MLDS CENTER
Maryland Longitudinal Data System
Better Data • Informed Choices • Improved Results

Using Social Network Methods to Inform MLDS Center Research: An Example with Student Mobility

Dr. Tracy M. Sweet &
Tessa L. Johnson
MLDS Center Research Series
February 7, 2019

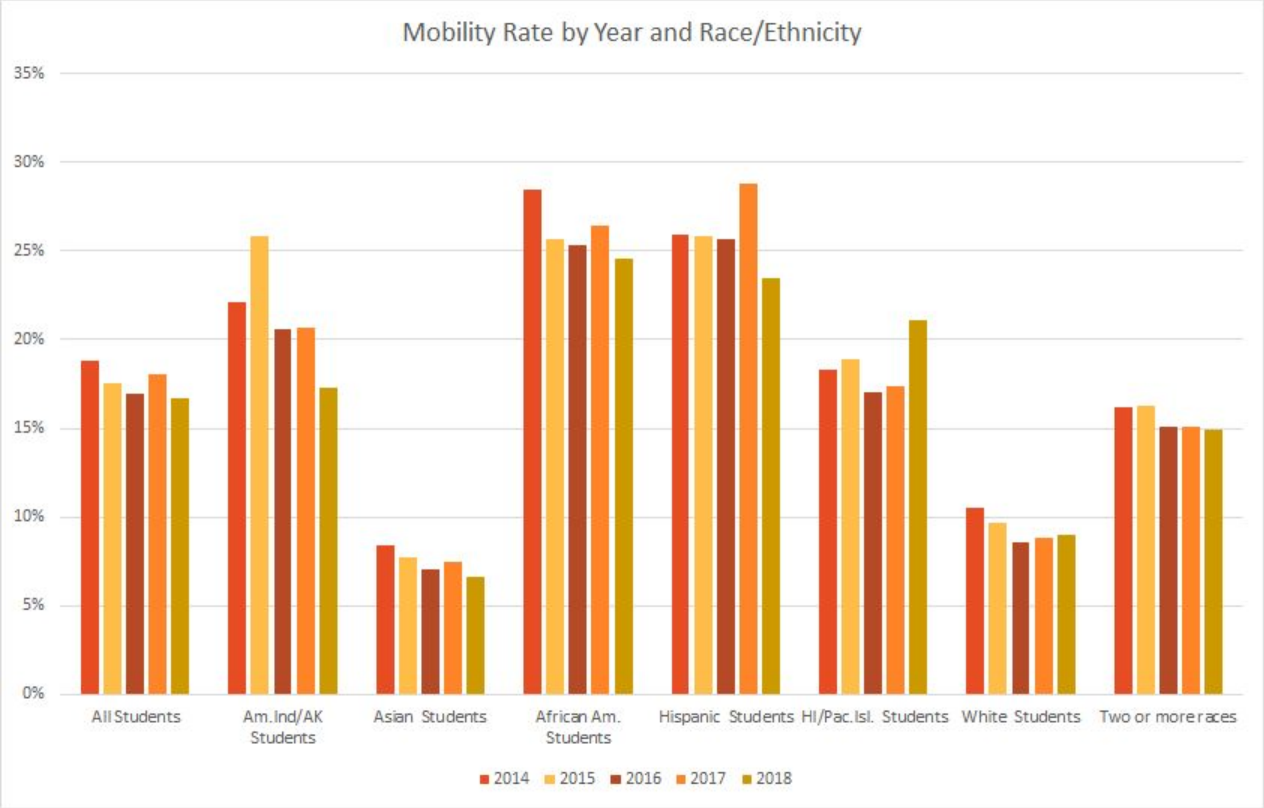
Acknowledgement

The contents of this presentation were developed under a grant from the Department of Education. However, these contents do not necessarily represent the policy of the Department of Education, and you should not assume endorsement by the Federal Government.

Introduction

Student mobility is defined by the Maryland State Department of Education as the total number of *entries* and *withdrawals* from a school within a school year.

