Modeling Student Mobility Using Hierarchical Networks

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UNIVERSITY OF MARYLAND

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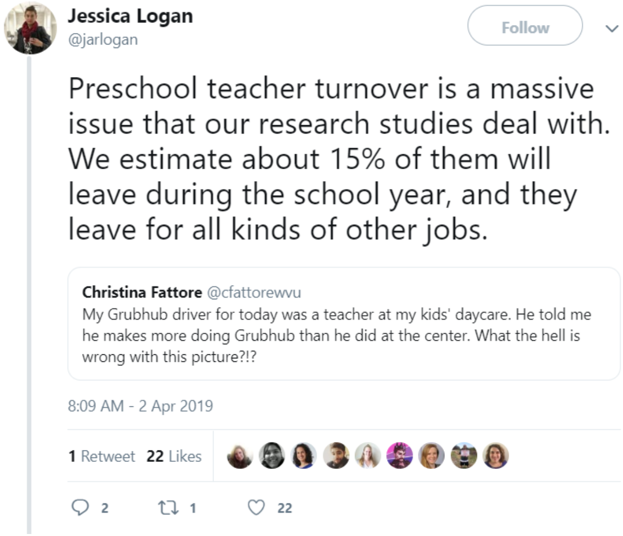
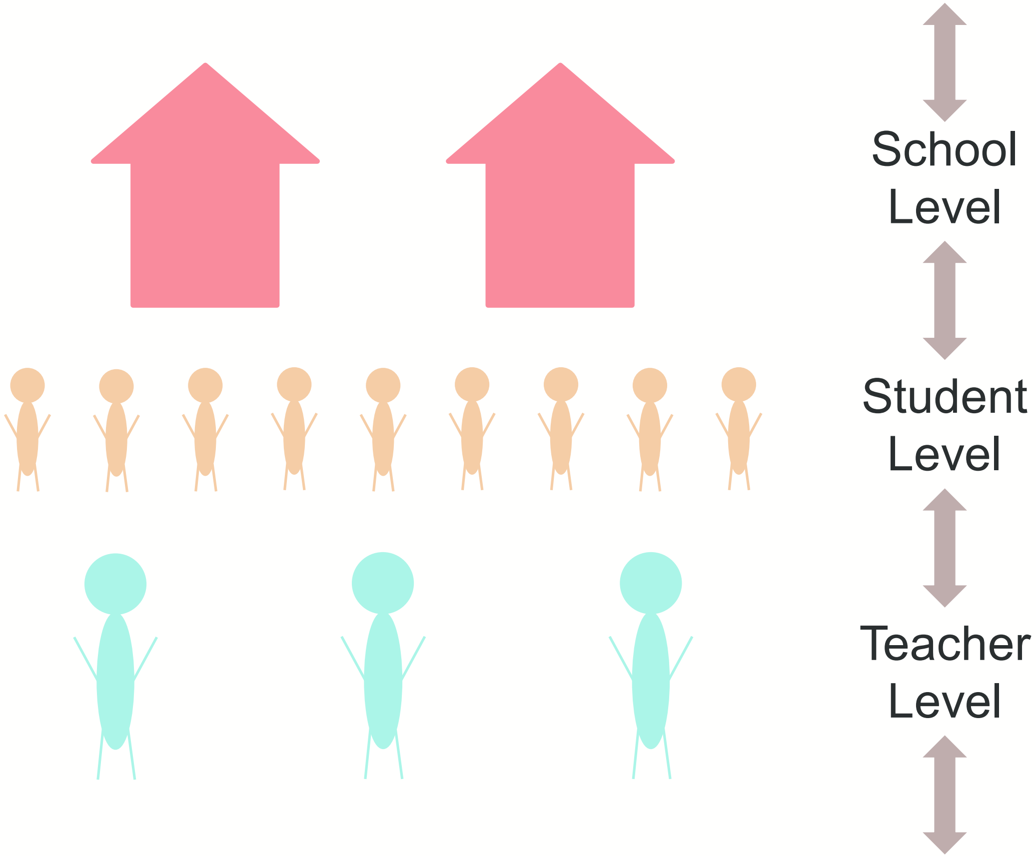
Overview

- “Mobility” is a complex and ongoing issue in education settings



Piasta, S. B., Logan, J. A. R., Pelatti, C. Y., & Capps, J. L. (2015). Professional development for early childhood educators: Efforts to improve math and science learning opportunities in early childhood classrooms. *Journal of Educational Psychology, 107*(2), 407-422.

Overview



Overview

- Common modeling procedures to handle mobility in education:
    - Multiple membership random effects model (MMREM; Browne, Goldstein, & Rasbash, 2001)
    - Use observed student mobility as a predictor or outcome in regression
    - Ignore it!

Overview

- We propose an alternative approach—multilevel network analysis

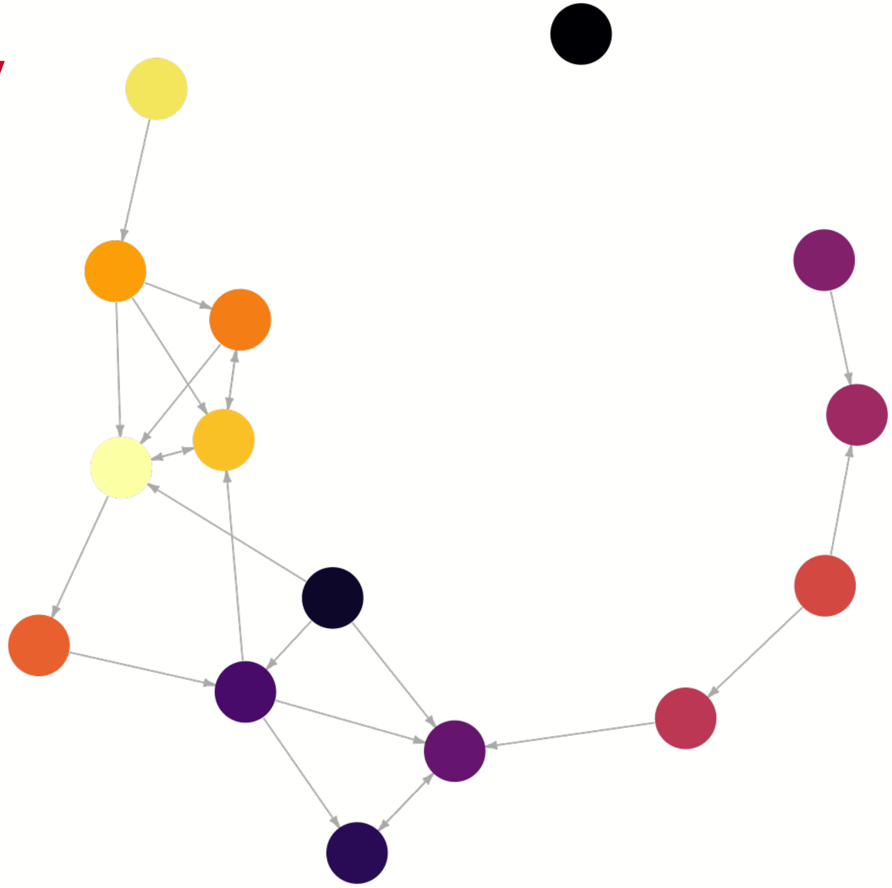
- Our findings, in brief:
  - Network models are capable of handling the complex dependencies among schools
  - Real data may contain few cluster-level observations and few nodes within clusters, which is problematic for estimation

Outline

- Introduction to mobility
- Social network modeling methods
- Results from the real data illustration
- Where do we go from here?

