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

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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 $j$:

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

- Intercept (1st grade GPA)
- Slope (annual change in GPA)

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 $j$):

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

  - Level 1 intercept (1st grade GPA)
  - Mean 1st grade GPA of all students in all schools

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

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

  - Level 1 slope (annual change in GPA)
  - 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)

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Intercept:

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

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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 \( j \)

How do you handle nesting if student belongs to more than one school?
Can ignoring mobility change your study’s findings?

YES

- Don’t delete mobile students from the analysis
- Don’t 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)
Multiple Membership

1st grade schools \{j\}
Subsequent Schools \( \{k\} \)

- Sch1
- Sch2
- Sch3
- Sch4
- Sch5
- Sch6

1st grade schools \( \{j\} \)

Multiple Membership
Subsequent Schools \( \{k\} \)

1\textsuperscript{st} grade schools \( \{j\} \)

Multiple Membership

Cross-classified
Growth models with mobility
(Adapted from Grady & Beretvas, 2010, pp. 405-407)

Level 1 (annual obs)
\[ \text{GPA}_{t_{ij}k} = \pi_{0i_{ij}k} + \pi_{1i_{ij}k} \text{Time}_{t_{ij}k} + e_{t_{ij}k} \]

Level 2 (student)
\[ \pi_{0i_{ij}k} = \beta_{00_{ij}k} + r_{0i_{ij}k} \quad \leftarrow \text{Initial status (1}\text{st grade GPA)} \]
\[ \pi_{1i_{ij}k} = \beta_{10_{ij}k} + r_{1i_{ij}k} \quad \leftarrow \text{Annual change in GPA} \]

Level 3 (school)
\[ \beta_{00_{ij}k} = \gamma_{0000} + \sum_{h \in \{j\}} w_{tih} u_{000h} \quad \leftarrow \text{Variation among 1}\text{st grade schools} \]
\[ \beta_{10_{ij}k} = \gamma_{1000} + \sum_{h \in \{j\}} w_{tih} u_{100h} + \sum_{h \in \{k\}} w_{tih} u_{10h} \quad \text{Variation among 1}\text{st grade schs} + \text{Variation among subsequent schs} \]
Using growth models with mobility to estimate effect of school changes

Level 1 (annual obs)

\[ \text{GPA}_{tijjk} = \pi_{0ijjk} + \pi_{1ijjk} \text{Time}_{tijjk} + \pi_{2ijjk} \text{Newschs}_{tijjk} + e_{tijjk} \]

Level 2 (student)

\[ \pi_{0ijjk} = \beta_{00ijjk} + r_{0ijjk} \]
\[ \pi_{1ijjk} = \beta_{10ijjk} + r_{1ijjk} \]
\[ \pi_{2ijjk} = \beta_{20ijjk} \]

Change in GPA for each new school

Level 3 (school)

\[ \beta_{00ijjk} = \gamma_{0000} + \sum_{h \in \{j\}} w_{tih} u_{000h} \]
\[ \beta_{10ijjk} = \gamma_{1000} + \sum_{h \in \{j\}} w_{tih} u_{100h} + \sum_{h \in \{k\}} w_{tih} u_{10h} \]
\[ \beta_{20ijjk} = \gamma_{2000} \]
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

<table>
<thead>
<tr>
<th>Level Variable</th>
<th>No. of Groups</th>
<th>Observations per Group</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Minimum    Average   Maximum</td>
</tr>
<tr>
<td>firstsch_1</td>
<td>781</td>
<td>1          59.2   5309</td>
</tr>
<tr>
<td>subsch1</td>
<td>831</td>
<td>1          55.6   5645</td>
</tr>
<tr>
<td>id</td>
<td>7267</td>
<td>1          6.4    14</td>
</tr>
</tbody>
</table>
Output, cont’d

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Burnin</td>
<td>500</td>
</tr>
<tr>
<td>Chain</td>
<td>5000</td>
</tr>
<tr>
<td>Thinning</td>
<td>1</td>
</tr>
<tr>
<td>Run time (seconds)</td>
<td>142</td>
</tr>
<tr>
<td>Deviance (dbar)</td>
<td>66499.76</td>
</tr>
<tr>
<td>Deviance (thetabar)</td>
<td>58023.77</td>
</tr>
<tr>
<td>Effective no. of pars (pd)</td>
<td>8475.99</td>
</tr>
<tr>
<td>Bayesian DIC</td>
<td>74975.75</td>
</tr>
</tbody>
</table>
## Output, cont’d