The ***mobility rate*** is the total student mobility divided by the average daily enrollment.



http://reportcard.msde.maryland.gov/

Student Mobility and Outcomes

- Student mobility is associated with
  - Lower test scores
  - Higher high school dropout rates
  - Lower likelihood of college enrollment and degree completion

(Anderson, 2017; Fomby, 2013; Friedman-Krauss & Raver, 2015; Leboeuf & Fantuzzo, 2018; Metzger et al., 2015; Rumberger, 2003)

Informing the Synthetic Data Project (SDP)

MLDS Center
Maryland Longitudinal Data System

- One goal of the SDP is to create synthetic versions of the data in the MLDS
- Generating synthetic data that are useful for education researchers requires incorporating multilevel structures within the data into the synthesization model
- This requires the examination of rates and patterns of student mobility to ensure that multilevel structures are modeled appropriately

SDP Research Question

What is the utility of social network measures for examining student mobility in relation to long-term academic and career outcomes?

MLDS Center
Maryland Longitudinal Data System

What is a Social Network?

A social network is a set of relations or ties among individuals or entities.

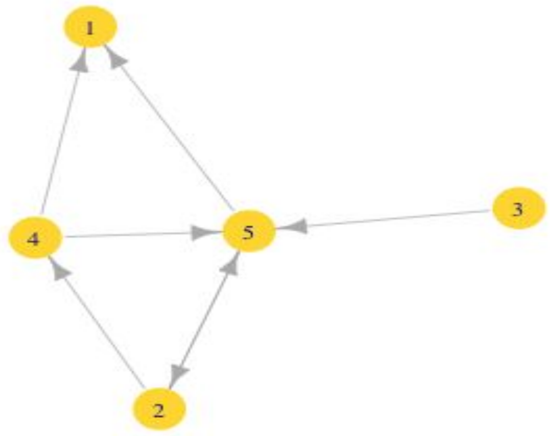
- Online relationships – e.g. Facebook (Lewis et al., 2008)
- Friendships and personal relationships (Ennett and Bauman, 1993)
- Workplace relationships (Krackhardt and Porter, 1986; Spillane et al., 2012)
- Political alliances (Smith and White, 1992)

How do we represent a network?

An adjacency matrix

$$Y = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{bmatrix}$$

A plot where vertices represent nodes and edges rep



Directionality

- Directed
- Undirected

Types of Ties

- Binary
- Ordinal
- Continuous

Methods

How can we use network data in our analyses?

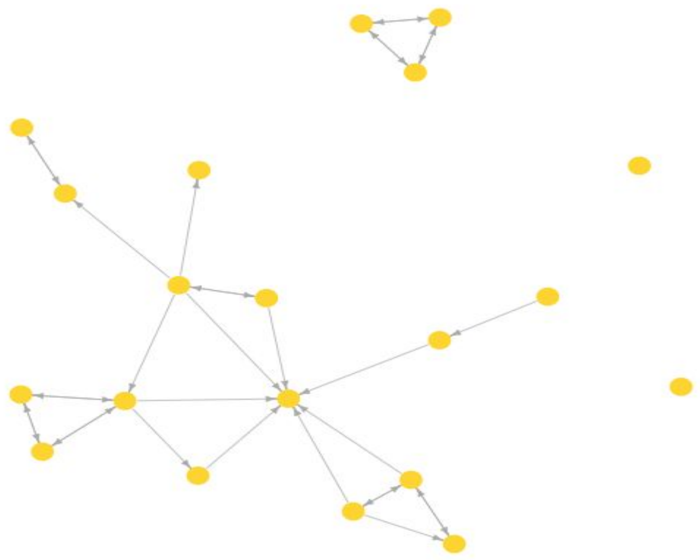
- Descriptive statistics particular to network models
- Extensions of regression analyses

Descriptive Statistics (about the network)