Patterns of Mobility

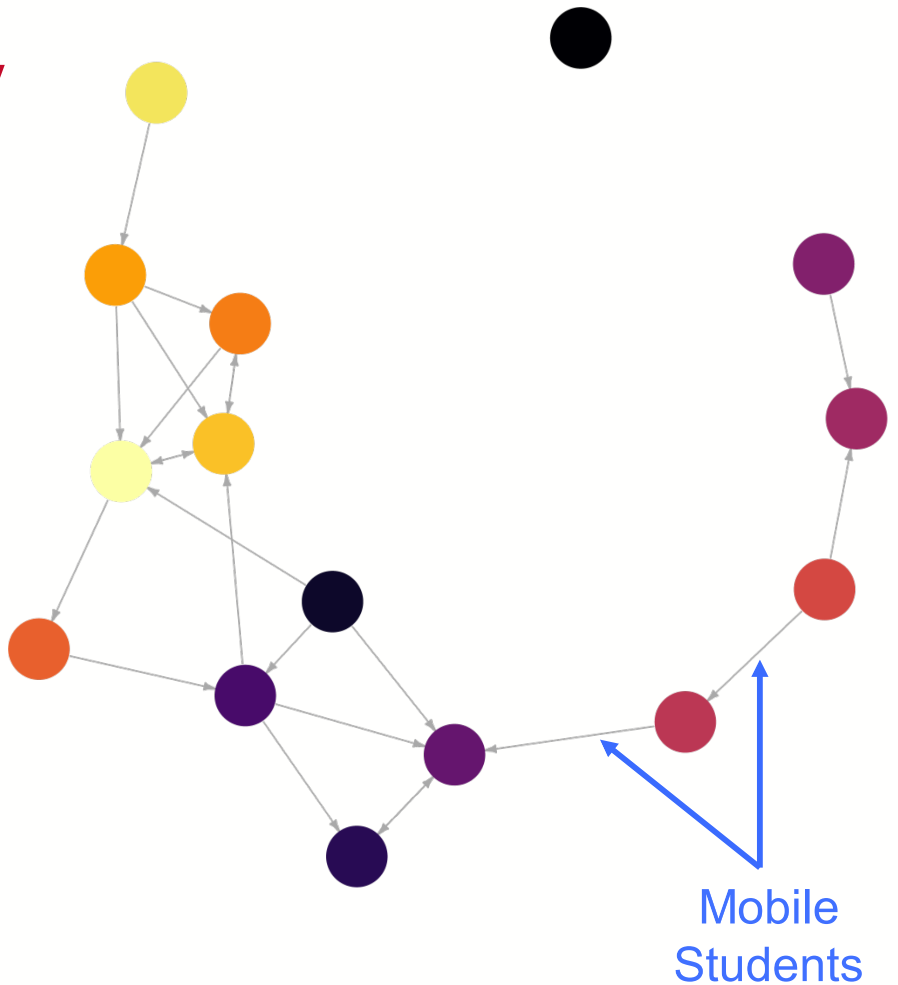
Students are mobile...but in a particular way



(Kerbow, 1996; Kerbow, Azcoitia, & Buell, 2003)

Patterns of Mobility

Students are mobile...but in a particular way



Patterns of Mobility

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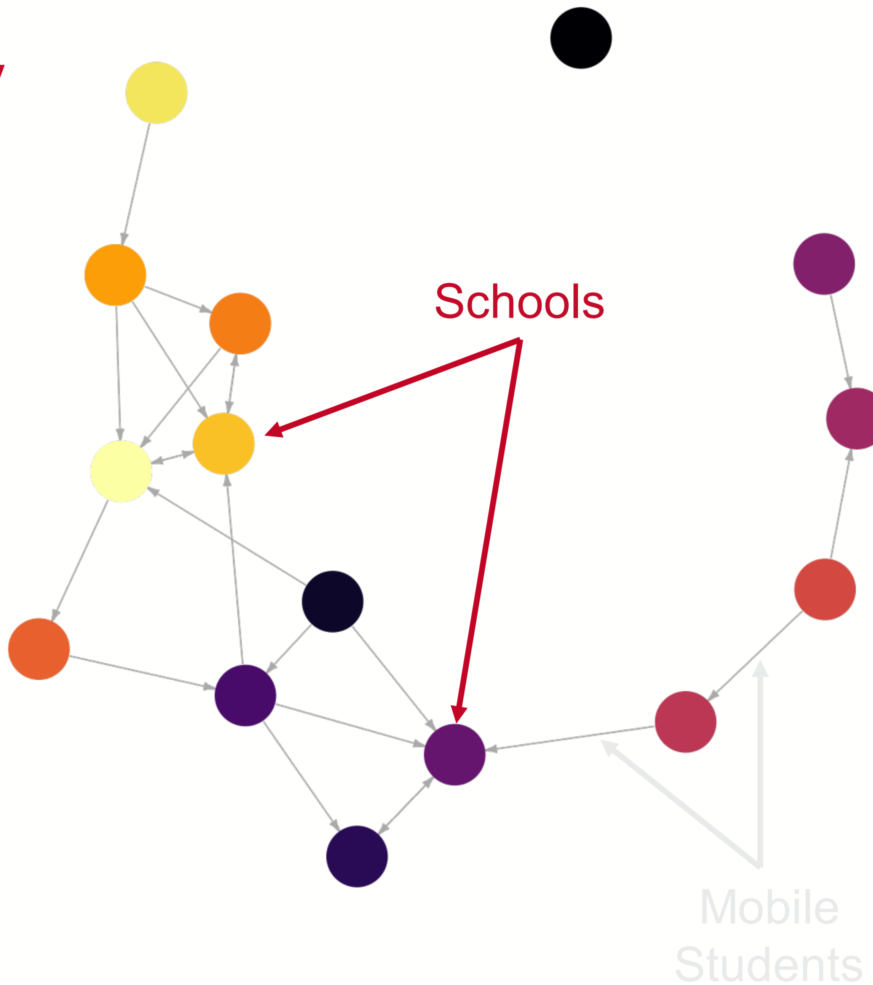
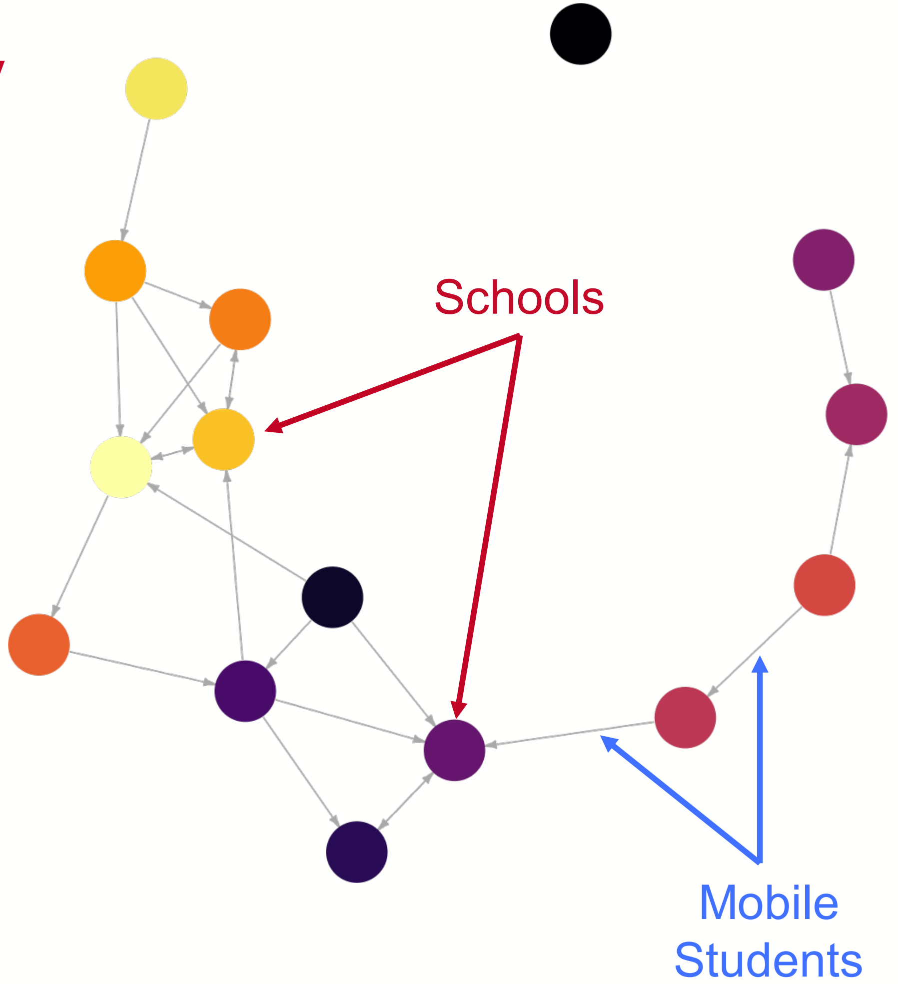


Patterns of Mobility

Students are mobile...but in a particular way

- Current “best practices” recommendations in education indicate the use of MMREMs

- MMREMs are problematic because they don’t account for complex relations among schools



Multiple Membership Model

$$\boldsymbol{\omega} \sim N\left(Z_{\mathrm{W}} \cdot \boldsymbol{\beta},\ \tau_{00} \right)$$

$$\boldsymbol{y} \sim N\left(\boldsymbol{\omega} + \boldsymbol{X} \cdot \boldsymbol{\gamma},\ \sigma^2 \right)$$

- Weights are often assigned (not estimated) as 1/*H*, where *H* is the number of schools attended by student *i*

- A naive, first-school approach is a special case of this model where the first school is given a weight of 1 and subsequent school weights are set at 0

- $\mathbf{Z_W}$ is constructed as $w_{i,1} * z_{p,1} + \ldots + w_{i,H} * z_{p,H}$ - assumes 0 correlation between schools

What do real data tell us? (SAT Math)

Correlations Among School Residuals (J=266)	1. N = 15926	2. N = 15185	3. N = 3902
1. First School Attended	—		
2. Second School Attended	0.479	—	
3. Third School Attended	0.396	0.392	—

