EXAMINATION OF STUDENT MOVEMENT IN THE CONTEXT OF FEDERAL TRANSFER POLICIES

Anna Nicotera
Bettie Teasley
Mark Berends

Vanderbilt University

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A few years into the implementation of the federal legislation of No Child Left Behind (NCLB), states continue to respond in different ways to the accountability requirements (Center on Education Policy, 2005, 2006; Erpenbach & Forte, 2005; Marsh, Barney & Russell, 2005). Although the requirements are complex, technical, and in some cases changing (Erpenbach and Forte, 2005), the goal remains—all students will be proficient in reading and mathematics by the year 2014. Toward that end, states are required to define proficiency targets (or benchmarks) to determine whether districts and schools are making Adequate Yearly Progress (AYP). This requirement calls for the federal government and states to monitor progress made by districts and schools towards teaching students content standards in different subject areas and bringing all students up to proficiency on the subject-specific assessments. Because test results need to reflect all the students in a district or school, NCLB requires that at least 95 percent of the students in a district or school take the assessments.

Even though the specific details of standards, assessments, and AYP differ across states, NCLB requires that districts provide students in schools that have not met AYP for two consecutive years the choice to transfer to a public or charter school within the district that has made AYP. Public school choice through NCLB is limited, however. Schools are required to offer school choice only if they are Title I schools. In addition, students are only allowed to transfer to a public or charter school within their district that has not also been identified for school improvement (e.g., not meeting AYP). Moreover, the district must give priority for school choice transfers to low-performing students from low-income families. The district is responsible for paying for student transportation to the new school. If the student's original school meets adequate yearly progress for two consecutive years and is removed from school improvement requirements, the student may return to the original school or remain at the new school until the completion of the last grade level in the new school. However, the district is not required to pay for transportation to the new school once the original school is removed from school improvement requirements.

A meaningful percentage of districts have schools that have not made such progress. In a recent study released by the Center on Education Policy (2006), about 14 percent of districts in the 2005-2006 school year were required to offer transfers, and about 43 percent of urban districts had schools that required this option (Center on Education Policy, 2006). Yet, hardly any students and their families are actually exercising the choice option. In 2005-2006, only about 1.6 percent of all eligible students took advantage of transferring to a school that was making AYP.

Although more evidence needs to be gathered on the reasons for this under utilization, recent research suggests that some reasons include finding physical space in schools for transfers, maintaining class size limits, overcoming parents' satisfaction with the quality of their existing schools, finding reasonable choices of schools to which students can transfer, and overcoming parents' desires to have a school close by vis-à-vis one is a distance away (Center on Education Policy, 2005, 2006; Marsh et al., 2005).

Despite the underutilization and possible reasons, the underlying premise of the federal transfer policy remains part of NCLB. The underlying theory is that the academic achievement of students from low performing schools will improve if they are able to choose and attend a higher performing school. However, empirical evidence supporting this claim is lacking.

In this paper, we analyze the longitudinal achievement growth database of the Northwest Evaluation Association (NWEA) to examine the achievement growth of students who transfer from low performing schools identified as not meeting AYP to higher performing schools that meet AYP. NWEA contracts with districts and states to provide computerized adaptive student assessments aligned to the academic standards of the state. Currently, NWEA tests students in 40 states across the nation. Although NWEA assessments are aligned to state academic standards, Idaho is the only state that uses the NWEA test as its statewide standards-based assessment to determine if schools meet AYP targets. In general, Idaho has participation rates for students tested by NWEA above 90 percent for students in grades 2 through 10. As a result, we will use NWEA data for Idaho to answer the following research question:

- Do students who move from low-performing schools to higher performing schools experience higher growth rates in mathematics achievement than students who stay in low-performing schools (i.e., schools that do not make AYP)?

The analysis uses a two-level Hierarchical Linear Model (HLM) to measure the differences in student achievement growth. We control for student differences when examining transitions to higher performing schools to explain different growth rates between students. In this analysis, we use NCLB standards-based performance levels of schools to empirically inform the federal transfer policy.

In these analyses, we cannot specify which of these transfers are actually due to parent choice. In fact, because so few parents across the nation are taking advantage of the choice option (less than 2 percent), it is likely that many of the transfers between schools in our sample are not due to parental choice. However, the analyses provide a framework to examine what might happen if students move from schools that do not make AYP to those that do in order to examine what might occur if more parents did have viable choice options under NCLB.

No Child Left Behind and School Choice: The Case of Idaho

In Idaho, 212 schools in the 2002-2003 school year and 111 schools in the 2003-2004 school year did not meet AYP.[1] Of these schools, 61 did not meet AYP for two consecutive school years. According to the NCLB legislative mandates, students in these 61 schools should be offered school choice for the 2004-2005 school year. Although we do not have data to specifically identify the students who transfer from a low performing school to a higher performing school because of the NCLB choice provision, we can model the NCLB policy by making certain assumptions about students in the database who move from schools identified as low performing to higher performing schools.

AYP decisions are based on the results from standards-based assessments administered in the spring of an academic year. As portrayed in Figure 1, the determinations of AYP status are applied to schools in the following school year. Schools were first measured on AYP in the 2002-2003 school year. The determinations from the 2002-2003 school year were then applied to schools for the 2003-2004 school year. For example, if a school did not make AYP in the 2002-2003 school year, the school is identified as in need of improvement for the 2003-2004 school year. Since 212 schools were identified as not making AYP in Idaho after the 2002-2003 school year, these schools are labeled low-performing for the 2003-2004 school year. Similarly, the 111 schools that did not make AYP in 2003-2004 are labeled low-performing for the 2004-2005 school year. Schools that did not meet AYP for two consecutive years will have the NCLB

[1] The Idaho Department of Education reports that overall 216 schools out of 645 statewide did not meet AYP for the 2002-2003 school year. Data reported for Idaho in this paper is calculated by authors from raw AYP determinations reported on the Idaho Department of Education web page. Discrepancies may reflect school waivers with AYP status.

choice provision invoked before the 2004-2005 school year. In turn, students who move from a low-performing school that did not meet AYP for two years to a higher performing school between 2003-2004 and 2004-2005 or within the 2004-2005 academic year match the conditions of the NCLB choice policy.