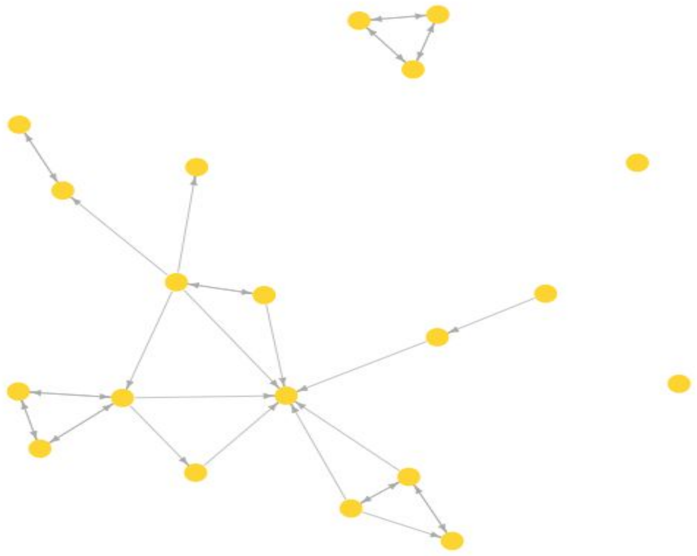
Density: the proportion of observed ties out of all possible ties

Reciprocity: the proportion of all ties from i to j such that a tie from j to i is also observed

Transitivity: the proportion of pairs of ties between i to j and between j to k such that a tie between i to k is also observed



Descriptive Statistics (about each node)



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

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

Degree: the total number of ties involving a node

Social Network Models

Social Selection

Network as outcome variable

Estimate the impact of covariates on network ties

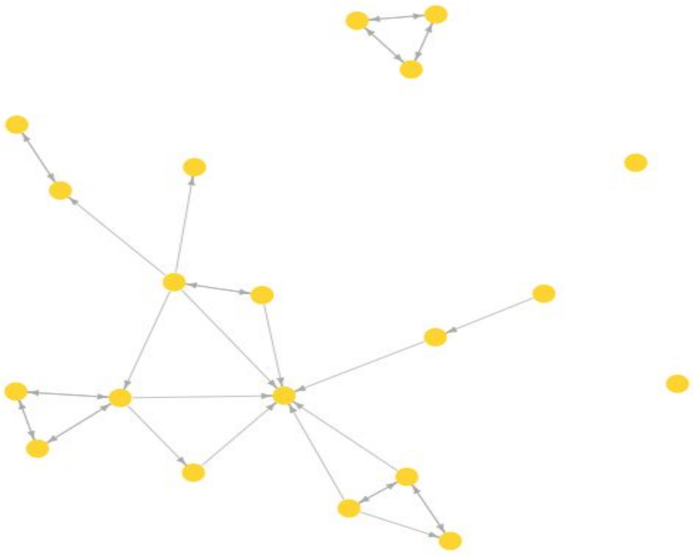
Social Influence

Network as a "predictor"

Estimate the impact of network ties on some outcome of interest

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)

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

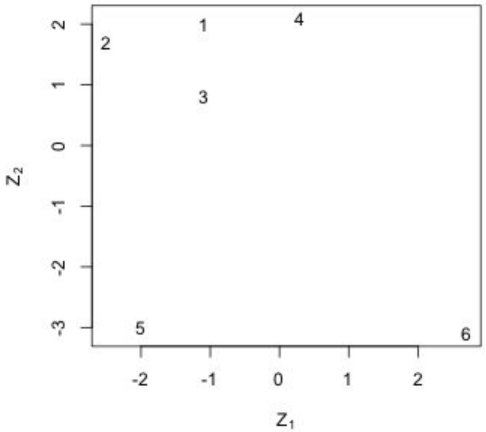
Y_{ij} Is the value of the tie from node i to node j

