Abstract Title Page
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Title: Addressing Selection Bias Using Partial Longitudinal Data: A Demonstration Using Recent and Past School Movers

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Abstract Body

Limit 4 pages single-spaced.

Background / Context:

Description of prior research and its intellectual context.

The United States is a mobile society, and many children are caught up in currents of residential and school mobility. According to the Early Childhood Longitudinal Study, 31% of eighth grade students in 2007 had changed schools three or more times since the beginning of kindergarten (GAO 2010: Appendix II). This statistic includes nearly ubiquitous transitions such as the promotion to middle school, but it is still remarkably high. This mobility is concentrated in urban school districts and among the poor (de la Torre and Gwynne 2009; GAO 2010; Kerbow 1996; Pianta and Early 2001). Mobile students unequivocally fare worse in school than non-mobile students in unconditional comparisons (GAO 2010; National Research Council and Institute of Medicine [NRC & IOM] 2010), but this poor performance may be a function of factors that confound the relation between moving and performance. Prior research shows that other factors explain much of the unconditional relation between mobility and performance (Alexander, Entwisle, and Dauber 1996; Gasper, DeLuca, and Estacion 2010; Pribesh and Downey 1999; Rumberger and Thomas 2000; Strand 2002; Temple and Reynolds 1999), but a small causal effect appears to remain after unobserved fixed student characteristics are accounted for (Grigg 2012). This potential effect is elusive, however, and the problem of selection looms large, especially because mobile students—by definition—are difficult to monitor.

Purpose / Objective / Research Question / Focus of Study:

Description of the focus of the research.

Mobile students offer potential insight into the influences of school context and peer relations as they integrate socially and academically into their new schools, but the problem of selection into mobility is acute. I integrate cognitive, academic, and social-psychological outcomes in the study of student mobility by identifying the effect of a recent school change on test scores, grade point average, and student survey responses in order to address two questions: 1) How do mobile student differ from non-mobile students? 2) Does the recent experience of moving influence student outcomes?

Setting & Population / Participants / Subjects:

Description of the research location and participants in the study: who, how many, key features, or characteristics.

This paper uses data from two cohorts of consented seventh grade students (N = 2,334) from a district-wide study conducted in a Midwestern school district (MSD) in 2011-2012 and 2012-2013. The sample represents 68% of the seventh grade population in the two cohorts. As shown in Figure 1, seventh grade students can experience an unscheduled school change either immediately before seventh grade ("recent movers") or two years earlier at the beginning of fifth grade ("past movers"). Seventh grade students referred to as "non-movers" have recently changed schools as well, however. Given the structural transition between fifth and sixth grade, the so-called "non-movers" in seventh grade have changed schools the year prior at the beginning of sixth grade. In this respect, comparing "recent movers" and "past movers" to "non-movers" in fact compares students who have experienced two school transitions—one scheduled and the other not—to students who have experienced the customary promotion from elementary to middle school.

Across the two cohorts, 124 students (5% of consented students) were new at the beginning of seventh grade and 141 of their seventh grade peers (6% of consented students) experienced an unscheduled move between fourth and fifth grade (see Table 1). As is shown in Table 1, past and recent movers differ substantially from non-movers and generally resemble each other. As has been found in other studies, the average mobile student—recent or past—has substantially lower levels of achievement when no other variables are accounted for.

Intervention / Program / Practice: n/a

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

Research Design/ Data Collection and Analysis

Description of the research design and the methods for collecting and analyzing data.

Academic outcomes (grades and test scores) were provided by the school district and a survey to measure student attitudes was collected by the research team for one cohort of students. Equation 1 presents the analytical model, in which the association between a recent move and the outcome for student *i* in school *j* at time *t* is represented by β_1 and the association between a past move and the outcome is shown by β_2. The model also includes a vector of student covariates ($\sum_{k=3}^{k=K} \beta_k X_k$) and middle school fixed effects (u_j).