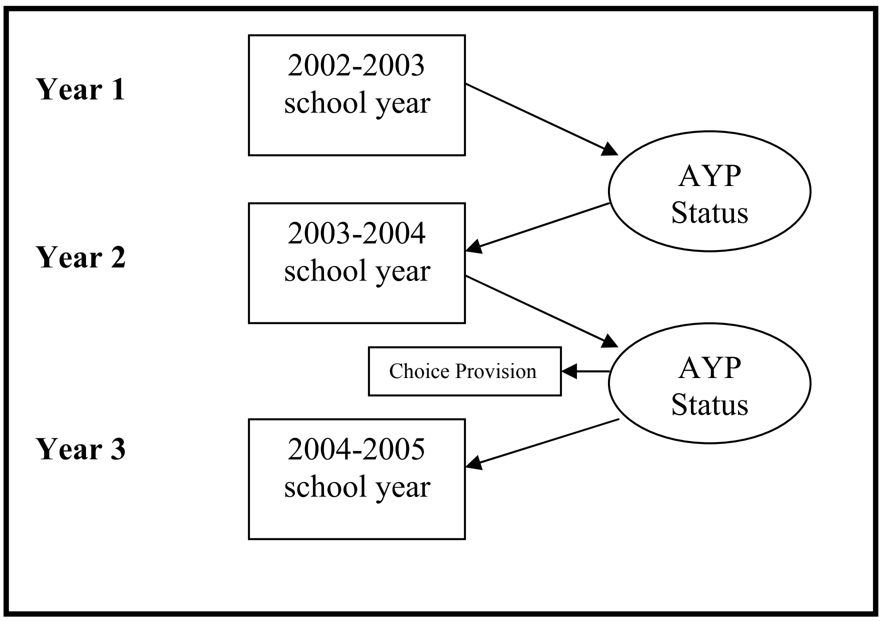

Figure 1. Determining AYP Status Based on Testing Dates in Idaho

When considering the growth in academic achievement of students who move from schools labeled low-performing to schools labeled higher performing, the application of AYP status to schools in the year after being identified limits our examination to students who move within the academic year of 2003-2004, between 2003-2004 and 2004-2005, and within the academic year of 2004-2005 based on the way in which AYP is determined and the applied (see Figure 1). However, we do not want to lose the academic achievement data of students from the 2002-2003 school year. First of all, student level academic achievement data in these time points add precision to the overall examination of growth rates. Second, student academic achievement from the 2002-2003 school year determines whether a school is labeled as not meeting AYP in the 2003-2004 school year. In turn, we keep the student information for 2002-2003 in our dataset by artificially setting AYP status to "meet AYP" for all schools in Fall 2002 and Spring 2003. Students who change schools between Spring 2003 and Fall 2003 can only move from a higher performing schools to another higher performing school or move from a higher performing school to a low-performing school. Students in these groups are included in our model to control for the substantive groups we are interested in—students who move from a low-performing school to a higher performing school compared with students who stay in low-performing schools.

For students who move from low-performing schools determined by AYP to higher performing schools, we want to determine whether that move is expected or unexpected, where unexpected moves more closely correspond to the NCLB choice policy. For example, students makes an expected transition between schools when they leave an elementary school after the highest grade offered and subsequently attend a middle school in the lowest grade offered. An unexpected move, on the other hand, takes place when students leave their school before the highest grade offered, including mid-year moves. In addition, an unexpected move occurs when students move to a school outside of the district, whether it is at an expected transition point or not.

Since we are interested in students who move from low-performing schools to high-performing schools based on AYP status determinations, we need a reference group of students for comparison purposes when examining academic achievement growth. The dichotomous nature of school AYP status along with student data for fall and spring of each school year allows us to identify a set of possible student transitions. First, students may stay in their school and not move between semesters, whether the semesters are spring to fall or fall to spring. These non-movers can be categorized as staying in low-performing schools (low-low) or staying in high-performing schools (high-high). Second, students may change schools between semesters. These movers can be categorized as moving from a low-performing school to a high-performing school (low-high) or moving from a high-performing school to a low-performing school (high-low). The two non-moving groups and the two moving groups can be further distinguished by our distinction between unexpected and expected movers. Students will be identified as one of these transitions for each semester (see Table 1).

Table 1. Student Transitions Based on School AYP Status

	Expected Movers	**Unexpected Movers**
AYP Status	Low – Low	Low – Low
	High – High	High – High
	Low – High	Low – High
	High – Low	High – Low

Unexpected movers in the low-high category represent students that the NCLB transfer policy suggests will show improvements in student achievement by leaving the low-performing school to attend a high-performing school. Again, we cannot determine whether these transfers were linked directly to the NCLB choice option, but they do provide a proxy for what might occur if more families had options to transfer to higher performing schools within the same district. Unexpected movers in the low-high category differ from expected movers in the low-high category because expected movers in this category did not make a change in schools that is out of the ordinary, given our assumptions. In other words, we cannot determine whether students who are expected movers and move from a low-performing school to a high-performing school made a choice besides the choice to attend the school that they would naturally attend.

Our comparison group will be expected movers who stay in low-performing schools—the expected movers low-low group. This group presents a counterfactual to the low-high group of unexpected movers because these are students who were in a low-performing school and stay in the low-performing school or move to an expected low-performing school. In either case, the low-low group of expected movers presents a comparison of students who stay in a low-performing school.

