Application of Cross-Classified Multiple Membership Growth Curve Modeling in a Study of the Effect of School Mobility on Students' Academic Performance

Bess A. Rose

Session 1B: Modeling Educational Effects,
M3 Conference, University of Connecticut

May 23, 2017

Acknowledgements

- Dr. Larry Rogers and the Maryland State Department of Education
- Annie E. Casey Foundation
- Johns Hopkins University interdisciplinary pre-doctoral research training program, funded by U.S. Department of Education's Institute of Education Sciences
- Dissertation committee: Drs. Stein, MacIver, Burdick-Will, and outside reader Dr. Beretvas
- Westat for conference support

Note: Funding for the original study was provided by The Annie E. Casey Foundation. Funding for the current study was provided by provided by a grant from the U.S. Department of Education’s Institute of Education Sciences (IES) to Johns Hopkins University’s interdisciplinary pre-doctoral research training program (R305B080020). The opinions expressed are those of the author and do not represent views of the Institute or the U.S. Department of Education.

Mobility

- Mobility is the norm
- This study illustrates methods for growth curve modeling accounting for mobility
  - Cross-classified (CC)
  - Multiple membership (MM)
- Also estimates effects of school changes on students

ANALYTIC METHODS

Review: multilevel growth models

- Repeated measures of the same students over time
  - Estimate their normal trajectories
  - Estimate changes to those trajectories associated with time-varying and non-time-varying covariates or independent variables
- In this illustration, dependent variable is grade point average (GPA), measured annually from 1st to 12th grade (!)

Review: growth models – level 1

- Growth models as a form of HLM
- Measurement occasions “nested” within students, students within schools
- So the GPA at time *t* for student *i* in school *j*:

Intercept
(1st grade GPA)

Slope
(annual change in GPA)

$$GPA_{tij} = \pi_{0ij} + \pi_{1ij} Time_{tij} + e_{tij}$$

Time has to start at 0 for CCMM

Review: growth models – level 2

- The intercept from the previous equation (starting GPA for student *i* in school *j*):

Level 1 intercept (1st grade GPA)

$$\pi_{0ij} = \beta_{00j} + r_{0ij}$$

Mean 1st grade GPA of all students in all schools

- And the slope (annual change in GPA for student *i* in school *j*):

Level 1 slope (annual change in GPA)

$$\pi_{1ij} = \beta_{10j} + r_{1ij}$$

Mean change in GPA of all students in all schools

Review: growth models – level 3 (no mobility)

Intercept:

$$\beta_{00j} = \gamma_{000} + u_{00j}$$

Predicted mean starting GPA of students in school *j* is the mean starting GPA of all students across all schools, plus the residual term for school *j*

Slope:

$$\beta_{10j} = \gamma_{100} + u_{10j}$$

Predicted mean annual change in GPA of students in school *j* is the mean annual change in GPA of all students across all schools, plus the residual term for school *j*

Review: growth models – level 3 (no mobility)

Intercept:

$$\beta_{00j} = \gamma_{000} + u_{00j}$$

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Predicted mean annual change in GPA of students in school *j* is the mean annual change in GPA of all students across all schools, plus the residual term for school *j*

How do you handle nesting if student belongs to more than one school?

Can ignoring mobility change your study's findings?

YES

- <u>Don't</u> delete mobile students from the analysis
- <u>Don't</u> assign them to a single school

Goldstein, Burgess, & McConnell (2007)

Chung (2009)

Grady & Beretvas (2010)