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>ESS</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>cons</td>
<td>3.194171</td>
<td>0.0135122</td>
<td>224</td>
<td>0.000</td>
</tr>
<tr>
<td>time</td>
<td>-0.1205852</td>
<td>0.0041899</td>
<td>57</td>
<td>0.000</td>
</tr>
<tr>
<td>Random Parameters</td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>ESS</td>
<td></td>
</tr>
<tr>
<td>-------------------</td>
<td>--------------</td>
<td>-----------</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td><strong>Level 4: firstsch_1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>0.0883889</td>
<td>0.0077531</td>
<td>565</td>
<td></td>
</tr>
<tr>
<td>cov(cons,time)</td>
<td>-0.0095343</td>
<td>0.0012274</td>
<td>157</td>
<td></td>
</tr>
<tr>
<td>var(time)</td>
<td>0.0015203</td>
<td>0.00024</td>
<td>121</td>
<td></td>
</tr>
<tr>
<td><strong>Level 3: subsch1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>var(time)</td>
<td>0.01062</td>
<td>0.0007602</td>
<td>328</td>
<td></td>
</tr>
<tr>
<td><strong>Level 2: id</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>0.2138489</td>
<td>0.0065058</td>
<td>688</td>
<td></td>
</tr>
<tr>
<td>cov(cons,time)</td>
<td>-0.0090847</td>
<td>0.0010284</td>
<td>365</td>
<td></td>
</tr>
<tr>
<td>var(time)</td>
<td>0.0052748</td>
<td>0.0002398</td>
<td>346</td>
<td></td>
</tr>
<tr>
<td><strong>Level 1: lev1_id</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>0.2467643</td>
<td>0.0019128</td>
<td>2500</td>
<td></td>
</tr>
</tbody>
</table>
## Output, cont’d

Estimates table, star (.05 .01 .001) b (%9.3g)

<table>
<thead>
<tr>
<th>Variable</th>
<th>active</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>FP1</strong></td>
<td></td>
</tr>
<tr>
<td>cons</td>
<td>3.19***</td>
</tr>
<tr>
<td>time</td>
<td>−.121***</td>
</tr>
<tr>
<td><strong>RP4</strong></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>.0884***</td>
</tr>
<tr>
<td>cov(cons\t~)</td>
<td>−.00953***</td>
</tr>
<tr>
<td>var(time)</td>
<td>.00152***</td>
</tr>
<tr>
<td><strong>RP3</strong></td>
<td></td>
</tr>
<tr>
<td>var(time)</td>
<td>.0106***</td>
</tr>
<tr>
<td><strong>RP2</strong></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>.214***</td>
</tr>
<tr>
<td>cov(cons\t~)</td>
<td>−.00908***</td>
</tr>
<tr>
<td>var(time)</td>
<td>.00527***</td>
</tr>
<tr>
<td><strong>RP1</strong></td>
<td></td>
</tr>
<tr>
<td>var(cons)</td>
<td>.247***</td>
</tr>
</tbody>
</table>

Legend: * p<.05; ** p<.01; *** p<.001
Output, cont’d

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>ESS</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>gpa</td>
<td>3.205194</td>
<td>.0137068</td>
<td>262</td>
<td>0.000</td>
</tr>
<tr>
<td>time</td>
<td>-.119758</td>
<td>.0038107</td>
<td>103</td>
<td>0.000</td>
</tr>
<tr>
<td>moball</td>
<td>-.0399817</td>
<td>.0054452</td>
<td>2973</td>
<td>0.000</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Type 1</th>
<th>Type 2</th>
<th>Type 3</th>
<th>Type 4</th>
<th>Type 5</th>
<th>Type 6</th>
<th>Type 7</th>
<th>Type 9</th>
</tr>
</thead>
<tbody>
<tr>
<td>No other change (closure/ rezoning)</td>
<td>School level change (promotion)</td>
<td>Setting change (parent-initiated)</td>
<td>Setting change (school-initiated)</td>
<td>No family change</td>
<td>Family structure change</td>
<td>Family financial issues</td>
<td>Solo transfer, reason unknown</td>
</tr>
<tr>
<td>n = 216</td>
<td>n = 5,427</td>
<td>n = 617</td>
<td>n = 166</td>
<td>n = 1,698</td>
<td>n = 760</td>
<td>n = 696</td>
<td>n = 1,642</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Type</th>
<th>Description</th>
<th>Counts</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>No social chg</td>
<td>n = 5,643</td>
<td>50%</td>
<td></td>
</tr>
<tr>
<td>Social group change</td>
<td>n = 5,579</td>
<td>50%</td>
<td></td>
</tr>
<tr>
<td>No residential change</td>
<td>n = 783</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>Residential change</td>
<td>n = 3,154</td>
<td>28%</td>
<td></td>
</tr>
<tr>
<td>Family change</td>
<td>n = 1,456</td>
<td>13%</td>
<td></td>
</tr>
<tr>
<td>Type 6 Family structure change</td>
<td>n = 760</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>Type 7 Family financial issues</td>
<td>n = 696</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td>Type 9 Solo transfer, reason unknown</td>
<td>n = 1,642</td>
<td>15%</td>
<td></td>
</tr>
</tbody>
</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 \textit{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

• 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)
References


References


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