Data & Methods

This paper uses the Northwest Evaluation Association (NWEA) database, a longitudinal growth research database. NWEA administers computerized adaptive assessments in the fall and spring of each academic year. For this paper, we rely on six semesters of testing, including Fall 2002, Spring 2003, Fall 2003, Spring 2004, Fall 2004, and Spring 2005. Students are assigned unique identification numbers so that their test scores can be linked longitudinally. NWEA reports student performance on a single, cross-grade developmental scale, called an RIT scale, for each of the following subject areas: mathematics, reading, and language arts. The RIT scores can be used to determine growth in academic achievement. That is, NWEA uses a one-parameter IRT model to place all students on a single developmental, vertically equated scale. For the purposes of this paper, only the math scores will be used to determine growth in achievement. NWEA aligns RIT scores with the performance levels of state academic standards. Table 2 presents the proficiency levels, or cut scores, for each of the grade levels tested in Idaho by NWEA.

Table 2. NWEA Proficiency Levels for Idaho Standards-Based Assessments

	Grade Level								
	2	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Basic	174	185	194	202	208	214	222	229	231
Proficient	185	196	205	213	219	225	233	240	242
Advanced	201	212	221	229	235	241	249	256	258

The sample includes students who were tested in Idaho in a public or charter school in each of the six semesters. Students who are tested in private non-denominational schools, private religious schools, or home schooled and who are in schools that do not have AYP data are not included for that semester. Schools that do not have AYP information are defined in three categories. First, there are schools where the raw AYP data was not accessible through the Idaho Department of Education web page. Second, there are schools that are not included in the AYP determinations, including technical schools and detention centers. And finally, there are schools that do not offer grade levels tested to determine AYP status.

Dependent Variable

Math RIT Score: Math achievement score from test administered in Fall 2002, Spring 2003, Fall 2003, Spring 2004, Fall 2004, and Spring 2005. Students are included in the sample if they have a test score for the semester. All the NWEA subject scores in mathematics, reading, and language arts reference a single, cross-grade, and equal-interval scale developed using Item Response Theory methodology (see Hambleton, 1989; Ingebo, 1997; Lord, 1980). The mathematics RIT scale is based on strong measurement theory, and it is designed to measure student growth in achievement over time. NWEA research provides evidence that the scales have demonstrated to be extremely stable over twenty years (Kingsbury, 2003; Northwest Evaluation Association, 2002, 2003).

Level-1 Predictors: Individual Time-Varying Covariates

Several time-varying covariates are used in the models we estimate. Because the mathematics achievement measure varies over time within students, the testing time points are included in the analyses. For example, if a student takes all 6 tests, the testing points start at time zero in the fall of 2002, and subsequent testing points in the spring of 2003 and fall of 2004 and so forth use the months since the first test was taken.

Many students were not tested in all six semesters. In order to improve the accuracy of the student transfer variables with respect to the school the student attended, we also used the reading and language arts data to construct the move-related variables when students were missing math assessment data for a semester. That is, if students were missing mathematics assessment data, but had either reading or language arts data, they were coded as being in the school where they took their other subject tests. If the student was still missing a school identifier, but appeared again in a later semester, the student was assumed to have stayed in the same school until a later test date shows a new school. If the student was missing a test date and did not show up in a later semester, then the student's movement pattern ends with the last test date available.

In addition, there are time-varying covariates that measure the students expected and unexpected changes between schools—e.g., unexpected movers who stay in low performing schools (Low-Low), unexpected movers who stay in schools that meet AYP over time (High-High), unexpected movers who transfer from a school that does not meet AYP to a school that does (Low-High), and unexpected movers who move from a school that meets AYP to one that does not (High-Low). Each of these (and other) measures for school transfer possibilities are described below.

Unexpected Movers (Low-Low): Dummy variable indicating whether the student makes an unexpected move from low-performing school to a low-performing school (1 = yes, 0 = no). Unexpected movers include students who leave the school before the highest grade offered, including mid-year movers. Unexpected movers also include students who make an inter-district move.

Unexpected Movers (High-High): Dummy variable indicating whether the student makes an unexpected move from a high-performing school to a high-performing school (1 = yes, 0 = no).

Unexpected Movers (Low-High): Dummy variable indicating whether the student makes an unexpected move from a low-performing school to a high-performing school (1 = yes, 0 = no).

Unexpected Movers (High-Low): Dummy variable indicating whether the student makes an unexpected move from a high-performing school to a low-performing school (1 = yes, 0 = no).

Expected Movers (Low-Low): Dummy variable indicating whether the student makes an expected move from a low-performing school to a low-performing school (1 = yes, 0 = no). Expected movers consist of students who do not change schools between semesters and students who move to a new school that is characterized as a natural transition for the student. Expected movers also include students in schools that consolidate from elementary and junior/senior high to a K-12 school and students who must find a new school when their school closes. This dummy will serve as the reference variable for the eight variables that indicate moves between schools based on AYP status.

Expected Movers (High-High): Dummy variable indicating whether the student makes an expected move from a high-performing school to a high-performing school (1 = yes, 0 = no).

Expected Movers (Low-High): Dummy variable indicating whether the student makes an expected move from a low-performing school to a high-performing school (1 = yes, 0 = no).

Expected Movers (High-Low): Dummy variable indicating whether the student makes an expected move from a high-performing school to a low-performing school (1 = yes, 0 = no).

Public to Public: Dummy variable indicating whether the move is from a public school to a public school (1 = yes, 0 = no). This dummy variable will serve as the reference variable for the four variables that indicate movement between school types.

Public to Charter: Dummy variable indicating whether the move is from a public school to a charter school (1 = yes, 0 = no).

Charter to Public: Dummy variable indicating whether the move is from a charter school to a public school (1 = yes, 0 = no).