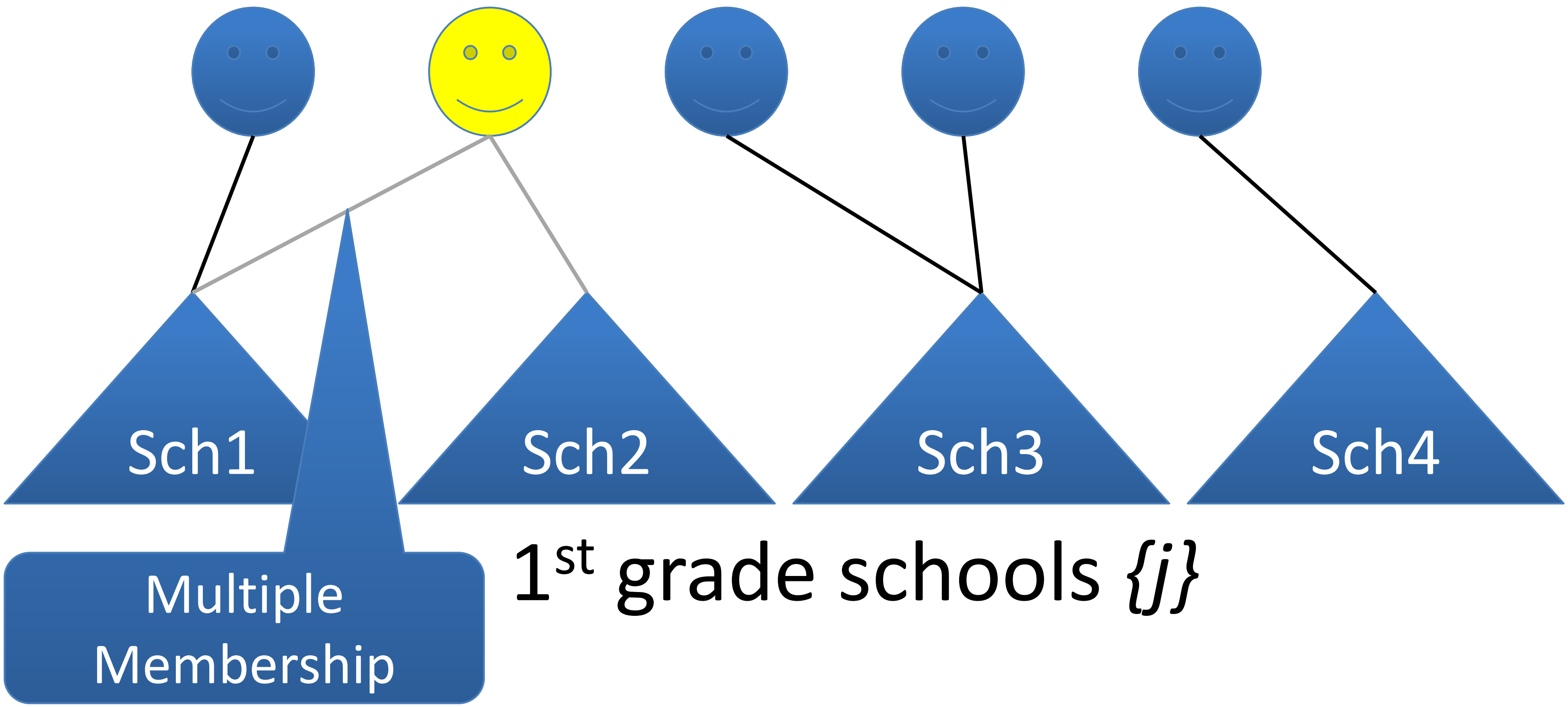
Luo & Kwok (2012)

