Abstract Title Page

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Title: Examining Variation in Effects of Student Mobility Using Cross-Classified, Multiple Membership Modeling

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Abstract Body

Limit 4 pages single-spaced.

Background / Context:

Description of prior research and its intellectual context.

Research on the effectiveness of educational interventions usually is based on samples of students who remain in the same school over time. In contrast, most students transfer schools at least once during their K-12 school career, not including normative transfers such as those from elementary to middle school (Rumberger, 2002). Even when looking at just the two years prior to the 1998 NAEP, one-third of fourth graders, 19 percent of eighth graders, and 10 percent of twelfth graders had changed schools at least once (Rumberger, 2002). Mobility is higher among low-income and minority populations (Rumberger, 2002). While many studies have investigated the relationship of student mobility with achievement (Alexander, Entwisle, & Dauber, 1996; Reynolds, Chen, & Herbers, 2009; Rumberger & Larson, 1998; Tucker, Marx, & Long, 1998), the degree to which this relationship might vary among schools has not been fully investigated; in other words, are some schools more effective with mobile students than others?

Purpose / Objective / Research Question / Focus of Study:

Description of the focus of the research.

The purpose of the present study was to investigate the effect of student mobility on the academic achievement of a representative sample of public school students in a mid-Atlantic state, demonstrating the use of CCMM modeling, and to examine whether there is significant variation among schools in terms of the impact of mobility on achievement.

Setting:

Description of the research location.
(May not be applicable for Methods submissions)

Data for the current study were obtained from a prior study of student mobility in a mid-Atlantic state that took place in 2001-2003. (A full description is available in Rogers, 2004.)

Population / Participants / Subjects:

Description of the participants in the study: who, how many, key features, or characteristics.
(May not be applicable for Methods submissions)

The sample for the present study included 1,669 students who were enrolled in one of the study schools (see below for further detail). The present study focuses on the students in their sixth year of schooling. Characteristics of these students are displayed in Table 1. Nearly half (45.4%) had made non-promotional transfers between schools at least once during these 6 years; 8.5% had made 3 or more moves in just six years. Similar to national studies of mobility patterns, highly mobile students in the present sample were disproportionately poor and non-white. All but 13 of the sample students were in 6th grade (i.e., had never been retained in grade). Scores on year 6 CTBS as well as prior reading tests tend to decrease as mobility increases.

Intervention / Program / Practice:

Description of the intervention, program, or practice, including details of administration and duration.

(May not be applicable for Methods submissions)

N/A

Significance / Novelty of study:
Description of what is missing in previous work and the contribution the study makes.

Methodological studies have examined the statistical consequences of ignoring student mobility and have found that parameter estimates and causal inferences are likely to be significantly problematic (Chung, 2009; Grady & Beretvas, 2010; Luo & Kwok, 2012). Because students are nested within multiple schools rather than a single school, correctly analyzing student-level data requires the use of cross-classified, multiple membership (CCMM) non-hierarchical models. While the use of CCMM models has been demonstrated in a number of studies, only a few have investigated the effect of student mobility on academic achievement (e.g., Goldstein et al., 2007).

Statistical, Measurement, or Econometric Model:
Description of the proposed new methods or novel applications of existing methods.

Details on the use of CCMM are provided in Browne (2012) and Goldstein (2003). This study applies these methods to investigate the impact of mobility on achievement and the variation in mobility gaps among schools.

Usefulness / Applicability of Method:
Demonstration of the usefulness of the proposed methods using hypothetical or real data.

Using MLwiN version 2.27 (Rasbash et al., 2012), a series of multilevel models were fitted. First, a series of traditional multilevel models were fitted assigning students to the first school attended in Year 6, ignoring their potential membership to multiple schools during Year 6 as well as their membership in prior schools.