Charter to Charter: Dummy variable indicating whether the move is from a charter school to a charter school (1 = yes, 0 = no).

Date of Test: A continuous variable indicating the month in the semester that the student took the NWEA test. Schools administer the computerized assessments at different times in the semester. Fall tests are generally given at the beginning of the semester, and spring tests are generally given at the end of the semester. This variable controls for the month in the semester that the student took the assessment

Duration in School: A continuous variable that measures how long a student who has made an unexpected move has been in their new school. The duration variable begins its count with the number of months since the beginning of the semester in the new school. For students who have made more than one unexpected move, only the duration in the school they most recently moved to is recorded in this variable. This variable controls for treatment exposure.

Grade Level: A continuous variable that indicates the grade level of the student in the semester tested.

Level-2 Predictors: Individual Time Invariant Variables

Our models also include characteristics of students that are time invariant in our models, including eligibility for free-reduced priced lunch, gender, race-ethnicity, special education designation, and a measure for more than one school move during the six semesters.

Free/Reduced-Price Lunch: Dummy variable indicating whether the student is eligible for the free and reduced-price lunch program at any point during the six semesters in the dataset (1 = yes, 0 = no).

Gender: Dummy variable indicating if the student is male (1 = yes, 0 = no).

White: Dummy variable indicating that the student is white (1 = yes, 0 = no).

Special Education: Dummy variable indicating whether the student is eligible for the special education services at any point during the six semesters in the dataset (1 = yes, 0 = no).

Move More Than Once: A dummy variable indicating whether the student makes more than one unexpected move over the six semesters (1 = yes, 0 = no). The variable measures transient students who make many moves between schools during the six semesters of testing.

Analytical Models

In our analyses, we estimate multilevel fixed-effects models in which test scores are nested within students. Ideally, we would estimate three-level models with testing points nested within students nested within schools, but because student changed school over time, in this paper we are unable to incorporate this nesting structure in out multilevel models. (We hope to pursue techniques that allow this estimation in our future work [see Rowley, 2005]). Rather, we use a modeling strategy that allows us to capture changing school conditions over time by modeling those characteristics in level 1 as time-varying covariates. A common technique for measuring nested, repeated measures data are hierarchical linear growth models (Raudenbush and Bryk, 2002; Singer and Willett, 2002). At level 1, each student's achievement is represented by an individual growth trajectory:

$$Achievement_{ti} = \pi_{0i} + \pi_{1i}(\text{Testing Points})_{ti} + \pi_{2i}(\text{Schooling Change})_{ti} + \pi_{3i}(\text{School Type Change})_{ti} + \pi_{4i}(\text{Grade Level})_{ti} + \pi_{5i}(\text{Duration})_{ti} + \varepsilon_{ti} \quad (1)$$

where $Achievement_{ti}$ is the observed mathematics score of student *i* in time period *t* and π_{0i} and π_{1i} are the growth trajectory parameters for student *i.* If the Testing Points measure is coded to correspond to the months elapsed over 6 testing points in the fall and spring between the 2002-2003 and 2004-2005 school years, we can interpret π_{0i} as the initial status of achievement for student *i* and π_{1i} as that student's growth rate in achievement over three school years.

In addition, there are time-varying covariates included at the level-1 model. Schooling Change is a set of dummies that compare students in differing schooling conditions, such as the student stayed in low performing or high performing schools or made a set of transitions between high- and low-performing schools across testing points. The reference group for this set of dummies is the group of students who were initially in a school that did not make AYP across school years. That is, students stayed in a low-performing school over time. This group is compared with dummy variables for students who stayed in a school that did make AYP across school years or made some move between schools. School Type Change is a set of dummies that compare the different school types of students who move, such as the student who moves from a public school to another public school or from a charter school to a charter school or from a public school to a charter school and vice versa across testing points. Grade Level is a continuous variable indicating the grade level the student is in at the testing point. Another time-varying covariate included in the analyses is Duration, which measures how many months students were in the new school between testing points.

We assume that both the initial status of mathematics achievement and the growth rate of achievement vary across individuals, represented by the following level-2 equations:

$$\pi_{0i} = \beta_{00} + \beta_{10}(\text{Student Characteristics})_{\mathrm{i}} + r_{0\mathrm{i}} \qquad (2)$$

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

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

$$\pi_{3i} = \beta_{30}$$

$$\pi_{4i} = \beta_{40}$$

$$\pi_{5i} = \beta_{50}$$

where β_{00} represents the mean initial achievement status and β_{10} represents the mean growth rate of mathematics achievement across students. Mean initial achievement status will be conditioned on student background characteristics such as eligibility for free or reduced priced lunch, gender, race-ethnicity, special education, and moved schools more than once.

Results

We present several sets of results. First, we provide descriptive statistics of students by school conditions who make unexpected and expected changes in schools are presented in Table 3 and Table 4, respectively. These tables provide various descriptive statistics for the mathematics scores by grade level and other student characteristics included in our models.[2] Second, we discuss the results of our growth models as presented in Tables 5-7, which provide information about whether the initial levels of mathematics achievement and their growth rates differ among students, the coefficients for changing school conditions, and the decomposition of the variance components. Finally, we compare the growth rates of several groups of interest in Figure 2 and Figure 3.

The students we are most interested in are the unexpected movers who move from a low-performing school to a higher performing school, the Low-High group. These students are highlighted in Table 3. There are 4,108 students who make a mid-year move at some point over the time period we examine (i.e., between Fall 2003 and Spring 2005) from a low-performing school to a high-performing school. Of these 4,108, about 40 percent (n=1,647) made a move between the fall and spring of either 2003-04 or 2004-05 school years.