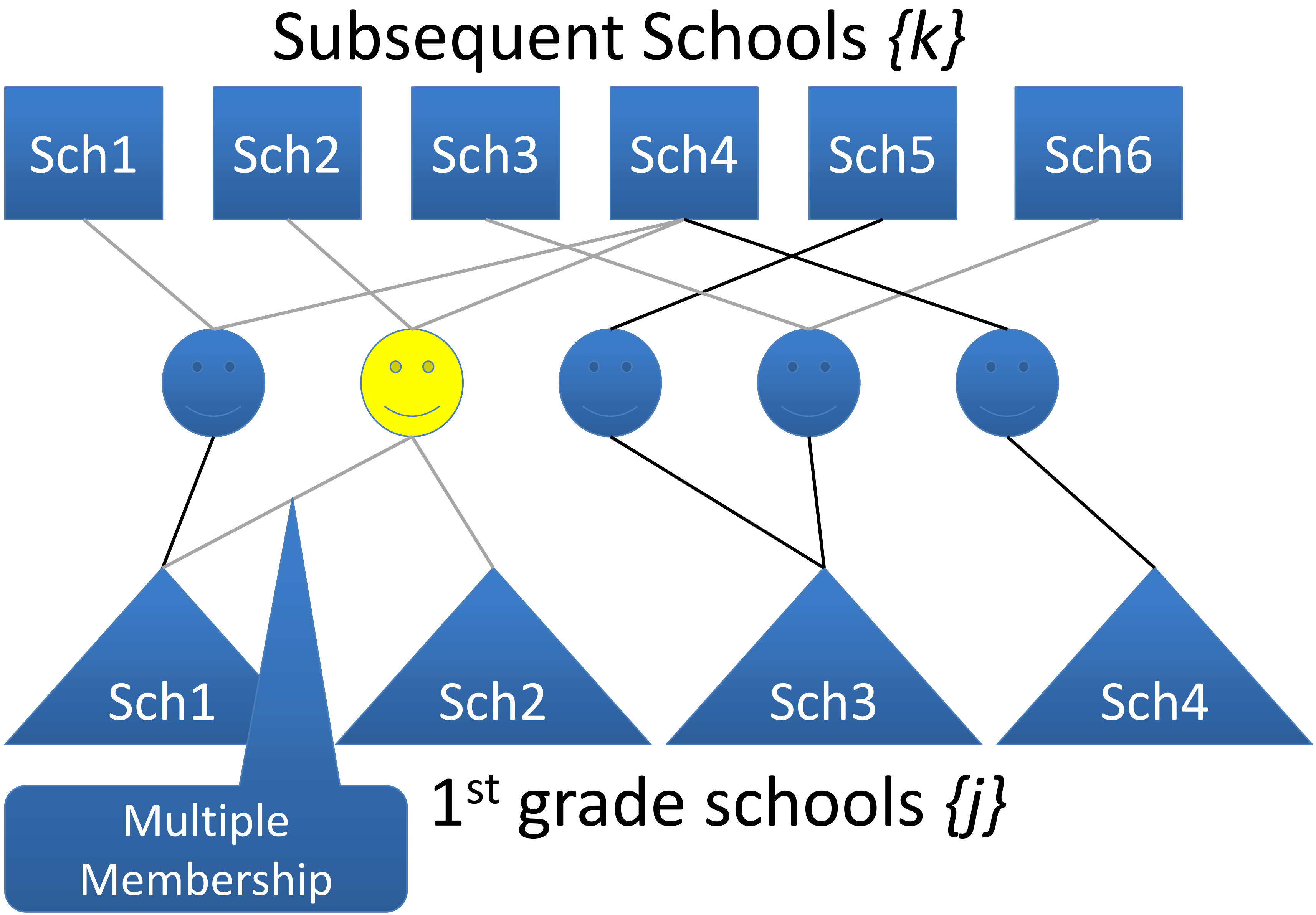
Multiple Membership

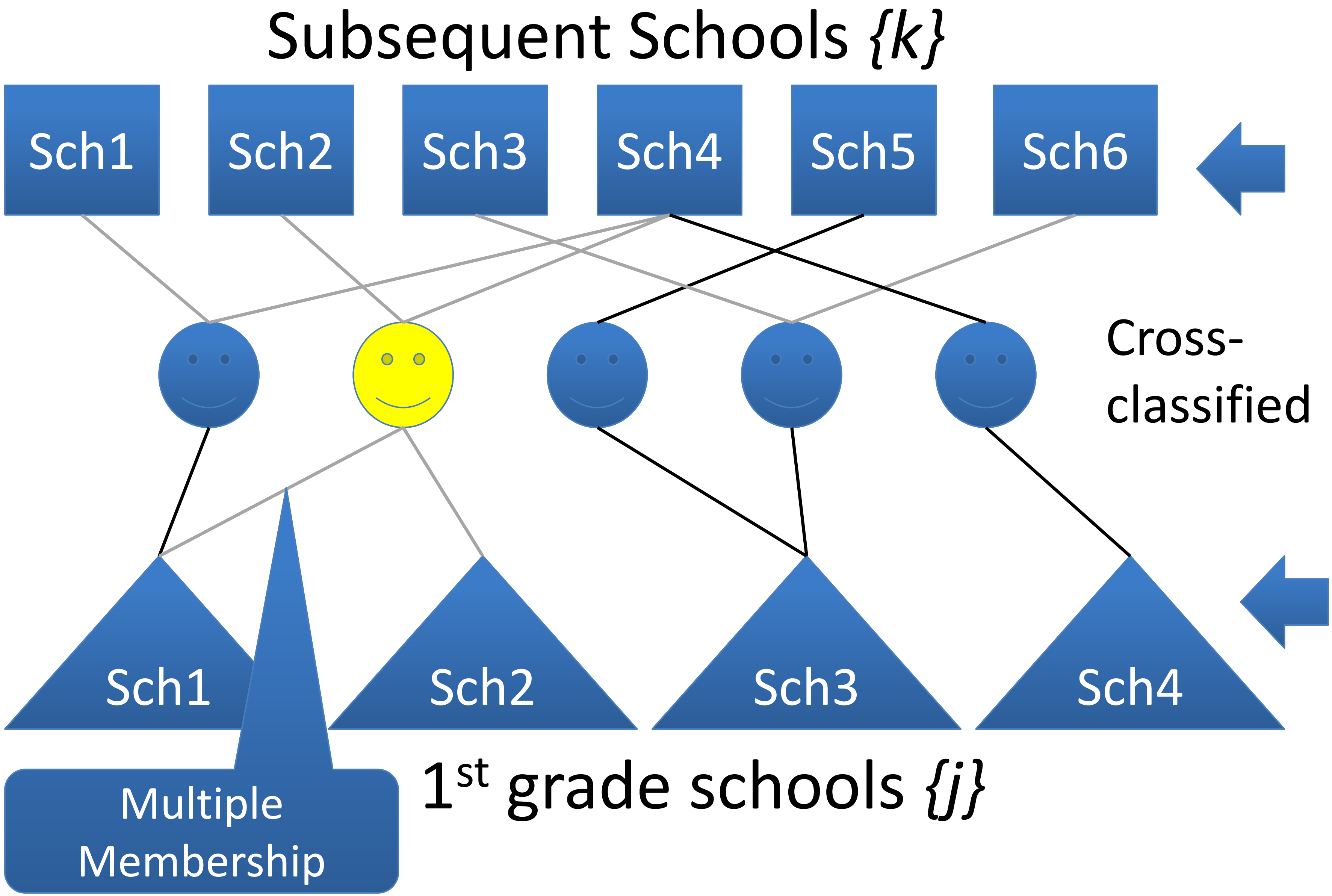
- Lower-level units belong to more than 1 higher-level *unit within the same classification*
- Examples:
  - Students attending more than one school
  - Patients served by multiple nurses
  - Doctors practicing in multiple hospitals
  - Students taking multiple classes

Cross-Classification

- Lower-level units belong to more than 1 higher-level *classification*
- Examples:
  - Students may attend the same school but live in different neighborhoods (e.g., Scotland Neighbourhood Study, Garner & Raudenbush, 1991)


Sch1
Sch2
Sch3
Sch4
Multiple Membership
1st grade schools {j}


Subsequent Schools {k}
Sch1
Sch2
Sch3
Sch4
Sch5
Sch6
Sch1
Sch2
Sch3
Sch4
Multiple Membership
1st grade schools {j}