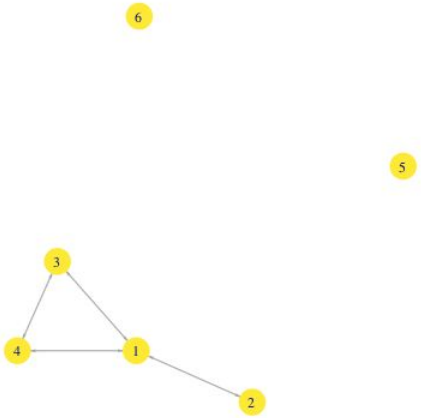
X_{ij} Is a set of covariates

Z_i Is the latent space position for node i

We assume ties are independent conditional on the latent space positions

Latent Space Model





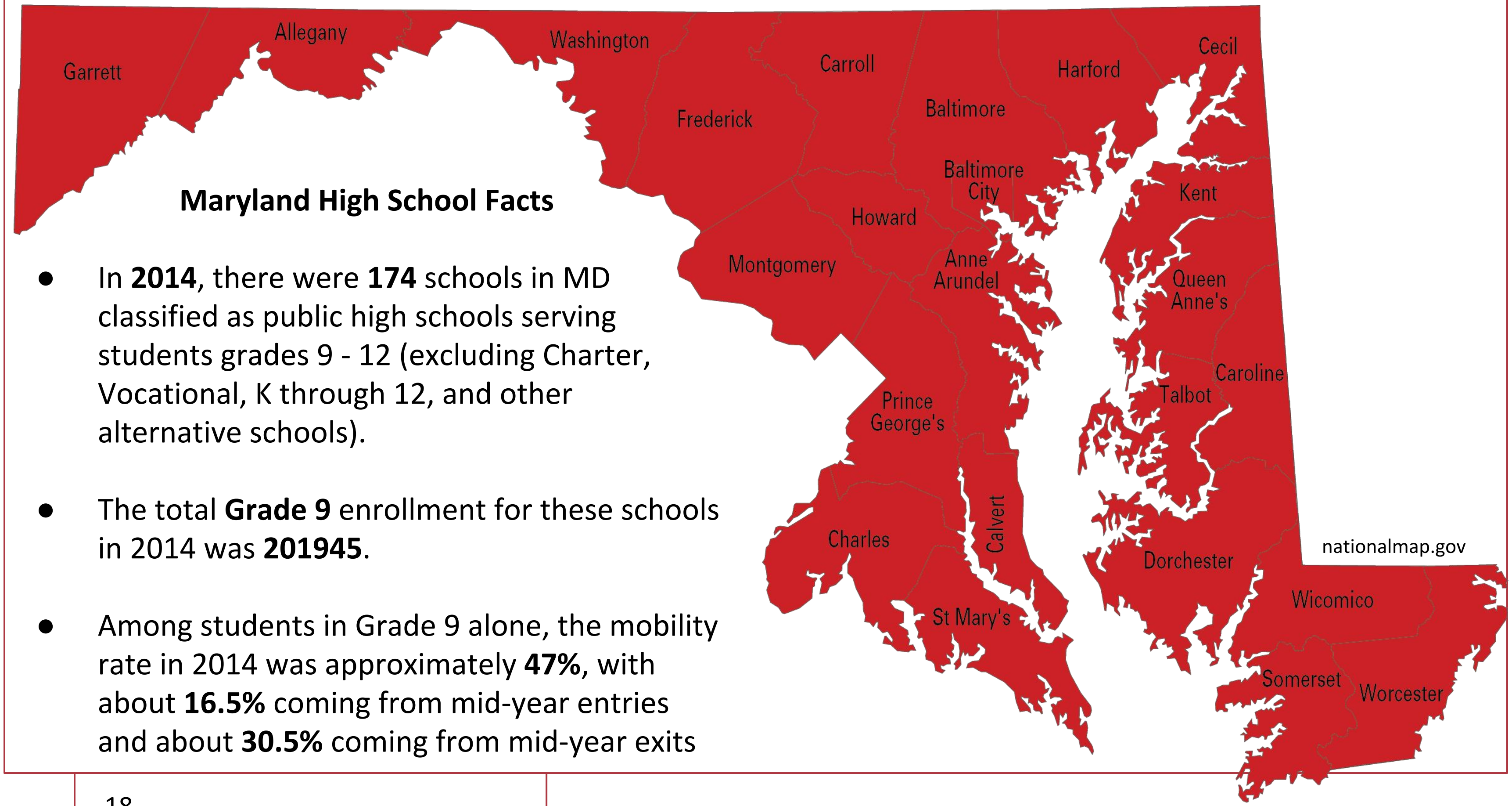
Application to MLDS Data

Research question:

What are the impacts of school attributes, such as aggregated student employment, behavior, and achievement on the probability of observing a mobile student in a within-school system mobility network?