An additional comparison group for this study is the expected Low-Low group (see Table 4). This group includes students who remained in their low-performing school and students who made an expected move between low-performing schools (e.g., from a low-performing elementary school to a low-performing middle school in the same district). Across the school years considered in these analyses, there were 135,924 students in this group (see Table 4). Moreover, we are interested in those 21,947 students in the expected Low-High group (see Table

[2] We also ran these descriptive statistics for each semester in which students were tested (these results are available from the authors upon request).

4). Although these students do not meet the policy specifications of NCLB in that the change in school status is not based on an unexpected move, the group remains relevant for our research question.

Table 3. Students Who Make an Unexpected Change in Schools

	N	Mean	Std Dev	Min	Max
Low-Low					
Math RIT Score	4,286	224.854	16.932	157.77	272.52
2	77	188.540	11.433	157.77	216.36
3	120	197.739	11.241	169.14	219.08
4	86	206.962	11.271	177.78	230.42
5	122	212.862	11.789	181.73	237.67
6	737	218.370	13.601	168.20	263.63
7	764	223.445	13.178	166.90	263.59
8	896	228.529	14.339	173.73	268.87
9	1,003	230.408	16.364	172.00	272.52
10	424	237.918	12.236	183.01	272.12
11	55	233.539	8.930	199.70	249.85
12	2	236.995	8.294	231.13	242.86
Gender (1 = male)	4,286	0.519	.500	0	1
White	4,286	.735	.441	0	1
Hispanic or Latino Ethnicity	4,286	.226	.418	0	1
Other/Unknown Ethnicity	4,286	.039	.193	0	1
Free/Reduced-Price Lunch	4,286	.726	.446	0	1
Special Education	4,286	.168	.374	0	1
Move More than Once	4,286	0.052	0.222	0	1
High-High					
Math RIT Score	19,148	211.305	19.810	146.02	283.27
2	1,626	190.170	10.413	152.12	222.72
3	3,901	195.866	11.280	152.67	241.18
4	3,831	205.189	11.844	146.02	253.47
5	3,051	211.909	12.767	156.21	254.05
6	1,714	219.296	13.892	163.95	260.02
7	1,074	223.243	16.545	158.65	265.07
8	831	226.592	14.741	172.65	272.85
9	1,374	230.794	17.245	168.14	279.89
10	1,562	241.253	14.405	176.53	283.27
11	181	229.804	12.273	187.50	263.73
12	1	236.220	--	236.22	236.22
13	2	228.265	15.974	216.97	239.56
Gender (1 = male)	19,148	0.519	0.500	0	1
White	19,148	0.830	0.376	0	1
Hispanic or Latino Ethnicity	19,148	0.118	0.322	0	1
Other/Unknown Ethnicity	19,148	0.053	0.224	0	1
Free/Reduced-Price Lunch	19,148	0.671	0.470	0	1
Special Education	19,148	0.190	0.392	0	1
Move More than Once	19,148	0.017	0.130	0	1

Table 3. Students Who Make an Unexpected Change in Schools (continued)

Low-High					
Math RIT Score	4,108	217.705	20.422	155.42	292.90
2	162	189.995	10.787	155.42	217.43
3	526	194.144	11.039	158.81	224.40
4	503	202.379	11.059	161.19	233.90
5	481	210.465	12.120	162.43	245.25
6	357	218.049	12.994	174.97	254.70
7	375	223.121	14.818	166.09	259.73
8	369	227.896	13.034	190.19	265.92
9	595	228.890	15.364	163.12	286.91
10	659	239.778	13.638	189.80	292.90
11	78	229.033	13.570	165.94	256.27
12	1	232.430	--	232.43	232.43
13	2	247.640	10.677	240.09	255.19
Gender (1 = male)	4,108	0.505	0.500	0	1
White	4,108	0.806	0.395	0	1
Hispanic or Latino Ethnicity	4,108	0.146	0.353	0	1
Other/Unknown Ethnicity	4,108	0.048	0.214	0	1
Free/Reduced-Price Lunch	4,108	0.722	0.448	0	1
Special Education	4,108	0.185	0.388	0	1
Move More than Once	4,108	0.044	0.206	0	1
High-Low					
Math RIT Score	6,214	219.051	19.633	151.77	275.19
2	133	189.202	10.669	155.30	209.24
3	550	191.992	11.227	157.92	224.88
4	511	201.500	11.428	163.25	232.76
5	413	208.815	13.851	152.20	242.42
6	1,187	217.957	13.574	157.60	258.49
7	954	222.723	13.961	166.88	269.72
8	658	226.460	14.729	171.2	265.84
9	771	229.226	16.606	151.77	271.00
10	899	236.516	16.124	170.64	275.19
11	137	229.416	15.143	190.78	259.11
12	1	222.520	--	222.52	222.52
Gender (1 = male)	6,214	0.507	0.500	0	1
White	6,214	0.794	0.405	0	1
Hispanic or Latino Ethnicity	6,214	0.155	0.362	0	1
Other/Unknown Ethnicity	6,214	0.051	0.220	0	1
Free/Reduced-Price Lunch	6,214	0.681	0.466	0	1
Special Education	6,214	0.183	0.387	0	1
Move More than Once	6,214	0.025	0.156	0	1

Table 4. Students Who Make an Expected Change in Schools (Includes Non-Movers)