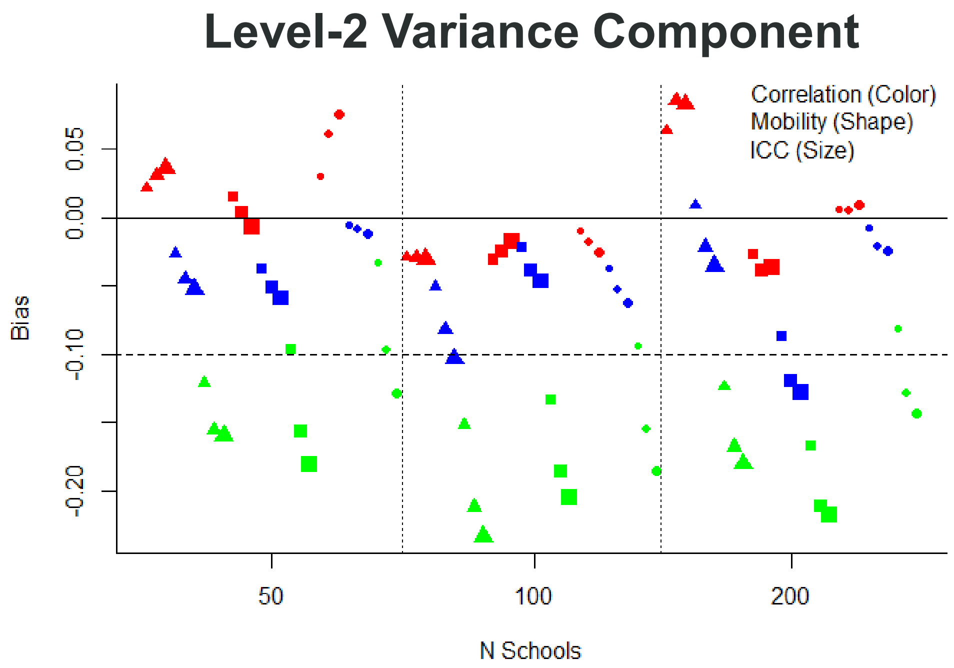
What do real data tell us? (HS Algebra)

Correlations Among School Residuals (J=266)	1. N = 15926	2. N = 15185	3. N = 3902
1. First School Attended	—		
2. Second School Attended	0.432	—	
3. Third School Attended	0.359	0.375	—

What do simulations tell us?

Where do MMREMs fail?

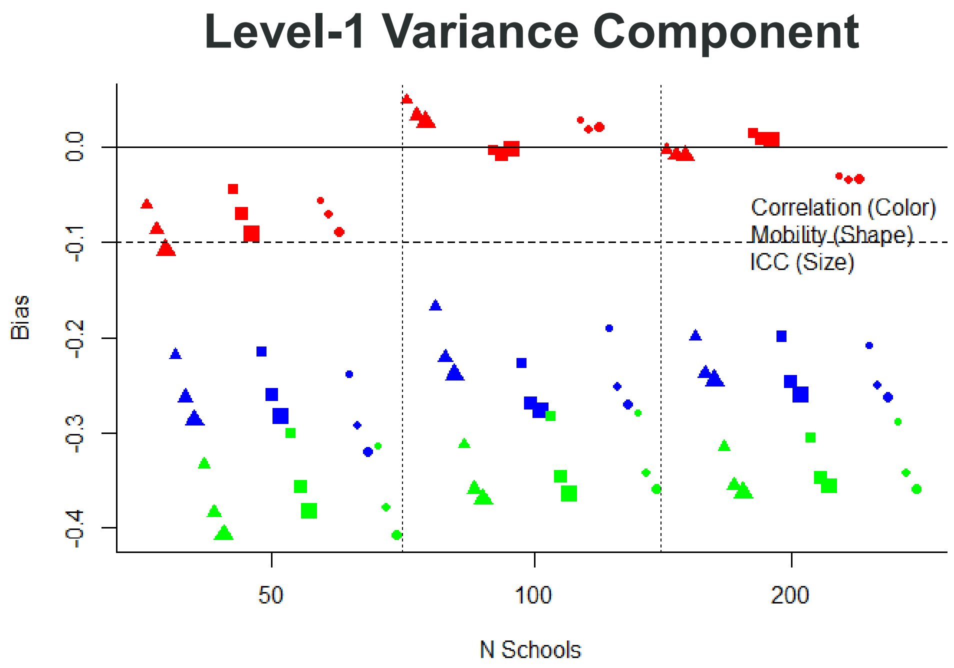
- High Correlation (all)
- Gets worse with increasing ICC



What do simulations tell us?

Where do MMREMs fail?

- High Correlations (0.25, 0.50)
- Gets worse with increasing ICC



Goals of the Current Study

- Demonstrate the need for more appropriate methodological approaches to student mobility
- Illustrate the use of network analyses in this context using statewide longitudinal data
- Provide guidelines for future methodological studies

What is a Social Network?

- A social network is a set of relations or ties among individuals or entities.
  - Online relationships – e.g. Facebook (Lewis et al., 2008)
  - Friendships and personal relationships (Ennett and Bauman, 1993)
  - Workplace relationships (Krackhardt and Porter, 1986; Spillane et al., 2012)
  - Political alliances (Smith and White, 1992)

Social Network Analyses

Network as outcome variable

Estimate the impact of covariates on network ties

Social Selection

Network as a "predictor"

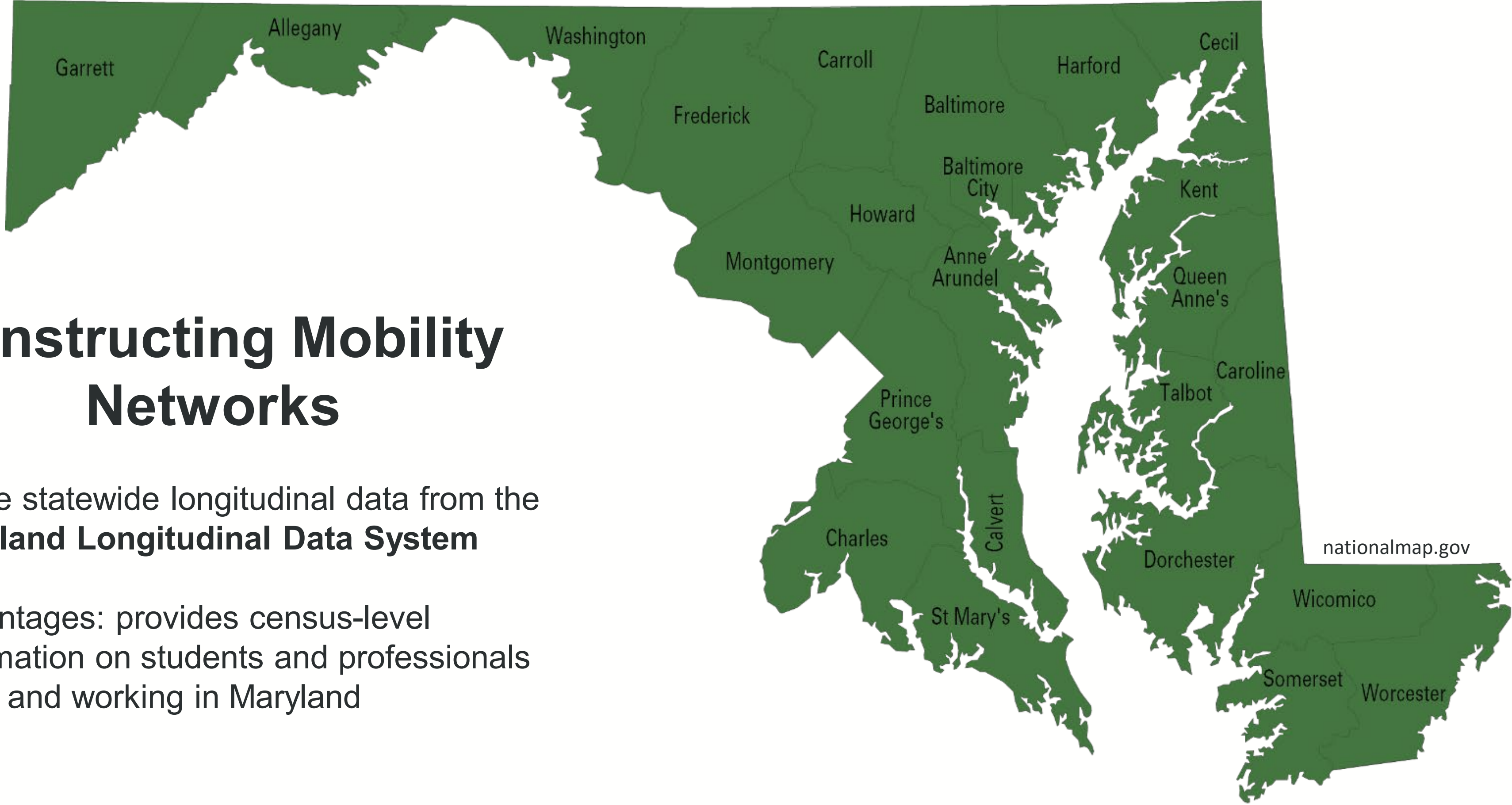
Estimate the impact of network ties on some outcome of interest