If the individual error term (η_i) is uncorrelated with mobility and the outcome conditional on the other variables including the receiving school fixed effects (Cov$[M_{it}, \eta_i] = 0, \text{Cov}[M_{i(t-2)}, \eta_i] = 0$), then the model shown in Equation 1 is unbiased and identifies the effect of mobility on student outcomes. This assumption, however, is heroic, since we know that mobile students differ from students who enjoy stable school enrollments in numerous ways, some of which are associated with student outcomes and—because they are unobserved—are included in the individual student error term (Cov$[M_{it}, \eta_i] \neq 0, \text{Cov}[M_{i(t-2)}, \eta_i] \neq 0$). Moreover, the unobserved factors associated with mobility are in general likely to harm school outcomes, with students negatively selected into mobility (Cov$[M_{it}, \eta_i] < 0, \text{Cov}[M_{i(t-2)}, \eta_i] < 0$). Consequently, comparing recent and past mobile students to all non-mobile students—even when observable demographic characteristics are accounted for ($\sum_{k=3}^{k=K} X_k \beta_k$)—provides an overly negative estimate of the impact of being new to a school in seventh grade.

To address the selection problems inherent in the naïve upper-bound estimate represented in Equation 1, I recover a new estimate for the effect of a recent move (β_K) from the estimates for recent and past movers from Equation 1 by relaxing the heroic assumption. This post-estimation strategy is shown in Equation 2.

The effect of a recent move is represented by β_K, which identifies the difference between recent movers (β_1) and past movers (β_2). This difference represents the "true" effect of a recent move under two assumptions: 1) how recent and past moves correlate with the error term and 2) that the effect of past moving attenuates over time. Relaxing the second assumption means that β_K represents a lower-bound estimate of a recent move rather than the true, unbiased, effect.

The first major assumption is that the estimate of the effect of mobility on student outcomes is biased, but that the bias is the same for unscheduled moves before fifth grade (β_2) as for unscheduled moves before seventh grade (β_1): Cov$[M_{it}, \eta_i] = \text{Cov}[M_{i(t-2)}, \eta_i] \neq 0$

(Assumption 1). In other words, conditional on the reasons for a move, I assume that whether an unscheduled move occurred before fifth or seventh grade is random.

Consider the simplified expressions for the outcomes for recent movers and past movers shown in Equations 3 and 4. The new terms in these equations are the error terms for recent and past movers, represented by v_1 and v_2. Again, we stipulate that that the covariances are equal (Assumption 1). Because these error terms are correlated with recent and past mobility, it follows that the estimates of the effect of recent and past mobility will be biased by Λ_1 and Λ_2, as shown in Equations 5 and 6. It follows from Assumption 1 that Λ_1 and Λ_2 are equal.

Assuming a similar selection process for past and recent movers (Assumption 1), the attenuation assumption (Assumption 2) determines the amount of bias in the estimate for β_R. This attenuation process can take one of three forms. First, the past move could be just as salient two years later as the recent move ($\beta_2 = \beta_1$). In this case, the estimated impact of the recent move (β_R) will equal zero ($\hat{\beta}_1 - \hat{\beta}_2 = 0$). Second, the impact of the past move could have fully decayed ($\beta_2 = 0$). If this is the case, then comparing recent to past movers will perfectly recover the impact of the recent move without bias ($\hat{\beta}_1 - \hat{\beta}_2 = \beta_R$). The third—and most reasonable—scenario is that the effect of the past move has partially attenuated. In this case, the estimate of the impact of a recent move recovered by comparing recent to past movers will be overly conservative ($\beta_2 < \beta_1$; $\hat{\beta}_1 - \hat{\beta}_2 < \beta_R$).
Under some conditions I can impose the attenuation assumption. Measures of sixth grade test score and GPA performance are available for students who attended a district school in sixth grade. This subsample includes the within-district transfers effective at the beginning of seventh grade but not the between-district transfers. These measures serve as a control for the prior achievement of the recent movers and they "control away" the effect of the past move for the past movers, since the sixth grade measures are collected after the past move occurred. In many cases controlling for a past effect with an intervening variable would introduce unwelcome endogenous selection bias (Elwert and Winship 2014), but here the strategy could guard against violations of the attenuation assumption. Moreover, the magnitude of the endogenous selection bias introduced is likely to be smaller than the bias reduced by including the intervening variable (Greenland 2003). The estimates for these students on these outcomes could be the most accurate of all.

Findings / Results:
Description of the main findings with specific details.