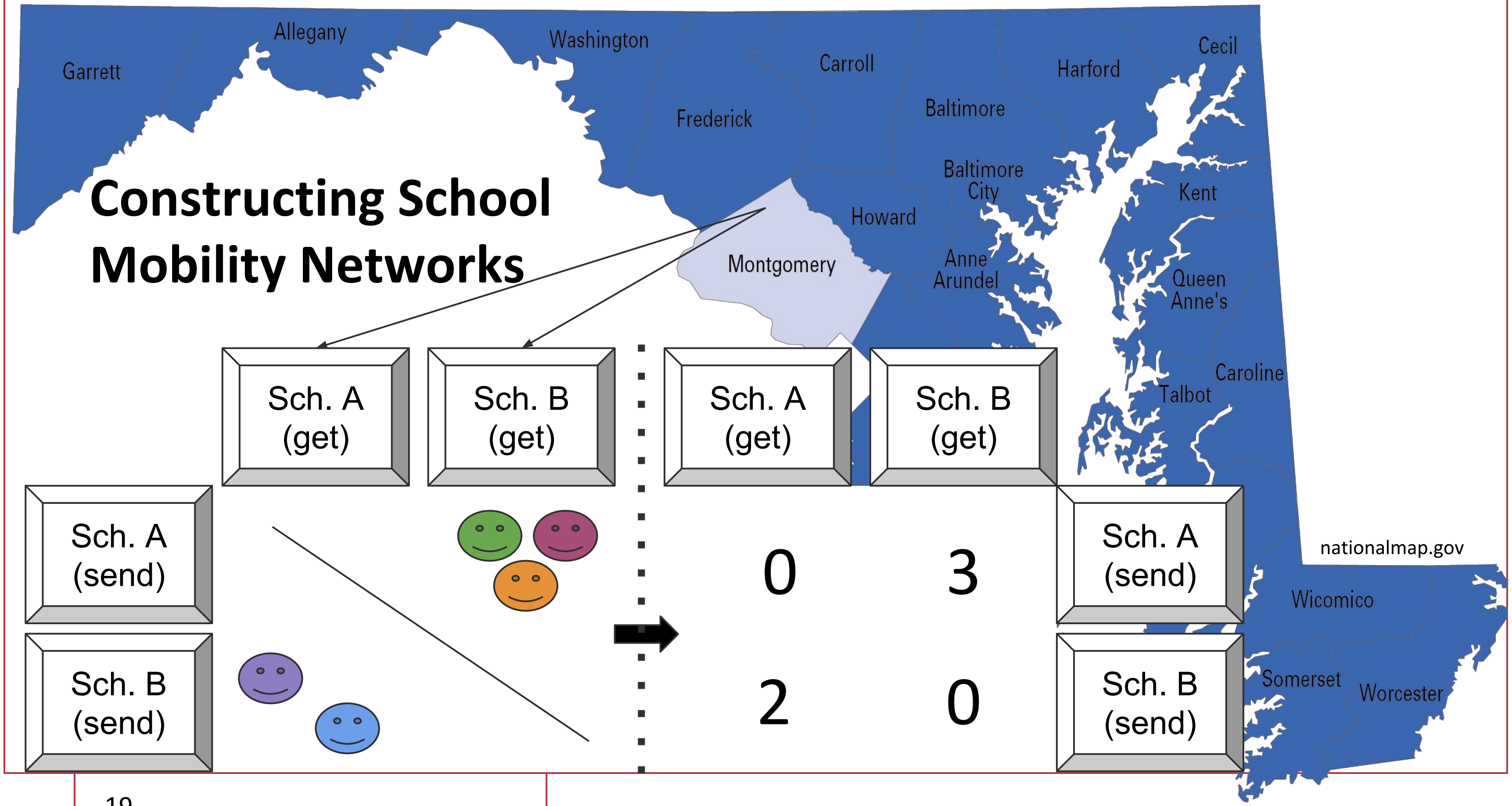
Maryland High School Facts

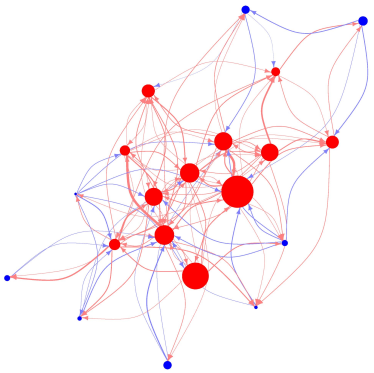
- In **2014**, there were **174** schools in MD classified as public high schools serving students grades 9 - 12 (excluding Charter, Vocational, K through 12, and other alternative schools).
- The total **Grade 9** enrollment for these schools in 2014 was **201945**.
- Among students in Grade 9 alone, 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

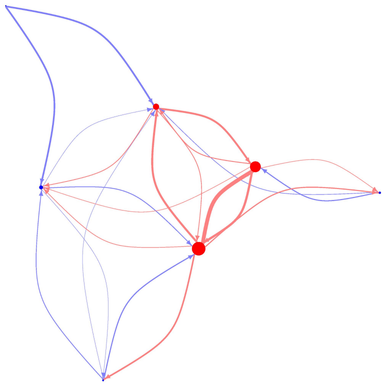


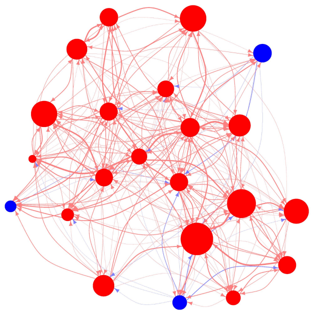
nationalmap.gov

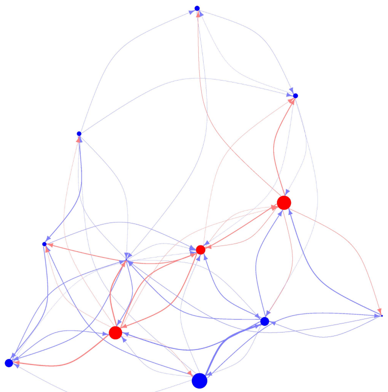
Constructing School Mobility Networks

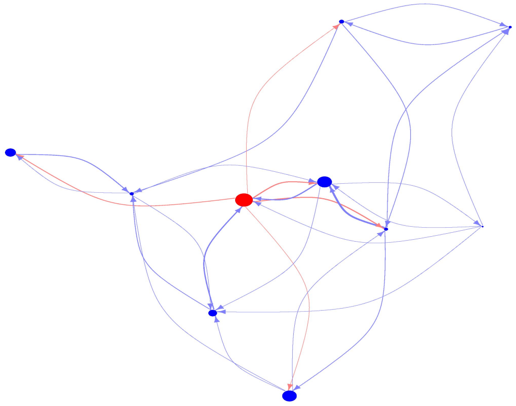












School Network Side-by-Side

MLDS Center
Maryland Longitudinal Data System

Modeling Network Mobility

- Covariates of interest were dichotomized relative to the school system median value
  - Average Student wages
  - Proportion of students falling below proficiency on the Maryland high school assessment (HSA)
  - Proportion of students eligible for free or reduced price lunch

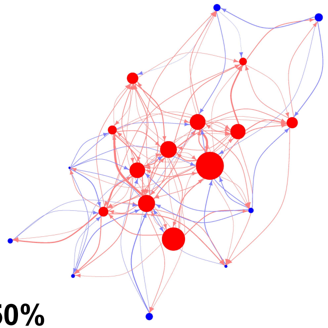
Modeling Network Mobility

- Covariates of interest were dichotomized relative to the county median
  - Number of suspensions divided by total enrollment
  - Number of 12th graders graduating divided by 12th grade enrollment
  - Percent of students who are white
  - Number of unlawful days absent divided by the total number of days school open