Social Influence

Constructing Mobility Networks

- Utilize statewide longitudinal data from the **Maryland Longitudinal Data System**

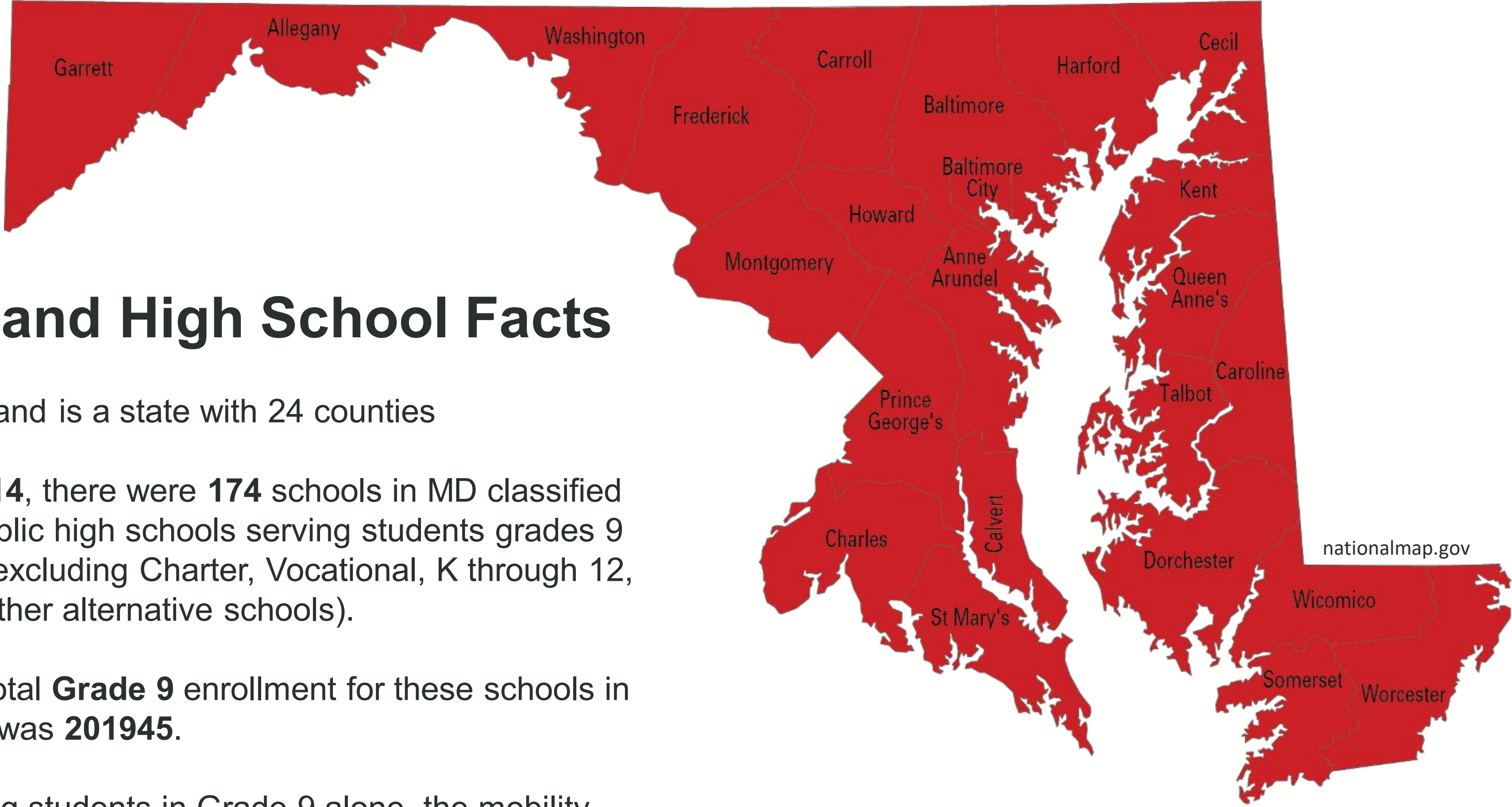
- Advantages: provides census-level information on students and professionals living and working in Maryland



nationalmap.gov

Maryland High School Facts

- Maryland is a state with 24 counties
- In **2014**, there were **174** schools in MD classified as public high schools serving students grades 9 - 12 (excluding Charter, Vocational, K through 12, and other alternative schools).
- The total **Grade 9** enrollment for these schools in 2014 was **201945**.
- Among students in Grade 9 alone, the mobility rate in 2014 was approximately **47%**, with about **16.5%** coming from mid-year entries and about **30.5%** coming from mid-year exits



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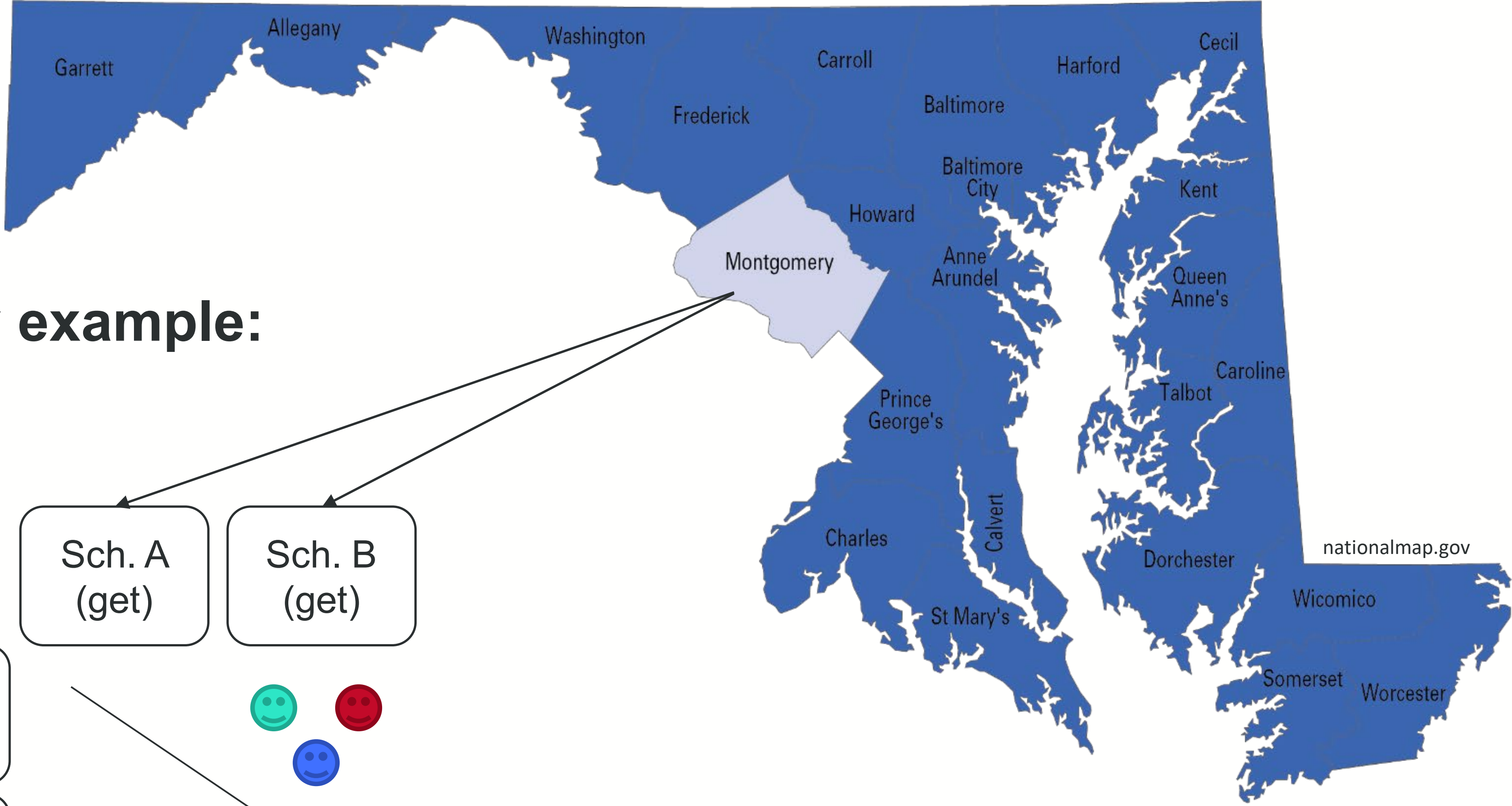
A toy example:



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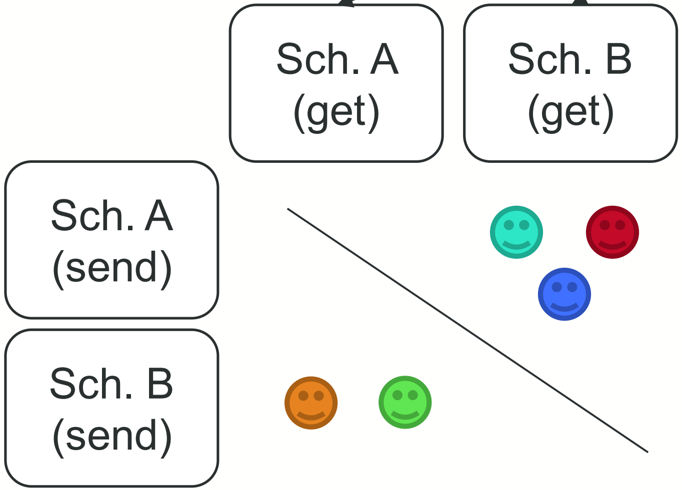