The results of these analyses—including mobile students with the attenuation assumption imposed—are presented in Tables 2-4. I find no evidence that mobility impacts test scores but I do find small deficits attributable to mobility on indicators that capture dimensions of social integration such as grade point average and student attitudes. Mobile students report lower measures of social belonging and locus of control on the student survey, especially at the beginning of the year. These non-cognitive differences narrow but do not entirely close by the spring. I interpret these findings to mean that changing schools is an important experience for students and that they monitor and attend to their social standing and ability to make new friends. The experience is acute at the beginning of the year, but for at least some students the challenge of integrating socially lasts at least through the school year.

As expected, selection plays a substantial role in the large unconditional differences between mobile and non-mobile students, since mobile students are systematically different from non-mobile students. The question, however, is not whether selection at play, but whether it is the entire story. Mobile students are clearly different from non-mobile students, and that difference appears to be shared by recent and past movers. That being said, there is limited evidence—even in the conservative lower-bound estimates—that recent mobility influences student well-being along outcomes such as GPA and student attitudes that reveal the role of social belonging and social integration in schooling, as well as subjective evaluations by teachers.

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

This paper makes two primary contributions. First, it explores potential effects of mobility on multiple student outcomes and finds that unscheduled school changes do not influence cognitive outcomes but may influence subjective measures such as GPA and student attitudes. These non-cognitive measures may function as "early warning" indicators that mobile students go on to experience. Hopefully future research on student mobility will continue to investigate student outcomes beyond test scores. Second, it introduces a formal method that accounts for unobserved fixed student characteristics without using complete longitudinal data. This approach can be used in future analyses of student mobility with larger datasets. This approach likely has additional applications in other substantive areas in which explanatory variables are available longitudinally (or perhaps even retrospectively) and outcome data are only available contemporaneously.

This study faces two principal limitations. First, the sample of mobile students is small, particularly for the survey analysis and the analyses of within-district transfers that have measures of prior achievement. Both of these constraints reduce statistical power, and in some cases the differences potentially attributable to mobility may not be detectable in these data. Some of the estimates of 0.1 standard deviations in magnitude could conceivably be statistically detectable in a larger sample. A recent meta-analysis estimated that the effect size of an additional move to be 0.12 to 0.14 standard deviations (Reynolds, Chen, and Herbers 2009). In light of this power limitation, I have in some instances interpreted the results liberally; but some caution is nonetheless warranted.

The second limitation is that the strategy to estimate the lower-bound effect of recent mobility on student outcomes may be overly conservative. It relies on the strong assumption that the effect of a past move decays or "washes out." Controlling for sixth grade achievement can mechanically enforce this assumption, but it comes at the cost of a severe reduction in the sample size for the group of interest as well as the potential introduction of additional inferential complications (Elwert and Winship 2014). If past movers are still affected by their own move, then this strategy depresses the estimate of recent mobility, since they resemble recent movers by virtue of being still affected by mobility.

To be sure, mobility may be an indicator—rather than a cause—of student cognitive performance, but it could be that mobile students struggle with the social dimensions of the transition to a new school which then is manifest in their course grades and perhaps later in their test scores. Future research may demonstrate this phenomenon more convincingly, but in the meantime, the psychological strain apparent among some mobile students is enough to warrant attention and concern for them.

Appendices

Not included in page count.

Appendix A. References

References are to be in APA version 6 format.

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Appendix B. Tables and Figures

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Table 1: Characteristics of Non-Movers, Recent Movers, and Past Movers

	Non-Mover	Recent Mover (7th Grade)	Past Mover (5th Grade)
Demographics			
Female	50%	48%	57%
Free/Reduced Lunch	39%	65%	77%
Limited English Proficiency	16%	10%	33%
Special Education	13%	11%	18%
Asian	13%	7%	9%
Black	20%	47%	45%
Hispanic	16%	11%	28%
Multiracial	7%	11%	7%
White	73%	54%	52%
Non-White, Non-Asian	29%	48%	62%
Homeless	3%	15%	11%
N	*2069*	*124*	*141*
Prior Achievement			
6th Grade GPA	3.23	2.77	2.81
N	*2068*	*58*	*141*
6th Grade Math	0.05	-0.34	-0.57
N	*2036*	*55*	*137*
6th Grade Reading	0.05	-0.29	-0.58
N	*2029*	*55*	*136*

Note: The race/ethnic categories add up to more than 100% because students can identify as more than one race/ethnicity.