Specifically, these traditional models predicted Year 6 CTBS reading score (Year6_Rdg) for student i in school j. Starting with an unconditional model:

$$\text{Year6\_Rdg}_{ij} = \beta_{0j} + e_{ij}$$
$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$u_{0j} \sim N(0, \sigma^2_{u0})$$

Then adding a series of student covariates: grade at Year 6, centered around 6 (students who had never been retained would be in 6th grade); prior reading score (the student's most recent reading score, standardized with a mean of 0 and standard deviation of 1); demographics (a set of dummy variables indicating free or reduced-price meals, special education services, limited English proficiency, minority, and female). Prior reading score was set to randomly vary among schools; the other Level 1 variables were fixed at Level 2. Finally, the variable indicating the number of non-promotional school transfers was added to the model, and set to random at Level 2. The full traditional model thus was:

$Year6\_Rdg_{ij} = \beta_{0j} + \beta_{1j}(Grade\text{-}6) + \beta_{2j}(Prior\_Rdg) + \beta_{3j}(FRPL) + \beta_{4j}(SpecEd) + \beta_{5j}(LEP) + \beta_{6j}(Min) + \beta_{7j}(Female) + \beta_{8j}(Moves) + e_{ij}$

$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20} + u_{2j}$
$\beta_{3j} = \gamma_{30}$
$\beta_{4j} = \gamma_{40}$
$\beta_{5j} = \gamma_{50}$
$\beta_{6j} = \gamma_{60}$
$\beta_{7j} = \gamma_{70}$
$\beta_{8j} = \gamma_{80} + u_{8j}$

School and student-level residuals were assumed to be normally distributed with means of 0 and variances σ^2_{uq} and σ^2_e, respectively. Next, a similar set of models was fitted using cross-classification and multiple membership. First, a naïve 3-level model was run, nesting students within first prior-year school within first current year school. This is done in order to provide starting values for the CCMM which is to be run using Monte Carlo estimation (Browne, 2012). Then the cross-classified and multiple membership structure was specified, so that students are nested within Year 6 schools (cross-classified factor 1, allowing multiple membership) cross-classified by prior schools (cross-classified factor 2, allowing multiple membership). Monte Carlo burn-in was set to 500 and chain length to 150000. MLwiN default (non-informative) priors were used. The full CCMM model was:

$Year6\_Rdg_{ij} = \beta_{0j} + \beta_{1j}(Grade\text{-}6) + \beta_{2j}(Prior\_Rdg) + \beta_{3j}(FRPL) + \beta_{4j}(SpecEd) + \beta_{5j}(LEP) + \beta_{6j}(Min) + \beta_{7j}(Female) + \beta_{8j}(Moves) + e_{ij}$

$\beta_{0j} = \gamma_{00} + \Sigma_{j,Year6schs(i)} w^{(3)}_{ij} u^{(3)}_{0j} + \Sigma_{j,Priorschs(i)} w^{(2)}_{ij} u^{(2)}_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20} + \Sigma_{j,Year6schs(i)} w^{(3)}_{ij} u^{(3)}_{2j}$
$\beta_{3j} = \gamma_{30}$
$\beta_{4j} = \gamma_{40}$
$\beta_{5j} = \gamma_{50}$
$\beta_{6j} = \gamma_{60}$
$\beta_{7j} = \gamma_{70}$
$\beta_{8j} = \gamma_{80} + \Sigma_{j,Year6schs(i)} w^{(3)}_{ij} u^{(3)}_{8j}$

Research Design:

Description of the research design.
(May not be applicable for Methods submissions)

The study utilized a quasi-experimental research design.

Data Collection and Analysis:

Description of the methods for collecting and analyzing data.
(May not be applicable for Methods submissions)

As part of a larger study of student mobility in the state that took place in 2001-2003, data were collected from the cumulative hard-copy records of 7,803 students in 117 elementary, 110 middle and 88 high schools from all 24 local education agencies (LEAs) in the state. These 315 schools were randomly selected using proportional stratified sampling based on LEA and grade-level (elementary, middle, and high) enrollment. Special schools (e.g., alternative or special education) were excluded from the sample frame. From each school, one fifth-, eighth-, or twelfth-grade classroom was selected for student record review. Complete school histories were able to be obtained for 6,819 students (87.4%). Demographics of the student sample were not statistically significantly different from overall student demographics in the state.

For the present study, students having complete school histories, a CTBS reading score at Year 6 of schooling, and a prior reading score were selected (N=1669). The prior reading test score was based on the most recent score from among three possible assessments: CTBS, a state accountability test, or a state functional reading test. These scores were standardized to have a mean of 0 and a standard deviation of 1 within groups by test and grade.