	N	Mean	Std Dev	Min	Max
Low-Low					
Math RIT Score	135,924	231.350	18.514	132.64	310.59
2	4,310	192.007	10.589	151.25	234.77
3	4,703	202.535	10.724	153.43	247.77
4	5,608	212.599	11.617	167.85	259.22
5	6,266	218.483	13.486	161.23	258.96
6	13,905	225.098	13.430	157.03	290.31
7	25,842	230.243	13.827	163.44	290.43
8	31,643	235.517	14.215	160.96	307.83
9	22,777	239.195	15.666	132.64	310.59
10	19,250	246.790	13.005	162.80	305.98
11	1,553	230.728	13.133	158.55	270.76
12	67	226.279	13.666	191.57	257.48
Gender (1 = male)	135,924	0.513	0.500	0	1
White	135,924	0.812	0.391	0	1
Hispanic or Latino Ethnicity	135,924	0.147	0.354	0	1
Other/Unknown Ethnicity	135,924	0.041	0.199	0	1
Free/Reduced-Price Lunch	135,924	0.502	0.500	0	1
Special Education	135,924	0.125	0.331	0	1
Move More than Once	135,924	0.002	0.046	0	1
High-High					
Math RIT Score	405,635	219.628	20.837	143.48	311.01
2	40,769	193.894	10.487	146.01	248.48
3	60,085	201.220	11.449	143.48	256.82
4	60,473	211.366	12.011	150.84	279.46
5	61,037	217.264	13.053	150.63	276.18
6	45,399	224.235	14.000	145.88	276.48
7	31,631	230.595	15.019	147.88	290.25
8	32,920	235.861	14.047	157.20	311.01
9	34,049	238.830	15.764	147.47	296.28
10	37,030	247.517	13.202	152.06	306.27
11	2,179	229.538	12.360	166.27	266.36
12	62	229.180	13.712	177.56	262.12
13	1	250.610	--	250.61	250.61
Gender (1 = male)	405,635	0.511	0.500	0	1
White	405,635	0.863	0.344	0	1
Hispanic or Latino Ethnicity	405,635	0.095	0.293	0	1
Other/Unknown Ethnicity	405,635	0.042	0.202	0	1
Free/Reduced-Price Lunch	405,635	0.466	0.499	0	1
Special Education	405,635	0.128	0.334	0	1
Move More than Once	405,635	0.001	0.037	0	1

Table 4. Students Who Make an Expected Change in Schools (Includes Non-Movers) (continued)

Low-High					
Math RIT Score	21,947	217.860	21.272	155.79	287.79
2	32	178.083	8.306	160.59	201.47
3	3,210	192.069	10.318	155.79	225.57
4	3,339	202.487	10.434	160.09	246.61
5	3,799	210.592	11.929	159.03	250.68
6	1,598	217.125	13.462	160.79	259.48
7	2,015	225.902	14.251	163.41	272.15
8	2,817	232.456	14.764	167.69	276.07
9	937	237.890	14.697	177.96	272.88
10	3,673	240.862	15.029	168.16	287.79
11	504	224.892	12.986	178.60	264.68
12	23	220.503	11.949	187.06	236.00
Gender (1 = male)	21,947	0.515	0.500	0	1
White	21,947	0.787	0.409	0	1
Hispanic or Latino Ethnicity	21,947	0.171	0.376	0	1
Other/Unknown Ethnicity	21,947	0.042	0.201	0	1
Free/Reduced-Price Lunch	21,947	0.583	0.493	0	1
Special Education	21,947	0.137	0.344	0	1
Move More than Once	21,947	0.001	0.032	0	1
High-Low					
Math RIT Score	68,143	224.103	19.933	149.73	287.34
2	46	177.835	9.183	157.29	206.28
3	3,684	191.425	10.529	152.99	223.81
4	4,499	200.854	10.893	152.48	240.44
5	4,675	207.198	11.781	155.56	247.59
6	7,391	216.309	13.410	149.73	263.99
7	11,335	223.519	14.738	159.49	265.49
8	13,605	230.303	15.442	154.46	280.68
9	10,645	235.628	15.679	156.11	279.47
10	10,061	240.010	16.149	157.97	287.34
11	2,183	225.653	14.516	154.60	268.15
12	19	220.246	15.422	185.51	239.64
Gender (1 = male)	68,143	0.511	0.500	0	1
White	68,143	0.820	0.384	0	1
Hispanic or Latino Ethnicity	68,143	0.141	0.348	0	1
Other/Unknown Ethnicity	68,143	0.039	0.194	0	1
Free/Reduced-Price Lunch	68,143	0.502	0.500	0	1
Special Education	68,143	0.126	0.331	0	1
Move More than Once	68,143	0.004	0.060	0	1

Table 5 provides the unconditional model to examine whether initial status and growth rates in mathematics achievement vary across students. The estimates for the variances of initial levels of mathematics achievement (r_{0i}) and the growth rate (r_{1i}) are 865.135 and 0.092, respectively. Examination of the χ^2 statistics leads us to reject the null hypotheses and conclude that students vary significantly in their initial level of mathematics achievement and in their growth rates. Moreover, the reliability statistics suggest that there is more signal in the NWEA data for these years in individual difference in initial mathematics achievement (0.890) than in individual growth rates in mathematics (0.421). Taken together, however, the statistics provided in Table 5 suggest that further modeling of student achievement growth is warranted.

Table 5. Linear Model of Mathematics Achievement Growth for Students in Idaho (Unconditional Model)

Fixed Effect	***Coefficient***	***Se***	***t-Ratio***	
Mean initial status, β_{00}	204.377	0.063	3254.663	
Mean growth rate, β_{10}	0.815	0.001	843.144	
Random Effect	***Variance Component***	***df***	χ^2	***p-Value***
Initial status, r_{0i}	865.135	211,025	4,062,882.644	<0.0001
Growth rate, r_{1i}	0.092	211,025	404,104.974	<0.0001
Level-1 error, εti	33.569			
Reliability of Regression Coefficient Estimate				
Initial status, π_{0i}	0.890			
Growth Rate, π_{1i}	0.421			

As seen in Table 6, the conditional model explains 81.1 percent of the variance of an individual's initial achievement status. The conditional model explains 54.3 percent of the variance in an individual's student growth rate.