Table 2: MAP Results with Prior Year Data, Movers to Non-Movers and Within-Mover Comparison

	N	Model 3			Model 3
		Non-Mover [Intercept]	Recent Mover (7th Grade)	Past Mover (5th Grade)	$\beta_R = \beta_1 - \beta_2$
Fall Math Scale Score	2172	228.425	-0.784	-0.698	-0.086
		[228.035, 228.815]	[-2.284, 0.716]	[-3.289, 1.894]	[-2.715, 2.543]
Fall Reading Scale Score	2168	219.317	-2.294	0.46	-2.754*
		[218.998, 219.636]	[-4.627, 0.038]	[-1.757, 2.677]	[-5.477, -0.032]
Fall Language Usage Scale Score	2170	218.263	-1.731	-0.122	-1.609
		[217.909, 218.617]	[-5.191, 1.728]	[-2.168, 1.923]	[-5.186, 1.967]
Spring Math Scale Score	2146	233.677***	-2.629	-0.627	-2.002
		[233.300, 234.055]	[-6.173, 0.916]	[-2.208, 0.955]	[-6.176, 2.172]
Spring Reading Scale Score	2112	221.590***	-2.063	0.49	-2.553
		[221.149, 222.031]	[-5.329, 1.203]	[-1.713, 2.694]	[-6.082, 0.976]
Spring Language Usage Scale Score	2105	220.713***	-1.719	0.587	-2.306
		[220.380, 221.045]	[-3.884, 0.447]	[-1.074, 2.248]	[-4.649, 0.036]

Notes: 95% Confidence intervals shown in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (omitted from intercept estimates); school indicator and prior year WKCE score included as covariates (Reading WKCE for Reading and Language Usage; Math for Math).

Table 3: GPA Results with Prior Year Data, Movers to Non-Movers and Comparison Among Movers

		Model 3			Model 3
	N	Non-Mover [Intercept]	Recent Mover (7th Grade)	Past Mover (5th Grade)	$\beta_R = \beta_1 - \beta_2$
7th Gr. GPA (Term 1)	2256	0.047 [-0.305, 0.399]	-0.053 [-0.236, 0.129]	-0.087* [-0.174, -0.001]	0.034 [-0.181, 0.249]
7th Gr. GPA (Term 2)	2246	-0.023 [-0.386, 0.340]	-0.111 [-0.345, 0.123]	-0.048 [-0.135, 0.040]	-0.063 [-0.281, 0.154]
7th Gr. GPA (Term 3)	2231	-0.105 [-0.405, 0.195]	-0.115 [-0.372, 0.143]	-0.092* [-0.177, -0.007]	-0.022 [-0.276, 0.232]
7th Gr. GPA (Term 4)	2216	-0.266 [-0.636, 0.103]	-0.140 [-0.351, 0.071]	-0.043 [-0.127, 0.041]	-0.097 [-0.315, 0.121]
7th Gr. GPA (Full Year)	2259	-0.099 [-0.432, 0.235]	-0.096 [-0.291, 0.099]	-0.061 [-0.133, 0.011]	-0.035 [-0.237, 0.167]

Notes: 95% Confidence intervals shown in brackets; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (omitted from intercept estimates); school attended and prior year GPA included as covariates.

Table 4: Comparing Recent to Past Movers on the Fall Survey

	N	Model 1 $\beta_R = \beta_1 - \beta_2$	Model 2 $\beta_R = \beta_1 - \beta_2$
Group Belonging	1137	-0.037 [-0.384, 0.310]	0.026 [-0.304, 0.355]
Social Belonging	1141	-0.270 [-0.590, 0.049]	-0.284 [-0.633, 0.065]
Self-Complexity	1140	0.149 [-0.538, 0.837]	0.003 [-0.664, 0.671]
External Locus of Control	1132	-0.436 [-0.936, 0.064]	-0.313 [-0.820, 0.195]
Internal Locus of Control	1136	-0.277** [-0.460, -0.094]	-0.307** [-0.488, -0.126]
Evaluation Anxiety	1134	0.028 [-0.299, 0.355]	0.049 [-0.292, 0.391]
Identify with School	1142	-0.106 [-0.348, 0.136]	-0.084 [-0.312, 0.144]
Self-Confidence	1132	-0.071 [-0.527, 0.386]	-0.130 [-0.615, 0.354]
Additional Covariates?		No	Yes

Notes: 95% Confidence intervals shown in brackets; * p < 0.05, ** p < 0.01, *** p < 0.001 (omitted from intercept estimates); covariates include gender, ethnicity, free/reduced lunch, limited English proficiency, special education status, and homelessness.