Modeling student mobility

- Network ties were dichotomized:
  - At least one student moved from School A to School B
  - Model coefficients interpreted as the change in the log odds of observing a tie, conditional on a set of sender/receiver/identical/latent variables associated with school attributes
- Models estimated using Bayesian estimation (MCMC)

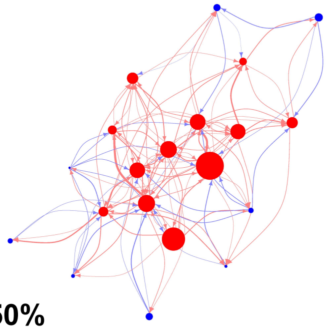
Example: Single-Network Model



Sender Coefficients

Variable (Aggregated by School and Dichotomized by School System Median)	Parameter Estimates			
	Mean	**SD**	**2.50%**	**97.50%**
% FARMS Eligible	-0.32	0.40	-1.07	0.32
% White	0.29	0.31	-0.30	0.85
% Below Proficiency (HSA)	1.59	0.62	0.49	2.67
% Unlawful Days Absent	0.04	0.39	-0.78	0.69
Avg. Student Wages	-0.60	0.25	-1.12	-0.17
% Suspensions	-0.55	0.43	-1.42	0.22
% Graduating Grade 12s	0.06	0.30	-0.50	0.61

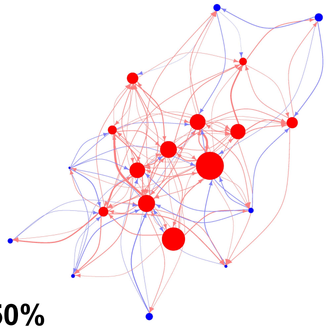
Example: Single-Network Model



Receiver Coefficients

Variable (Aggregated by School and Dichotomized by School System Median)	Parameter Estimates			
	Mean	**SD**	**2.50%**	**97.50%**
% FARMS Eligible	-0.70	0.40	-1.58	0.00
% White	-0.39	0.29	-0.96	0.12
% Below Proficiency (HSA)	1.99	0.72	0.56	3.34
% Unlawful Days Absent	0.02	0.39	-0.65	0.76
Avg. Student Wages	0.14	0.25	-0.29	0.62
% Suspensions	-0.43	0.35	-1.16	0.22
% Graduating Grade 12s	-0.02	0.30	-0.51	0.53

Example: Single-Network Model



Variable (Aggregated by School and Dichotomized by School System Median)	Identical Coefficients			
	Parameter Estimates			
	Mean	SD	2.50%	97.50%
% FARMS Eligible	0.51	0.29	-0.21	0.92
% White	0.37	0.17	0.04	0.69
% Below Proficiency (HSA)	-2.73	0.96	-4.74	-1.22
% Unlawful Days Absent	-0.31	0.28	-0.78	0.29
Avg. Student Wages	-0.15	0.18	-0.47	0.15
% Suspensions	0.45	0.24	-0.03	0.89
% Graduating Grade 12s	-0.25	0.21	-0.67	0.14

MLDS Center
Maryland Longitudinal Data System

Summary of Findings

- Aggregated student employment
  - Schools with above school system average student wages are less likely to send students to another school
- Student demographics
  - Schools with the same demographic characteristics relative to the rest of the school system (e.g., both above school system average in terms of % white students) are more likely to send students to one another
- Student achievement
  - Mobile students are more likely to appear when sender and receiver schools have below school system average pass rates on the Maryland HSA, but less likely to occur between two schools with the same pass rate (e.g., two high-performing schools are less likely to send mobile students to one another)

Informing the Synthetic Data Project (SDP)

- Mobility networks are an innovative way to model patterns of mobility within Maryland
- The mobility networks analyzed in this study provide information on both the patterns of mobility within the real data as well as expected proportions and rates of mobility within school systems

Future Research

- Examine college mobility within Maryland in order to understand how high school mobility is related to future postsecondary mobility
- Examine how high school mobility networks impact future postsecondary enrollment and achievement

MLDS Center
Maryland Longitudinal Data System

Contact

Dr. Tracy M. Sweet

tracy.sweet@maryland.gov

Tessa L. Johnson

tessa.johnson@maryland.gov