Table 6. Variance Explained in Initial Status and Growth Rate for Students in Idaho

Model	***Initial Status Var (π_{0i})***	***Growth Rate Var (π_{1i})***
Unconditional	865.135	0.092
Conditional	163.486	0.042
Proportion of Variance Explained	0.811	0.543

The estimates for our multilevel growth model that nests test scores, school conditions, and duration within students appear in Table 7. All of the student measures are related to the initial mathematics achievement level, but some of these relationships are tiny due to the fact that the large sample size has a great deal of power to detect small effects. The coefficients that are larger (≥ 0.20 SD units) in Table 7 include those for white students scoring significantly higher than non-white students in initial mathematics achievement (5.801 points or 7.3 months ahead of non-white students) [3]; students who are eligible for free/reduced price lunch scoring below students who do not receive those services (-4.904 points or 6.2 months behind non-free/reduced price lunch students); special education students scoring significantly lower than students not designated as special education (-13.456 points or almost two years (17 months) behind non-

[3] Month estimates are based on expected achievement increases for proficient students. Depending on grade, students are expected to increase scores by 2 – 11 points per year, with an average of 7.125 points (see Table 2). Monthly estimates are calculated based on a percentage of the average achievement expected and converted into months by assuming a nine-month school year.

special education students); and an increase in one grade level is associated with a 5.815 point change in initial score (or 81.6 percent or 7.4 months of the average increase expected for proficient students in one school year). Students who make unexpected transfers two or more times over the time period considered in our analyses score 1.031 points lower than (or test 1.3 months behind) students who do not make such moves.

To address the question posed at the beginning of this paper, we are interested in school conditions dummies related to individual mathematics growth rates in the bottom panels of Table 7. In comparison to students who make expected transitions and remain in low-performing schools over time (expected low-low), we find that generally most transfers are not associated with higher achievement, whether those moves are expected or not. For example, students who make unexpected moves between low-performing schools have growth rates 0.975 points below students who remain in low-performing schools over time.

In addition, moving from a low-performing school to a high-performing school does not seem to benefit students in Idaho. Although the coefficient for students who make such moves is -0.783, suggesting that students who move from a low- to a high-performing school have lower growth rates than students who remain in low performing schools, this is a very tiny effect. In short, there seems to be no advantage of making a move from a low to a high performing school in these data.

Table 7. Linear Model of Mathematics Achievement Growth for Students in Idaho: Associations with Student Characteristics and Varying School Conditions

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*p-Value*
Model for initial status, π_{0i}				
Base, β_{00}	173.710	0.093	1877.743	<0.001
Gender (male = 1)	1.593	0.051	30.944	<0.001
White	5.801	0.071	81.338	<0.001
Free-reduced lunch	-4.904	0.054	-91.221	<0.001
Special Education	-13.456	0.081	166.167	<0.001
Move schools more than once	-1.031	0.504	-2.045	<0.05
Model for growth rate, π_{1i}				
Base, β_{10}	0.340	0.001	252.108	<0.001
Duration	-0.005	0.002	-2.372	<0.05
Grade Level	5.815	0.009	661.549	<0.001
Unexpected Changes				
Low-Low	-0.975	0.126	-7.759	<0.001
High-High	2.671	0.058	45.602	<0.001
Low-High	-0.783	0.123	-6.347	<0.001
High-Low	-1.101	0.094	-11.714	<0.001
Expected Changes				
High-High	4.845	0.017	289.355	<0.001
Low-High	-3.174	0.040	-78.551	<0.001
High-Low	-1.864	0.025	-74.600	<0.001
Public to Charter	-1.043	0.160	-6.520	<0.001
Charter to Public	0.715	0.201	3.566	<0.001
Charter to Charter	1.400	0.123	11.398	<0.001

There are some exceptions to the pattern of transfers being negatively associated with growth rates in mathematics. Students who make either expected or unexpected moves from high-performing schools to other high-performing schools have higher mathematics achievement growth than students who remain in low-performing schools. For example, students who make unexpected moves from one school making AYP to another (i.e., unexpected high-high) score have growth rates 2.671 points higher than students who remain in schools that do not make AYP. If students make expected transfers between schools making AYP (expected high-high), their mathematics growth rates are even higher as indicated by the coefficient of 4.845.

Examples of the difference in growth rates between students are presented in Figure 2 and Figure 3. Students who make an unexpected move from a low-performing school to a higher performing school have a smaller growth rate than students who stay in low-performing schools (see Figure 2). Students in either of the comparison groups who qualify for free/reduced-price lunch have smaller growth rates than students who do not qualify for free/reduced-price lunch. Figure 3 compares groups of students who qualify for free/reduced-price lunch. Students who make an expected or unexpected move between high-performing schools have higher growth rates than students who stay in low-performing schools or students who move from a low-performing school to a higher performing school. These results suggest that unexpected mobility between schools is not necessarily bad for student achievement if the student moves from a high-performing school to another high-performing school based on AYP determinations.