Figure 1: School Transition Patterns

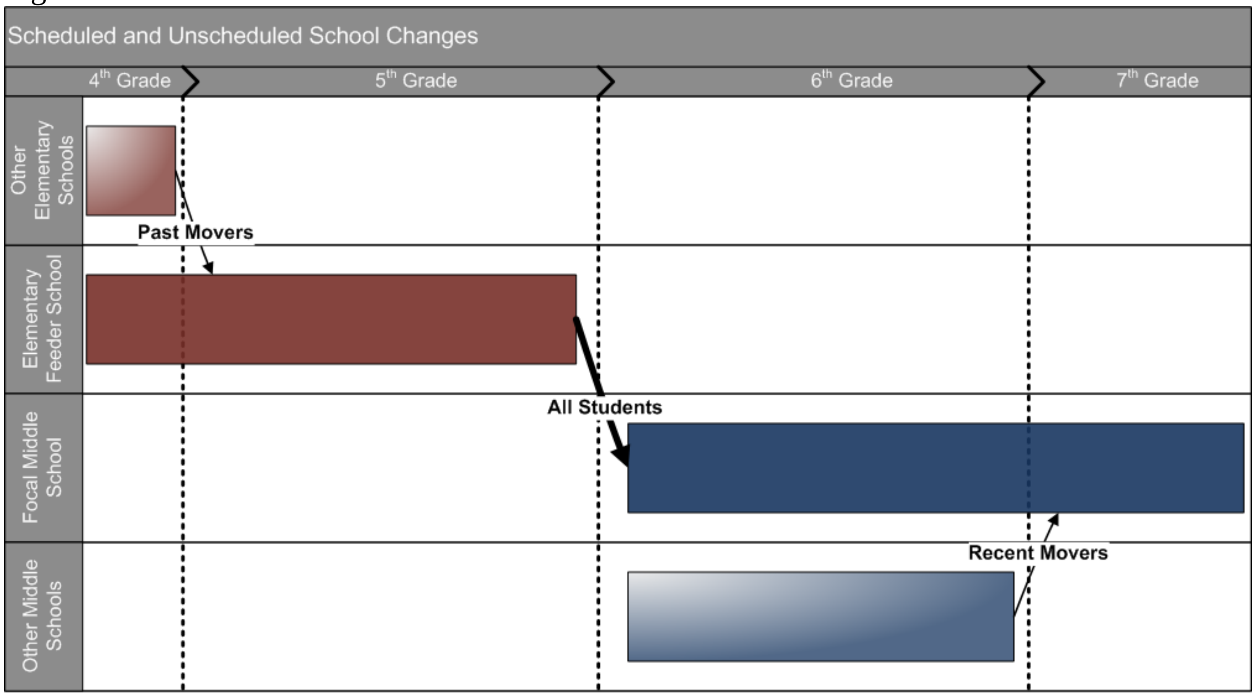

Figure 2: Equations

$$Y_{ijt} = \alpha + \beta_1 M_{it} + \beta_2 M_{i(t-2)} + \sum_{k=3}^{k=K} \beta_k X_k + u_i + \eta_t \tag{1}$$

$$\beta_R = \beta_1 - \beta_2 \tag{2}$$

$$Y_{it} = \beta_1 M_{it} + v_1, \quad Cov\,(M_{it}, v_1) \neq 0 \tag{3}$$

$$Y_{it} = \beta_2 M_{i(t-2)} + v_2, \quad Cov\,(M_{it}, v_2) \neq 0 \tag{4}$$

$$\hat{\beta}_1 = \beta_1 + \frac{Cov\,(M_{it}, v_1)}{Var\,(M_{it})} = \beta_1 + A_1 \tag{5}$$

$$\hat{\beta}_2 = \beta_2 + \frac{Cov\,(M_{i[t-2]}, v_2)}{Var\,(M_{i[t-2]})} = \beta_2 + A_2 \tag{6}$$