Findings / Results:
Description of the main findings with specific details.
(May not be applicable for Methods submissions)

Results of both the traditional and CCMM models are displayed in Table 2 (Appendix B). Comparison of the traditional and CCMM model results shows that estimates of fixed effect parameters are similar. Estimates of random effects, however, differ in that where the traditional model allocates Level 2 variance to a single school (student's first Year 6 school), the CCMM model distributes this variance among the set of Year 6 schools ($u^{(3)}$) and the set of prior-year schools ($u^{(2)}$). Thus, the proportion of total variance that is attributed to differences among schools (intra-cluster coefficient, ICC) is estimated by the CCMM model to be slightly higher (.285) than the traditional HLM model (.274).

The present study investigated the effect of student mobility on reading achievement, and whether this effect varied significantly among schools. Focusing on the CCMM results (Table 3), 6^{th} grade white male students in the sample, with average prior reading scores, who are not receiving any special services, and who have never had any non-promotional school transfers, are predicted to have a CTBS reading scale score of about 663. Holding all other factors constant, a single school transfer is estimated to predict a decline in scores by about .6; while this estimate is not statistically significantly different from 0, the variance for this estimate shows significant spread among Year 6 schools, $\Omega^{(3)}_{8,8} = 11.64$ (SE 3.83). Comparing the partial model to the full model, the addition of the mobility variable improves model fit significantly ($p<.0001$). Assuming normality, we would expect 95% of the schools to have mobility slopes within the range $-.611 \pm 1.96(11.640)^{1/2}$. Thus, mobility gaps range from -7.298 to 6.076.

In addition, there is a negative covariance between intercepts and β_8 slopes, estimated as -37.932 (SE 12.276), indicating that schools with higher average reading scores tend to have steeper slopes; in other words, student mobility has an ever stronger impact on achievement in high-performing schools.

Conclusions:
Description of conclusions, recommendations, and limitations based on findings.

The present study was limited in its lack of school-level measures for achievement and mobility. Indeed, inclusion of these contextual measures, if they were available, might alter the study findings (Raudenbush & Bryk, 2002). This study examined complete school history data from a statewide sample of students in order to investigate the relationship between mobility and reading achievement in the sixth year of schooling. Cross-classified, multiple membership models were used to accurately account for students' membership in multiple schools during Year 6 as well as prior years. The relationship between mobility and reading scores was found to be non-significant on average, but examination of the variance components revealed that the impact of student mobility on reading achievement varied significantly among schools. Furthermore, the covariance estimate suggests that mobility gaps are especially large in schools with higher overall levels of achievement. This suggests that further research is necessary that more closely examines the contextual effects of mobility.

Appendices

Not included in page count.

Appendix A. References

References are to be in APA version 6 format.

Alexander, K. L., Entwisle, D. R., & Dauber, S. L. (1996). Children in motion: School transfers and elementary school performance. *Journal of Educational Research, 90*, 3-12.

Browne, W. J. (2012). MCMC estimation in MLwiN version 2.26. Centre for Multilevel Modelling, University of Bristol.

Chung, H. (2009). The Impact of Ignoring Multiple-Membership Data Structures. Dissertation. The University of Texas at Austin.

Goldstein, H. (2003). *Multilevel Statistical Models*, 3rd ed. London: Arnold.

Goldstein, H., Burgess, S., & McConnell, B. (2007). Modelling the effect of pupil mobility on school differences in educational achievement. *Journal of the Royal Statistical Society, 170*, 941-954.

Grady, M. W., & Beretvas, S. N. (2010). Incorporating student mobility in achievement growth modeling: A cross-classified multiple membership growth curve model. *Multivariate Behavioral Research, 45*, 393-419.

Luo, W., & Kwok, O. (2012). The consequences of ignoring individuals' mobility in multilevel growth models: A Monte Carlo study. *Journal of Educational and Behavioral Statistics, 37*, 31-56.

Rasbash, J., Browne, W. J., Healy, M., Cameron, B., & Charlton, C. (2013). MLwiN Version 2.27. Centre for Multilevel Modelling, University of Bristol.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*, 2nd ed. Thousand Oaks, CA: SAGE.

Reynolds, A. J., Chen, C.-C., & Herbers, J. E. (June 2009). School Mobility and Educational Success: A Research Synthesis and Evidence on Prevention. Paper presented at the Workshop on the Impact of Mobility and Change on the Lives of Young Children, Schools, and Neighborhoods, National Research Council, Washington, DC. Retrieved from http://www.bocyf.org/children_who_move_reynolds_paper.pdf

Rogers, L. (2004). *Student mobility in Maryland: A report to The Annie E. Casey Foundation*. Baltimore, MD: Maryland State Department of Education.

