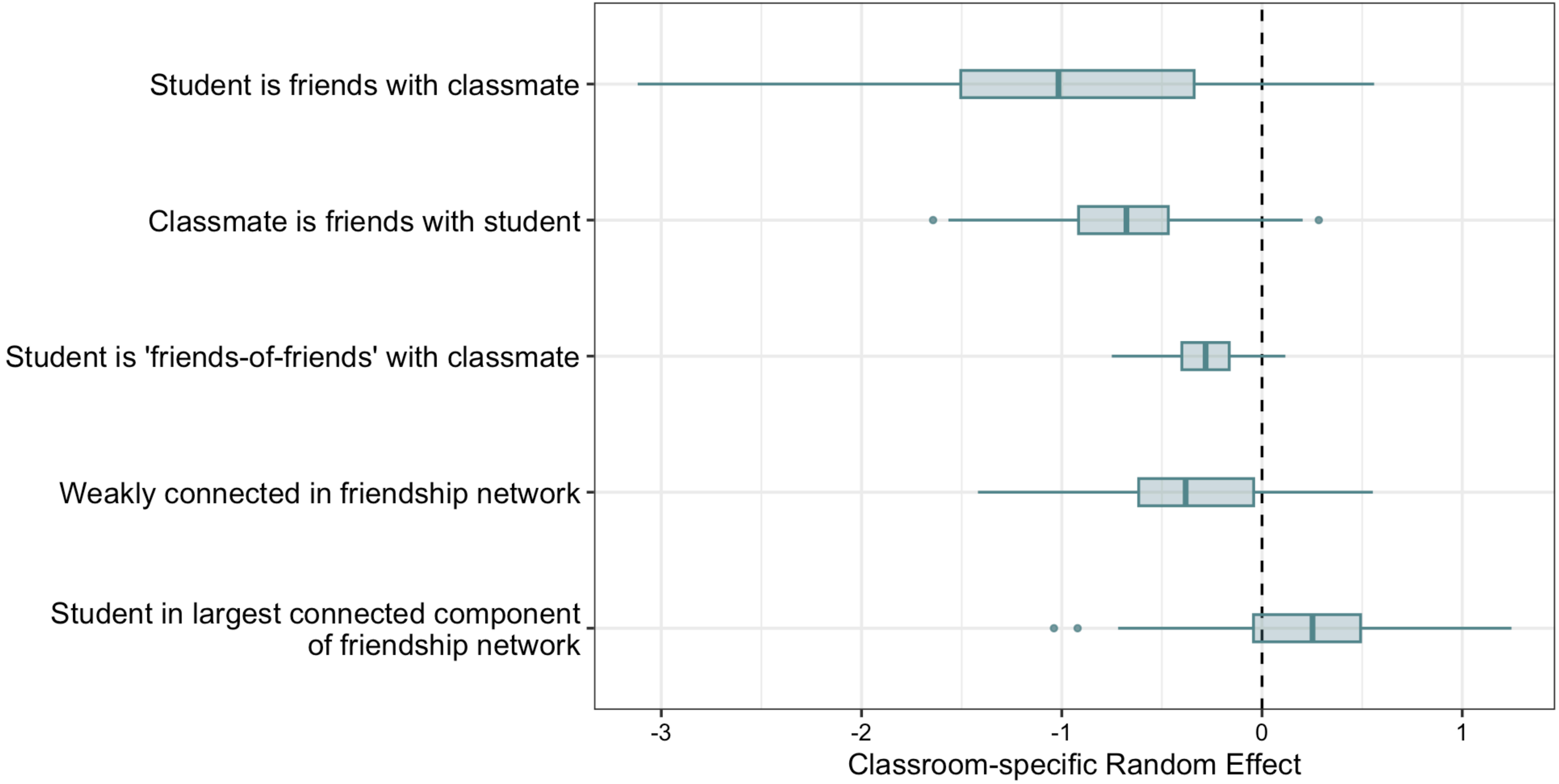


Avoidance tends to be reciprocated (OR = 1.83, 95% CI [1.68, 1.99])



Many students avoid none of their classmates (OR = 3.08, 95% CI [2.68, 3.54])

Variability in friendship effects across classrooms



Conclusions and future work

On average, classroom avoidance networks:

(1) are highly associated with classroom friendship networks

(2) exhibit strong reciprocity and degree-related endogenous effects

However, the magnitude of these effects can vary substantially between classrooms

E.g., we estimate that students in the largest connected component of the friendship network are <u>less</u> likely to avoid others in 54 (38%) of the classrooms

Future work: evaluating goodness-of-fit

Thank you! Questions?

Appendix Slides

Bayesian estimation details

The Bayesian framework described by Agneessens et al. (2024) is a two-part Markov Chain Monte Carlo (MCMC) Algorithm

(1) Update $(\theta^{(1)}, \ldots, \theta^{(193)})$ via approximate exchange algorithm (Caimo and Friel, 2011)

(2) Update (μ, Σ) via Gibbs sampling

For part (1): For each classroom $k \in \{1,\ldots,193\}$

Set maximum outdegree to 5

(1) Propose $\theta_*^{(k)}$ as update to the current parameter vector $\theta_0^{(k)}$

(2) Simulate a hypothetical classroom avoidance network $y_*^{(k)}$ using $\theta_*^{(k)}$

(3) Compare sufficient statistics from $y_*^{(k)}$ with the sufficient statistics from $y^{(k)}$

We accept/reject the proposed parameter vector $\theta^{(k)*}$ based on this comparison

Bayesian estimation details

For part (2): Place a Normal-Inverse Wishart prior on (μ, Σ):

$$\mu \mid \Sigma \sim \text{Normal}(0, \Sigma)$$

$$\Sigma \sim \text{InvW}(\Lambda, \nu)$$

where $\nu = 1$ and $\Lambda = \text{diag}(0.1)$

Currently, we have:

- 50,000 MCMC iterations
- 40,000 iterations are discarded (burn-in) and thinning factor of one

Last 10,000 samples are used to estimate the hierarchical ERGM parameters