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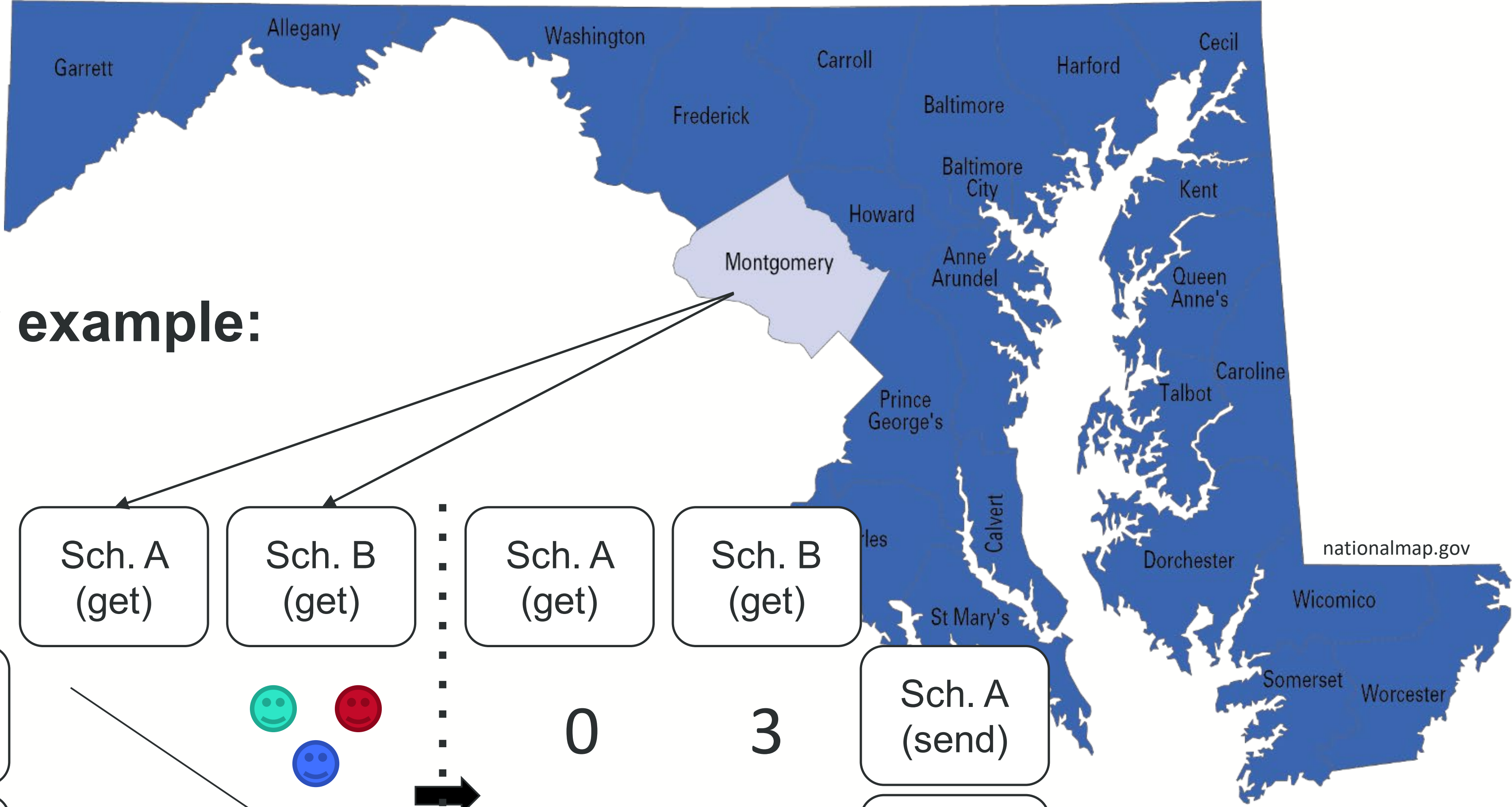
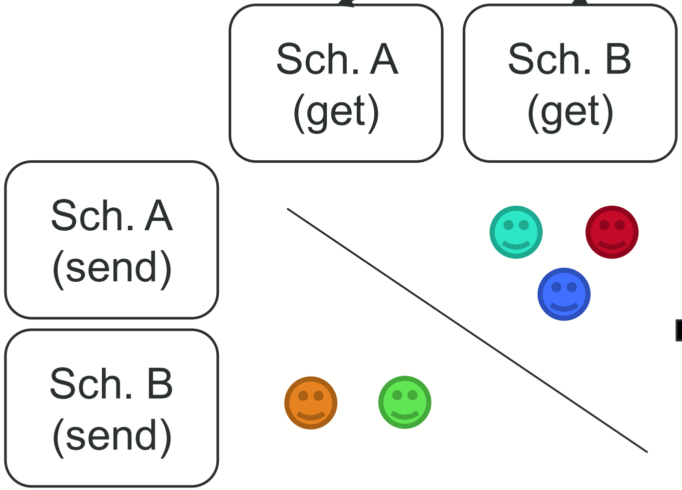
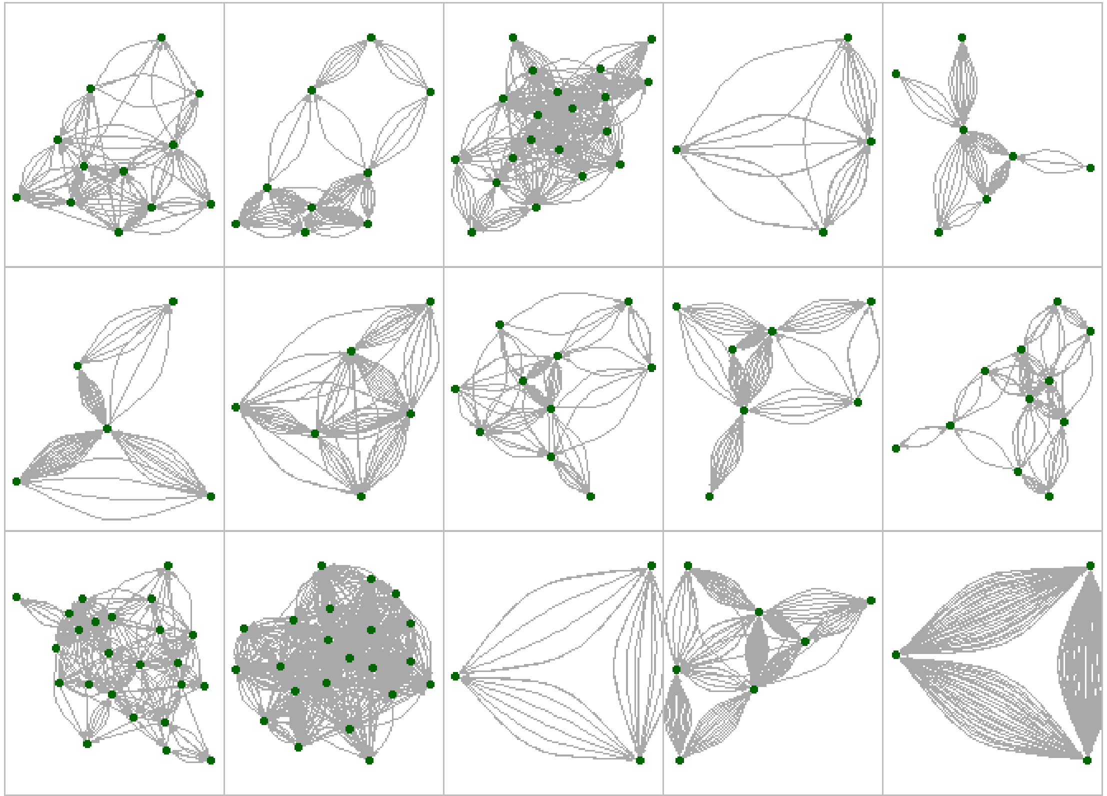