Subsequent Schools {k}
Sch1
Sch2
Sch3
Sch4
Sch5
Sch6
Cross-classified
Sch1
Sch2
Sch3
Sch4
Multiple Membership
1st grade schools {j}

Growth models with mobility

(Adapted from Grady & Beretvas, 2010, pp. 405-407)

Level 1 (annual obs)

$$GPA_{ti\{j\}\{k\}} = \pi_{0i\{j\}\{k\}} + \pi_{1i\{j\}\{k\}}\text{Time}_{ti\{j\}\{k\}} + e_{ti\{j\}\{k\}}$$

Level 2 (student)

$\pi_{0i\{j\}\{k\}} = \beta_{00\{j\}\{k\}} + r_{0i\{j\}\{k\}}$ ← Initial status (1st grade GPA)

$\pi_{1i\{j\}\{k\}} = \beta_{10\{j\}\{k\}} + r_{1i\{j\}\{k\}}$ ← Annual change in GPA

Level 3 (school)

$\beta_{00\{j\}\{k\}} = \gamma_{0000} + \Sigma_{h\in\{j\}} w_{tih} u_{000h}$ **← Variation among 1st grade schools**

$$\beta_{10\{j\}\{k\}} = \gamma_{1000} + \Sigma_{h\in\{j\}} w_{tih} u_{100h} + \Sigma_{h\in\{k\}} w_{tih} u_{10h}$$