Rumberger, R. W. (2002). Student mobility. In *Encyclopedia of Education* (2nd ed., Vol. 7, pp. 2381-2385). New York: Macmillan Reference USA.

Rumberger, R. W., & Larson, K. A. (1998). Student mobility and the increased risk of high school dropout. *American Journal of Education, 107*, 1-35.

Tucker, C. J., Marx, J., & Long, L. (1998). “Moving on”: Residential mobility and children's school lives. *Sociology of Education, 71*, 111-129.

Appendix B. Tables and Figures

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Table 1. Mean sample characteristics, by mobility level

	0 (N=912)	1 (N=436)	2 (N=179)	3+ (N=142)
CTBS reading	665.532 (38.841)	659.638 (41.099)	653.743 (37.880)	648.838 (35.547)
Prior reading	.120 (.956)	.013 (.953)	-.200 (.960)	-.266 (.932)
6^{th} grade	.997 (.057)	.995 (.068)	.978 (.148)	.972 (.166)
FRPL	.178 (.382)	.222 (.416)	.369 (.484)	.465 (.501)
Special education	.067 (.250)	.085 (.279)	.061 (.241)	.070 (.257)
LEP	.002 (.047)	0	.006 (.075)	0
Minority	.310 (.463)	.431 (.496)	.553 (.499)	.599 (.492)
Female	.524 (.500)	.498 (.501)	.514 (.501)	.585 (.495)

Note. Standard deviations are in parentheses.

Table 2. CTBS reading scale scores in year 6, full model, traditional HLM vs. CCMM

Variable	Traditional HLM	CCMM
Fixed effects		
Intercept	663.683 (1.900)	663.381 (1.963)
Grade-6	9.726 (4.827)	10.509 (4.948)
Prior reading	21.804 (1.009)	21.667 (1.039)
FRPL	-6.018 (1.801)	-5.930 (1.805)
Special education	-8.639 (2.817)	-8.374 (2.828)
Limited English proficient	-47.134 (18.603)	-48.064 (18.943)
Minority	-6.562 (1.756)	-6.292 (1.769)
Female	1.348 (1.322)	1.344 (1.317)
School transfers	-0.483 (0.657)	-0.611 (0.664)
Random parameters		
Year 6 school(s)		
σ2(3), intercept	261.664 (45.328)	278.572 (51.861)
σ2(3), prior reading	46.340 (15.906)	51.752 (15.316)
σ2(3), school transfers	11.683 (6.451)	11.640 (3.828)
Prior schools		
σ2(2), intercept	N/A	11.776 (14.952)
Students		
σ2e	635.544 (25.004)	624.347 (25.656)
Total variance	955.231	978.087
ICC	0.274	0.285
Deviance	15813.24	15477.98

Note. Standard errors are in parentheses.

Table 3. CCMM sequential models

Variable	Unconditional	Partial	Full
Fixed effects			
Intercept	653.422 (1.9)	663.007 (1.816)	663.381 (1.963)
Grade-6		9.506 (4.846)	10.509 (4.948)
Prior reading		21.79 (1.041)	21.667 (1.039)
FRPL		-6.354 (1.794)	-5.930 (1.805)
Special education		-8.838 (2.852)	-8.374 (2.828)
Limited English proficient		-47.08 (18.921)	-48.064 (18.943)
Minority		-6.381 (1.781)	-6.292 (1.769)
Female		1.229 (1.33)	1.344 (1.317)
School transfers			-0.611 (0.664)
Random parameters			
Year 6 schools			
$\Omega^{(3)}_{0,0}$, intercept	497.725 (76.548)	206.832 (38.569)	278.572 (51.861)
$\Omega^{(3)}_{2,2}$, prior reading		50.24 (16.984)	51.752 (15.316)
$\Omega^{(3)}_{8,8}$, school transfers			11.640 (3.828)
$\Omega^{(3)}_{0,8}$, intercepts/school transfers			-37.932 (12.276)
Prior schools			
$\Omega^{(2)}_{0,0}$, intercept	90.436 (37.516)	22.567 (18.263)	11.776 (14.952)
Students			
$\Omega_{e0,0}$	981.753 (39.603)	635.883 (26.199)	624.347 (25.656)
Total variance	1569.914	915.522	978.087
ICC	0.3170397	0.225917	0.285
Deviance	16233.061	15508.272	15477.98

Note. Standard errors are in parentheses.