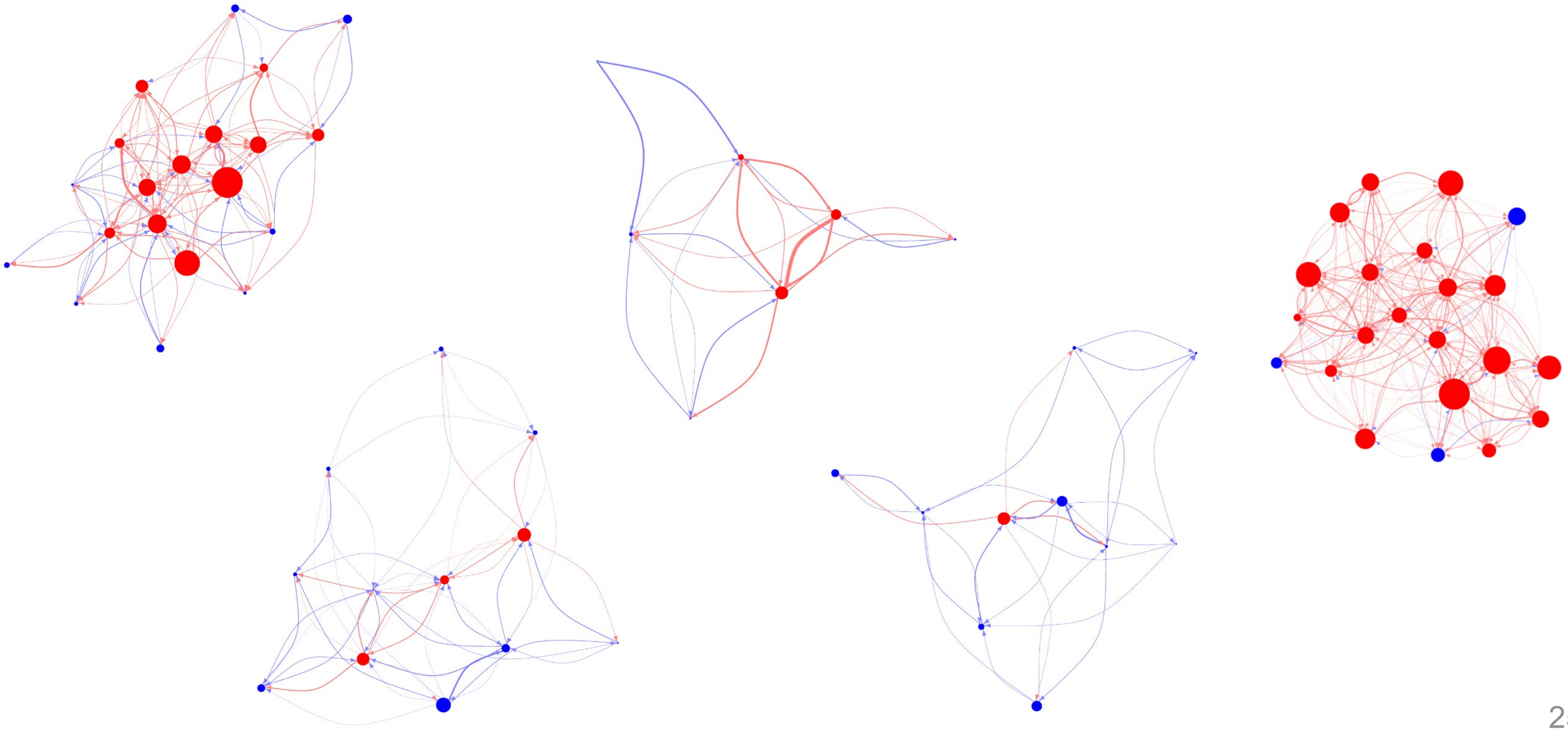


	Sch. A (get)	Sch. B (get)
Sch. A (send)	0	3
Sch. B (send)	2	0

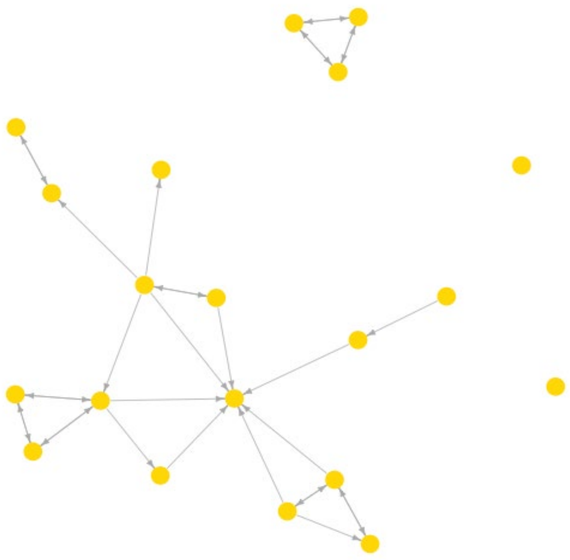
Maryland School Networks



Visualization by Covariates



Descriptives: Node-level disruption



Out-degree: the number of ties sent by a node

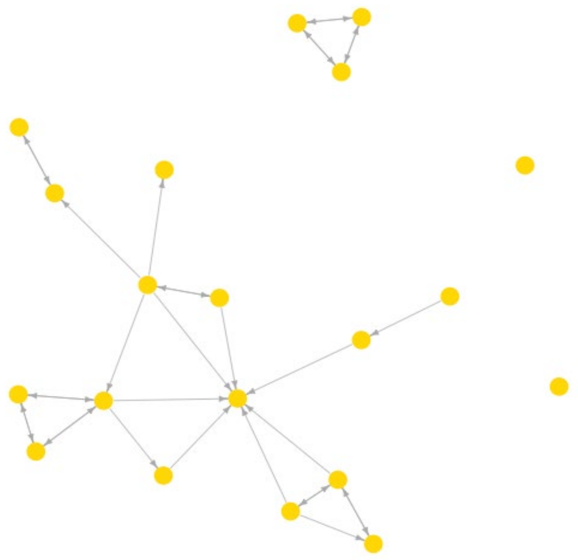
In-degree: the number of ties received by a node

Predicting a Network

To predict binary (ordinal) network ties, we could use logistic (ordinal/probit) regression

Standard GLMs assume independent observations

Network ties are NOT independent.



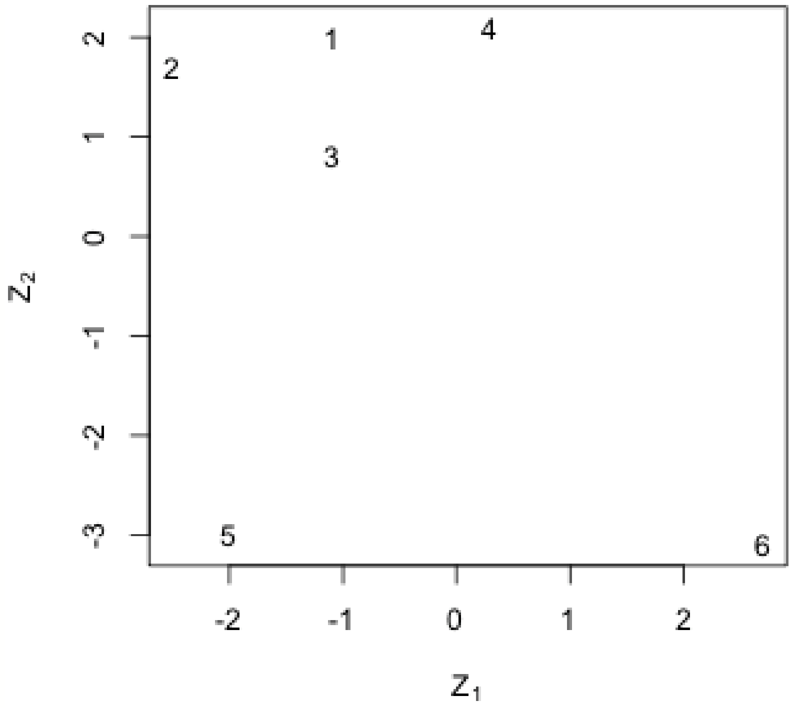
Latent Space Model (for binary ties)

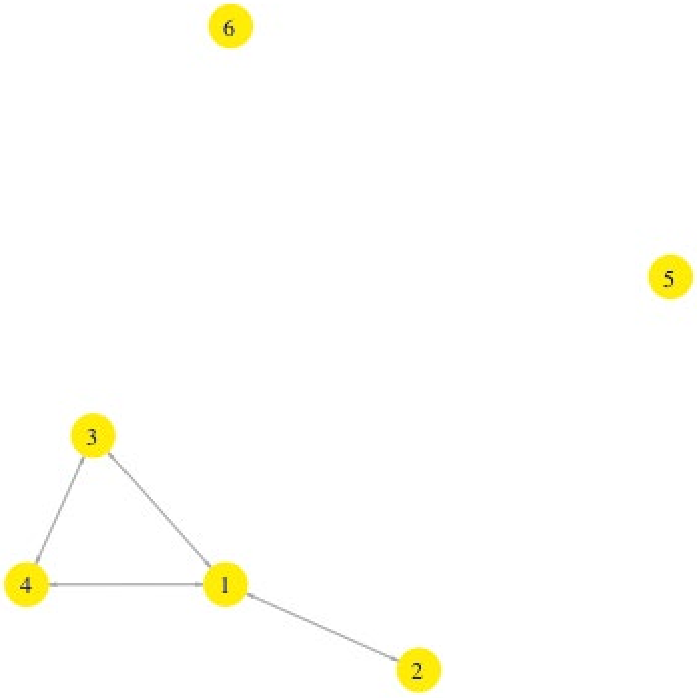
$$\operatorname{logit} P[Y_{ij} = 1] = \beta X_{ij} - |Z_i - Z_j|$$