Variation among 1st grade schs + Variation among subsequent schs

Using growth models with mobility to estimate effect of school changes

Level 1 (annual obs)

$$GPA_{ti\{j\}\{k\}} = \pi_{0i\{j\}\{k\}} + \pi_{1i\{j\}\{k\}}Time_{ti\{j\}\{k\}} + \pi_{2i\{j\}\{k\}}Newschs_{ti\{j\}\{k\}} + e_{ti\{j\}\{k\}}$$

Level 2 (student)

$$\pi_{0i\{j\}\{k\}} = \beta_{00\{j\}\{k\}} + r_{0i\{j\}\{k\}}$$

$$\pi_{1i\{j\}\{k\}} = \beta_{10\{j\}\{k\}} + r_{1i\{j\}\{k\}}$$

$$\pi_{2i\{j\}\{k\}} = \beta_{20\{j\}\{k\}}$$

Change in GPA for each new school

Level 3 (school)

$$\beta_{00\{j\}\{k\}} = \gamma_{0000} + \Sigma_{h\in\{j\}}w_{tih}u_{000h}$$

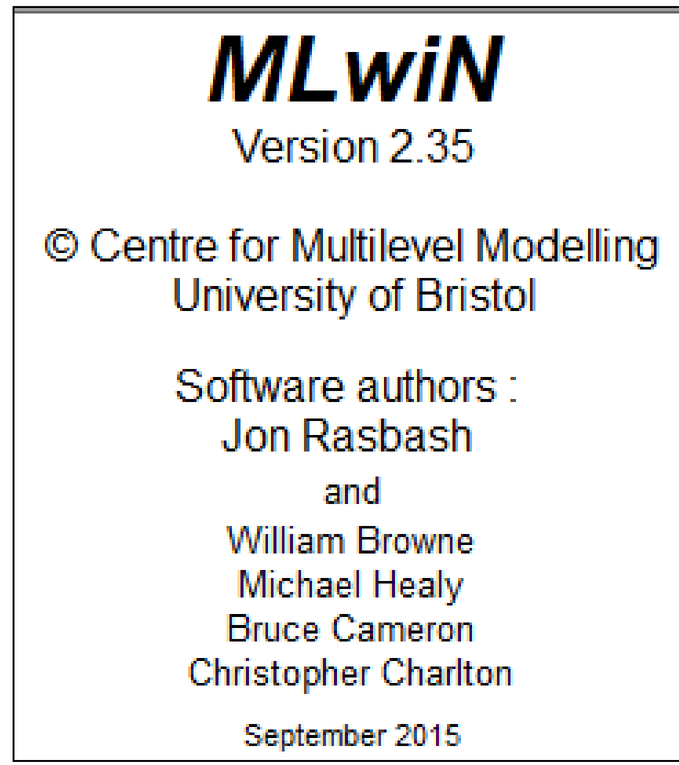
$$\beta_{10\{j\}\{k\}} = \gamma_{1000} + \Sigma_{h\in\{j\}}w_{tih}u_{100h} + \Sigma_{h\in\{k\}}w_{tih}u_{10h}$$

$$\beta_{20\{j\}\{k\}} = \gamma_{2000}$$

RUNNING MODELS

MLwiN

- MLwiN uses Markov Chain Monte Carlo (MCMC) to run these CCMM growth curve models (shout out to Bayesians in the room)
- There are extensive instructional materials on the MLwiN website
- Stata now has a module to call MLwiN



Setting Up Data

- Single "long" data file
- Each row is a measurement occasion; multiple records per student
- Student and school info repeated within student

Data for MLwiN

- Columns:
  - Time (starts at 0)
  - lev1_id (Level 1 ID)
  - id (student ID)
  - GPA
  - firstsch_1, firstsch_2, firstsch_3, firstsch_4
  - firstsch_1_wt, firstsch_2_wt, firstsch_3_wt, firstsch_4_wt
  - subsch1 through subsch12
  - subschwt1 through subschwt12
  - Student covars, panel vars
  - Constant = 1 (required by MLwiN)