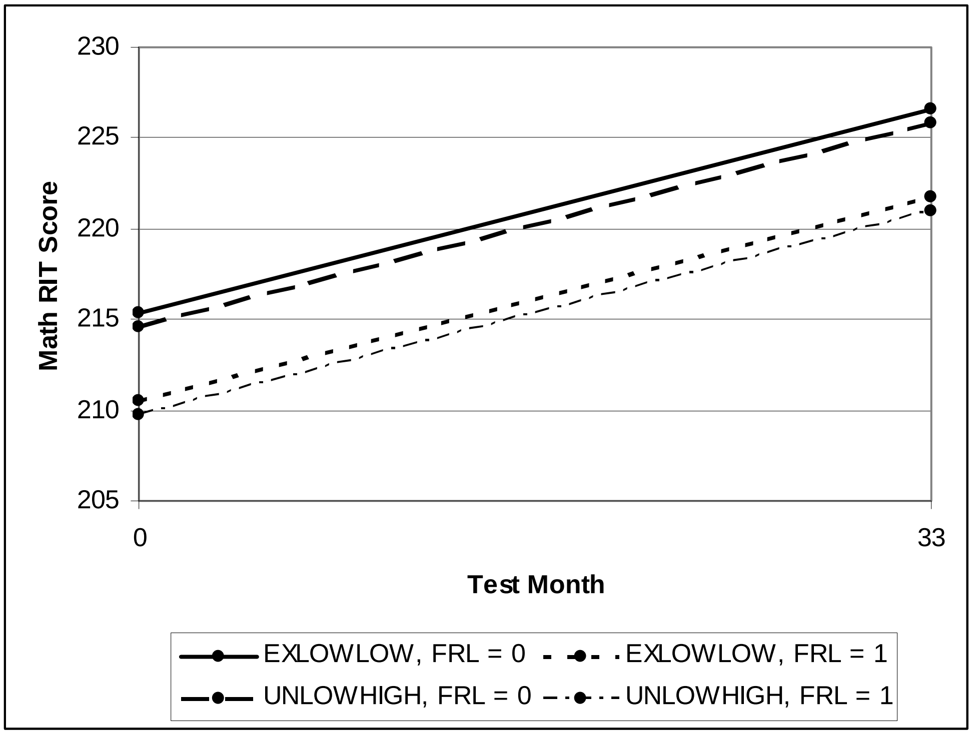

Figure 2. Unexpected Low-High vs. Expected Low-Low, by Free/Reduced Price Lunch

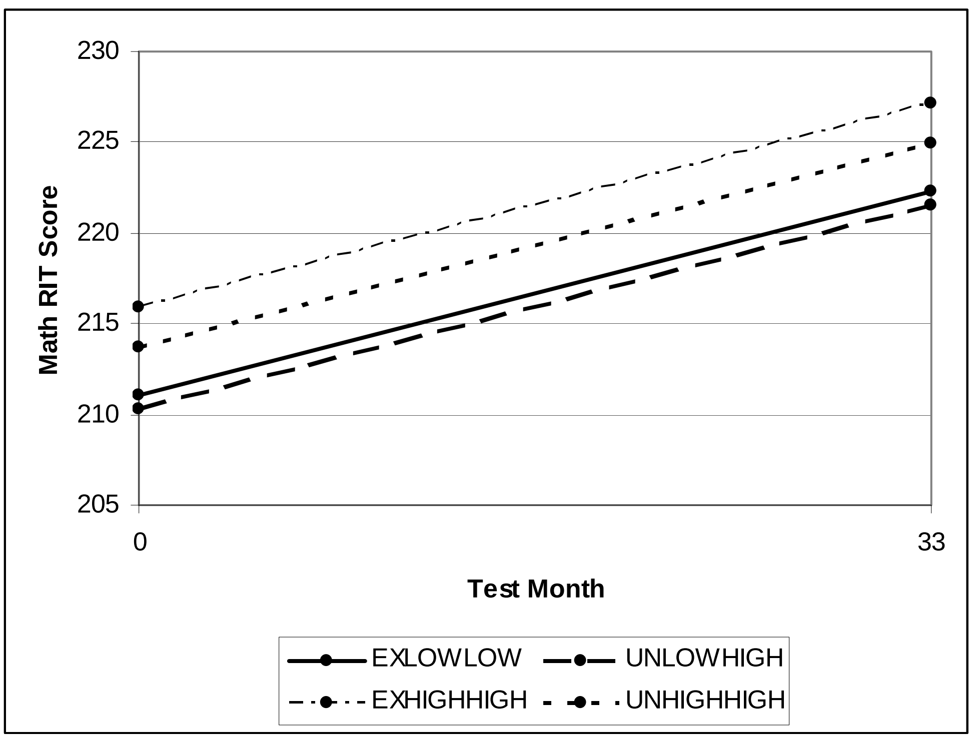

Figure 3. Unexpected Low-High and Expected Low-Low vs. Expected High-High and Unexpected High-High, Qualify for Free/Reduced Price Lunch

Discussion

Although the student transfer policy under NCLB is intended to provide parents and their children the option of attending higher performing schools, the evidence to date suggests that this provision is not being implemented on a wide scale. For instance, over the past couple of years only about 1.6 percent all eligible students took advantage of transferring to a school that was making AYP (Center on Education Policy, 2005, 2006). Over time, perhaps more eligible students will have this choice, but given the current barriers of viable school options and the reluctance of parents to actually transfer their children to a new school, it is doubtful whether the transfer option under NCLB will be widespread across the United States.

Even if students make these transfers, the evidence provided here on Idaho suggests that students my not benefit in their achievement growth if they make a choice. Our modeling suggests that students who move from a low-performing school to a higher performing school do not benefit in their mathematics achievement growth compared with students who remain in schools that are low-performing (i.e., do not make AYP over time).

However, several caveats are in order. First, we examine student transfers only within one state (Idaho), which may not be representative of the nation, as whole. Second, our modeling of student transitions between low-performing and higher performing schools is merely a proxy for the NCLB transfer option. There are several assumptions that should be included in future models, such as the Title I status of schools and the exclusion of unexpected inter-district movement. Furthermore, our proxy of the NCLB policy is not able to disentangle the way in which poverty influences student mobility. For example, there may be improvements in family conditions that explain the movement from a low-performing school to a higher performing school apart from NCLB policy. Third, it may be too early to examine the effects of students who transfer from low- to high-performing schools. Over time, as NCLB, and its provisions are further implemented, the results of this paper may be altered. Our future analyses of the NWEA data (updated over time) will address this issue. Fourth, the models here are at the student level, and therefore, our models do not take into the consideration that students are nested within schools. This could be particularly problematic if the variance between schools (i.e., the intraclass correlation) changes significantly over time. Indeed, this could be the case if students change schools over time at a higher rate. We hope to examine this issue in our future analyses by examining cross-classified random effects models.

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