Y_{ij}	Is the value of the tie from node i to node j
X_{ij}	Is a set of covariates
Z_i	Is the latent space position for node i

We assume ties are independent conditional on the latent space positions

Latent Space Positions

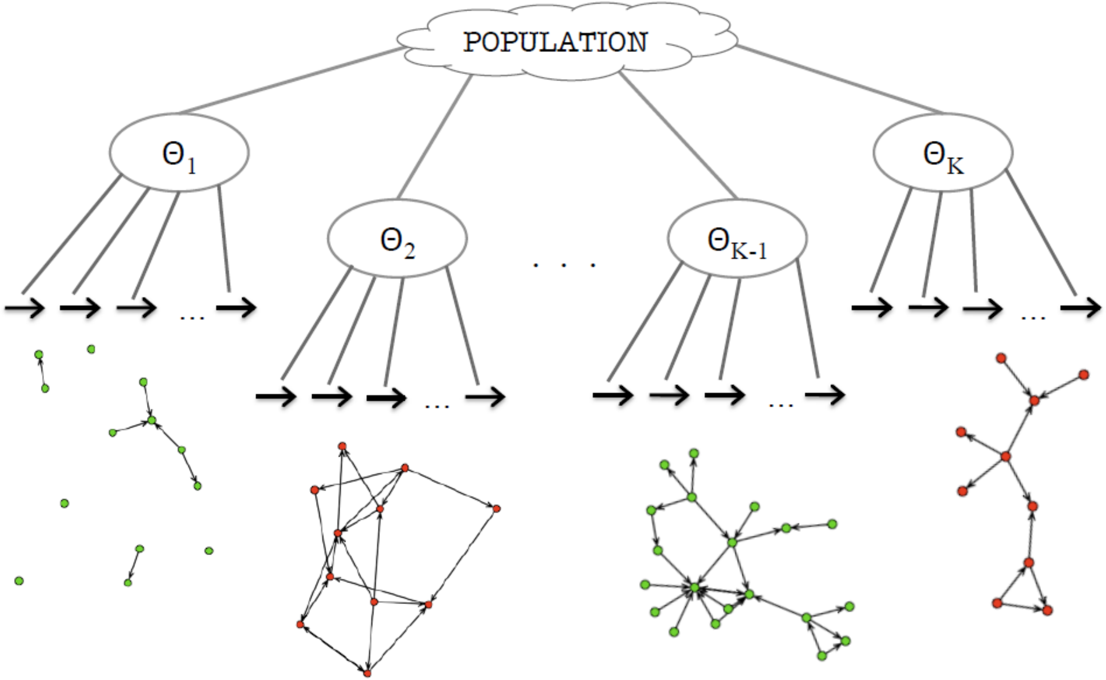




Hierarchical Latent Space Models

$$P(\mathbb{Y}|\mathbb{X},\Theta) = \prod_{k=1}^{K} \text{LSM for } Y_k$$

$$(\Theta_1, \ldots, \Theta_K) \sim F \;,$$

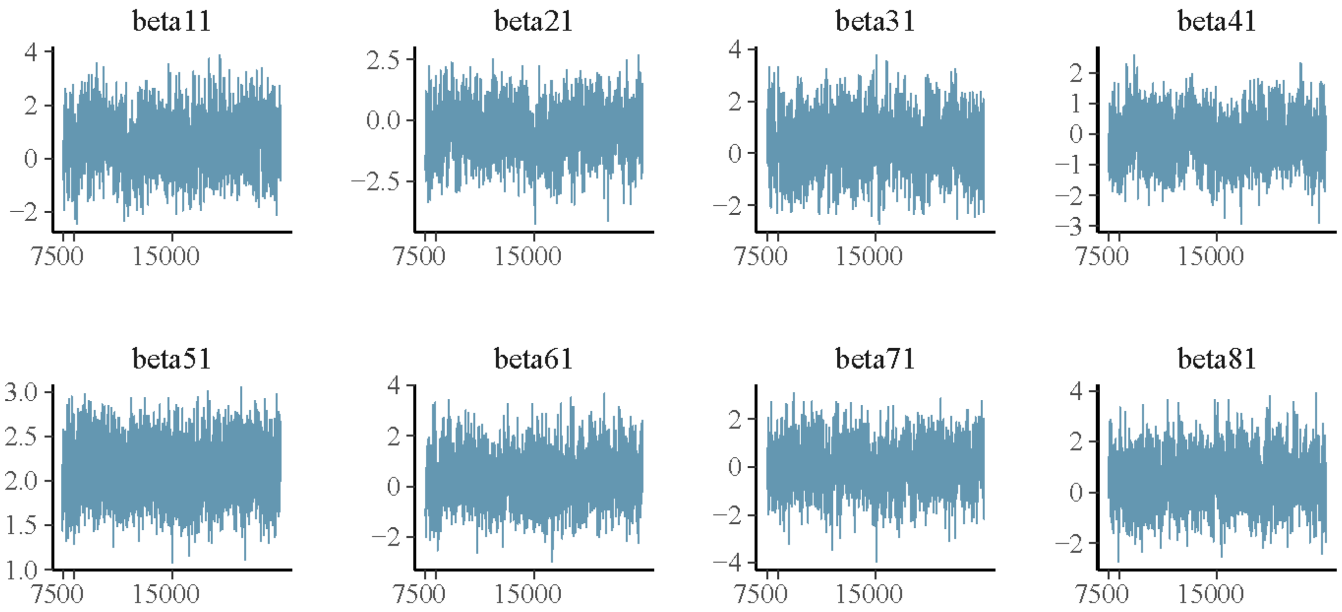


Sweet, T. M., Thomas, A. C., & Junker, B. W. (2013).

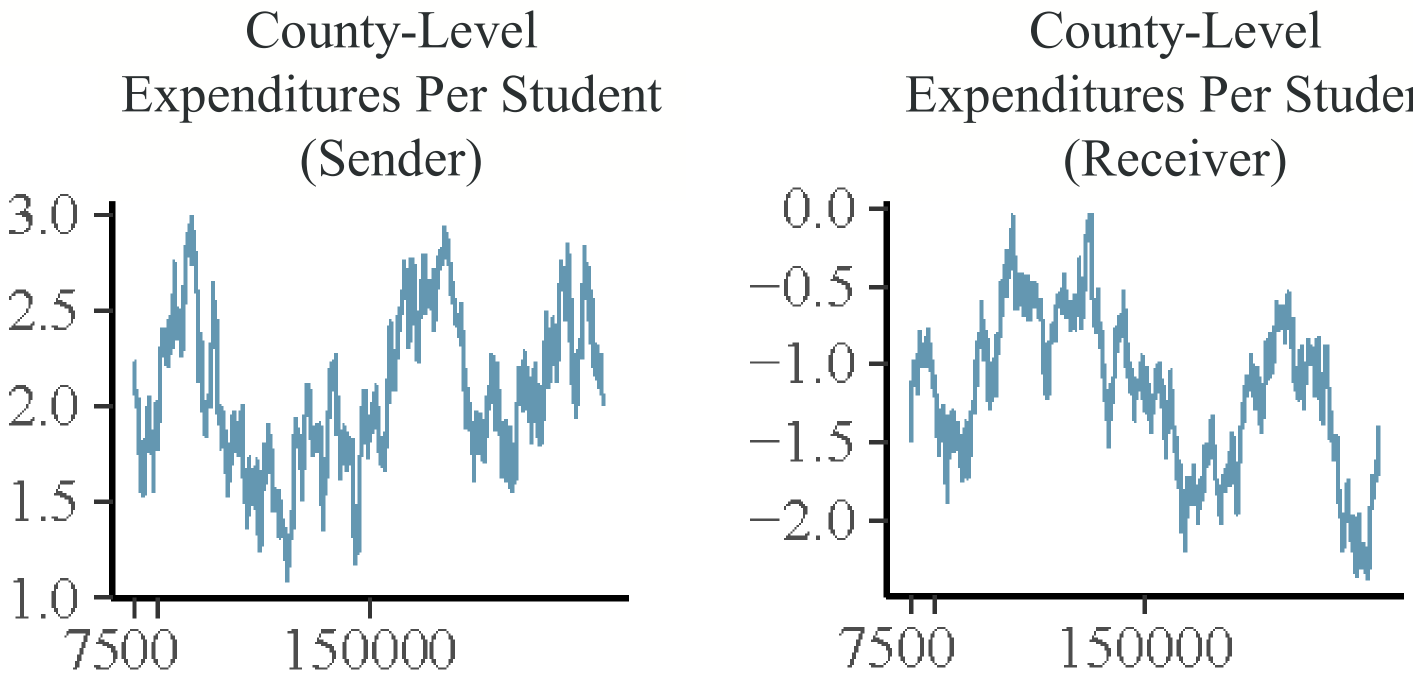
Implementation of the HLSM

- Aggregated student-level, school-level information, and county-level information assessed
  - Aggregated student-level
    - FARMS, suspensions, assessment performance, attendance
  - School-level
    - Previous year graduation and college enrollment rates
  - County-level
    - Previous-year average county wages, expenditures per student