Stata code to run models in MLwiN

```
use data_models_20160423, clear
**** UNCONDITIONAL REPEATED-MEASURES MODEL
* First run IGLS to get starting values
runmlwin gpa cons time, level4(firstsch_1: cons time) level3(subsch1: time)
    level2(id: cons time) level1(lev1_id: cons) nopause
* Now run CCMM,  multiple membership in firstsch and subsch, cross-classified
runmlwin gpa cons time, ///
level4(firstsch_1: cons time, mmids(firstsch_1 firstsch_2 firstsch_3 firstsch_4)
    mmweights(firstsch_1_wt firstsch_2_wt firstsch_3_wt firstsch_4_wt)) ///
level3(subsch1: time, mmids(subsch1 subsch2 subsch3 subsch4 subsch5 subsch6
    subsch7 subsch8 subsch9 subsch10 subsch11 subsch12) ///
 mmweights (subschwt1 subschwt2 subschwt3 subschwt4 subschwt5 subschwt6
    subschwt7 subschwt8 subschwt9 subschwt10 subschwt11 subschwt12)) ///
level2(id: cons time ) level1(lev1_id: cons) ///
mcmc(cc) initsprevious
```

Output

```
MLwiN 2.35 multilevel model     Number of obs =  46226
Normal response model
Estimation algorithm: MCMC

-------------------------------------------------------
                |   No. of     Observations per Group
 Level Variable |   Groups   Minimum    Average  Maximum
----------------+--------------------------------------
 firstsch_1     |      781         1       59.2     5309
 subsch1        |      831         1       55.6     5645
 id             |     7267         1        6.4       14
-------------------------------------------------------
```

Output, cont'd

```
Burnin                              =        500
Chain                               =       5000
Thinning                            =          1
Run time (seconds)                  =        142
Deviance (dbar)                     =   66499.76
Deviance (thetabar)                 =   58023.77
Effective no. of pars (pd)          =    8475.99
Bayesian DIC                        =   74975.75
```

Output, cont'd

gpa	Mean	Std. Dev.	ESS	P
cons	3.194171	.0135122	224	0.000
time	-.1205852	.0041899	57	0.000

Output, cont'd

```
   Random Parameters |       Mean   Std. Dev.    ESS
Level 4: firstsch_1  |
           var(cons) |  .0883889  .0077531     565
      cov(cons,time) | -.0095343  .0012274     157
           var(time) |  .0015203    .00024     121
Level 3: subsch1     |
           var(time) |    .01062  .0007602     328
Level 2: id          |
           var(cons) |  .2138489  .0065058     688
      cov(cons,time) | -.0090847  .0010284     365
           var(time) |  .0052748  .0002398     346
Level 1: lev1_id     |
           var(cons) |  .2467643  .0019128    2500
```

Output, cont'd

```
estimates table, star(.05 .01 .001) b(%9.3g)
      Variable |    active
FP1            |
   cons        |       3.19***
   time        |     -.121***
RP4            |
   var(cons)   |     .0884***
   cov(cons\t~) |   -.00953***
   var(time)   |    .00152***
RP3            |
   var(time)   |     .0106***
RP2            |
   var(cons)   |      .214***
   cov(cons\t~) |   -.00908***
   var(time)   |    .00527***
RP1            |
   var(cons)   |      .247***
legend: * p<.05; ** p<.01; *** p<.001
```

Output, cont'd

gpa	Mean	Std. Dev.	ESS	P
cons	3.205194	.0137068	262	0.000
time	-.119758	.0038107	103	0.000
moball	-.0399817	.0054452	2973	0.000

RESULTS

Research questions

- What is the relationship between changing schools and academic performance (GPA) in the year of the school change?
- How does this relationship vary among different types of concurrent changes in children’s social, educational, residential, and familial environments?