Selected traceplots for the full HLSM

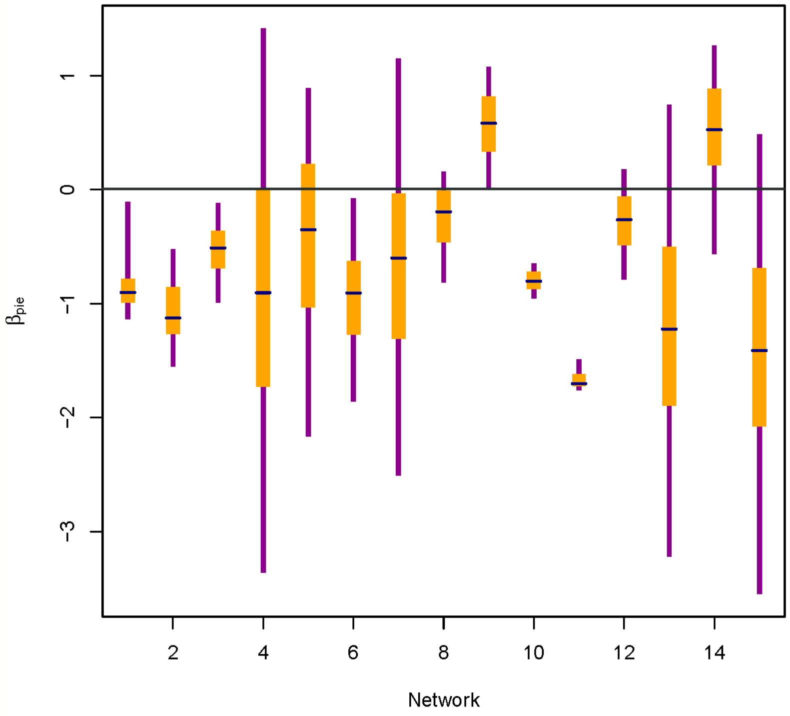


Examples of parameter non-convergence

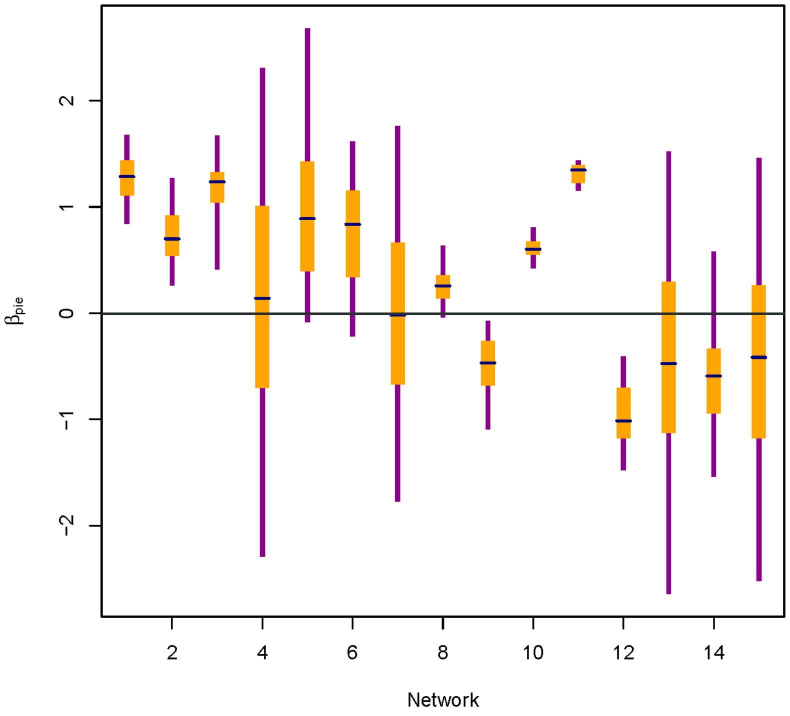


County-Level Expenditures Per Student

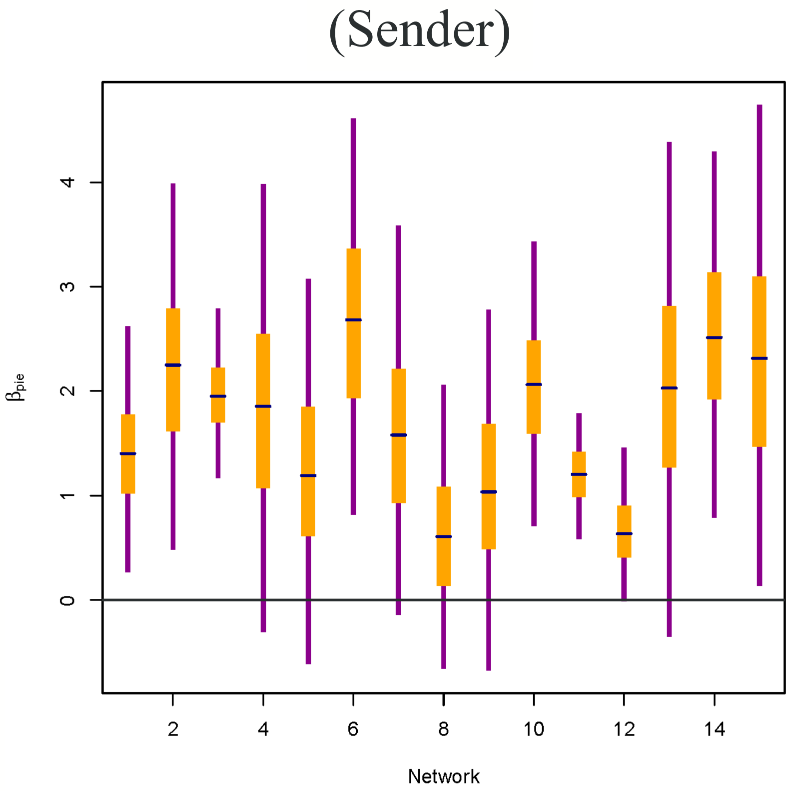
(Sender)

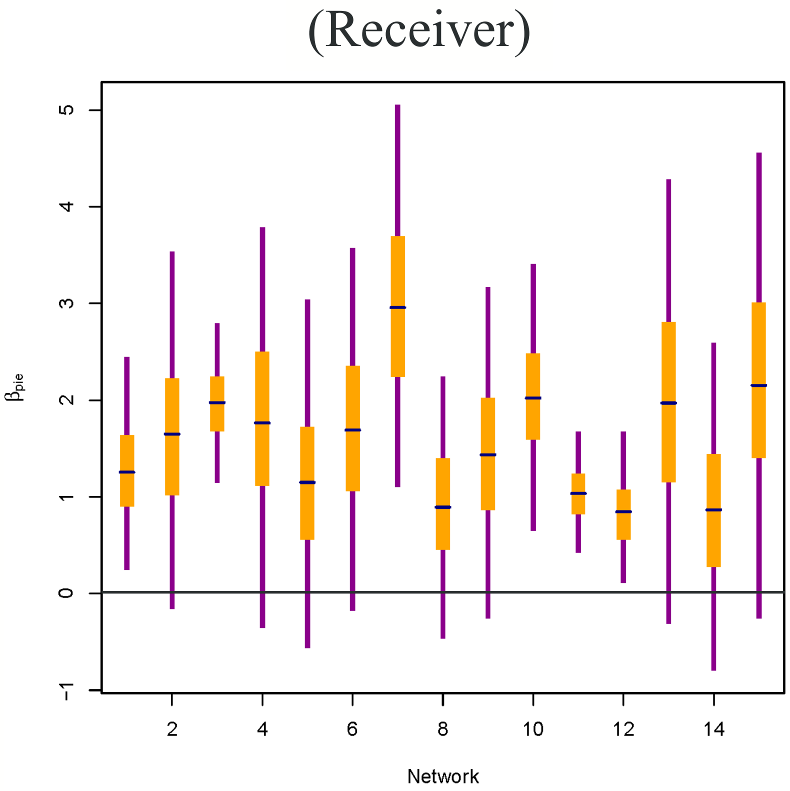


(Receiver)



Percent of FARMS Eligible Students





Results summary

- County-level expenditures have an important school sender/receiver effects above and beyond aggregated student characteristics (more $$ = more students received)

- Measures of student poverty remained important predictors of network ties for many counties (higher poverty rates increased the likelihood of observing a tie for both sender & receiver schools)

Where do we go from here?

- Future methodological work needed to investigate the following issues
  - Small cluster-level sample sizes and within-network sample sizes are problematic for estimation
  - Social selection models do not fully place mobility networks in their causal systems
- Explore use of multilevel social influence modeling against MMREMs
  - Agneessens, F., & Koskinen, J. (2016).

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