Measures

- Dependent variable: GPA
- Independent variable: School changes
- Time-varying covariates
  - Panel variables
  - Chronic absence
- Non-time-varying covariates
  - Student demographics

Distilling among types of school changes

- First series of models to estimate overall mobility effect
  - *Newschs* (Level 1)
  - Controlling for panel design and chronic absence (Level 1) and student demographics (Level 2)
- Second series of models to distinguish among types of transfers
  - Variables for school change types in place of the overall mobility variable *Newschs* (Level 1)

Overall mobility effect

- On average first grade GPA = 3.45; annual change = -0.13
- When students changed schools, GPA dropped 0.02 points
- Controlling for panel design, student demographics, and chronic absence

Why Students Change Schools

<table>
<tr><td colspan="2">No social chg
n = 5,643
50%</td><td colspan="6">Social group change
n = 5,579
50%</td></tr>
<tr><td rowspan="3">Type 1
No other change
(closure/ rezoning)

n = 216
2%</td><td rowspan="3">Type 2
School level change
(promotion)

n = 5,427
48%</td><td colspan="2">No residential change
n = 783
7%</td><td colspan="3">Residential change
n = 3,154
28%</td><td rowspan="3">Type 9
Solo transfer, reason unknown

n = 1,642
15%</td></tr>
<tr><td rowspan="2">Type 3
Setting change
(parent-initiated)

n = 617
5%</td><td rowspan="2">Type 4
Setting change
(school-initiated)

n = 166
1%</td><td rowspan="2">Type 5
No family change

n = 1,698
15%</td><td colspan="2">Family change
n = 1,456
13%</td></tr>
<tr><td>Type 6
Family structure change

n = 760
7%</td><td>Type 7
Family financial issues

n = 696
6%</td></tr>
</table>

Not all school changes have negative effects

- When social, residential, and familial environments remain stable, school changes have no effect (school closures and promotions)
- Declines occur only when familial environments change along with school changes

DISCUSSION

Long term effects?

- This study examined performance *in the year of the school change only*
- Changes in school and other settings may also affect long term
  - Modeling long-term effects is "one of the most challenging aspects of modeling longitudinal achievement data"
  - Growing attention with "value added"
  - Should examine short-term as well as long-term patterns to disentangle the immediate and lasting impacts of mobility

School mediators and moderators?

- School-level variation in GPAs accounted for about a third of the overall variation
- School contextual variables including school-level mobility rates were not included in the analyses
- Did not examine variation in mobility effect among schools (fixed effect)
- Preliminary research on this dataset suggests mobility gaps were especially large in schools with higher overall levels of achievement

Q&A

My contact info:
Bess Rose
barose129@gmail.com

ADDITIONAL SLIDES

Background

- Changing schools creates instability and stress for children
- Most school changes are accompanied by social, educational, residential, and/or familial changes
- These concurrent changes are likely to exacerbate the stress of changing schools and to negatively impact academic performance

Sample

- Random sample of schools from all districts in Maryland in 2001
- Proportional stratified sampling based on district and grade span enrollment
- 315 schools (117 elementary, 110 middle and 88 high schools)
- Representative of the population of public schools in Maryland in 2001

Data collection

- At each school, the roster of one 5th, 8th, or 12th grade classroom was selected for student record review.
- Data were collected from their cumulative folders
- Total 7,803 students
- Covers 1987-88 – 2001-02

Mobility and educational policy

- Data covered 1988 to 2002, just prior to implementation of NCLB
  - Fairly stable educational policy context in Maryland
  - Stable backdrop for investigating changes in GPA over time
  - Similar to the accountability policies in all states under NCLB

Mobility and Common Core?

- Some of mobility's negative impact may be due to dissimilar curricula and standards from school to school
- Common Core could establish consistent educational standards and expectations across states
- States may be moving away from the same set of standards across states (although they may be retaining CC's central idea of aligning standards, curriculum, and assessment)
  - Within states, greater consistency
  - Between states, may continue to be lack of consistency
- Understanding effects of school mobility and policies will continue to be important
  - Could leverage differences between states

Required Reading:

MLwiN online course at Center for Multilevel Modelling www.bristol.ac.uk/cmm/

- Fielding & Goldstein (2006): Cross-classified and Multiple Membership Structures in Multilevel Models http://www.education.gov.uk/publications/eorderingdownload/rr791.pdf
- Grady & Beretvas (2010): Incorporating student mobility in achievement growth modeling: A cross-classified multiple membership growth curve model *Multivariate Behavioral Research*
- Leckie & Bell (2013): MLwiN Practical on Cross-Classified Multilevel Models (MLwiN course)
- Leckie & Owen (2013): MLwiN Practical on Multiple Membership Multilevel Models (MLwiN course)

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