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What is the impact of changing schools on the academic outcomes of elementary and middle school students?

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We study how different kinds of school changes shape achievement in grades 4–8 using data from six California districts (2016–17 through 2019–20). We estimate the effects of structural (promotional), nonstructural summer, and midyear moves and find that structural and summer moves have near-zero effects on ELA and math, while midyear moves lower ELA by 0.073 SD and math by 0.083 SD. Midyear impacts hinge on destination quality: moves to lower-achieving schools produce steep losses, whereas moves to higher-achieving schools close the gap and can even raise achievement above their stayer counterparts. Midyear effects are most negative for students in middle school and for students with disabilities, English learners, low-income, and homeless students. We find minimal fade-out effects.

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Abstract

We study how different kinds of school changes shape achievement in grades 4–8 using data from six California districts (2016–17 through 2019–20). We estimate the effects of structural (promotional), nonstructural summer, and midyear moves and find that structural and summer moves have near-zero effects on ELA and math, while midyear moves lower ELA by 0.073 SD and math by 0.083 SD. Midyear impacts hinge on destination quality: moves to lower-achieving schools produce steep losses, whereas moves to higher-achieving schools close the gap and can even raise achievement above their stayer counterparts. Midyear effects are most negative for students in middle school and for students with disabilities, English learners, low-income, and homeless students. We find minimal fade-out effects.

Introduction

All students make scheduled school changes—most commonly as the result of being promoted from one type of school to another, such as elementary school to middle school—what we term a "structural" move. In addition, a significant percentage of students move from one school to another for reasons other than normal promotion (Ashby, 2010; National Research Council, 2010), and such "nonstructural" moves can occur during the summer break or in the

middle of the school year. A recent study by Santibañez, Guarino, Ream, Li, and Kang (2025) in six California districts established that among the roughly 30 percent of K-12 students who change schools every year, a non-trivial percentage make nonstructural moves. Close to nine percent of students make a nonstructural move in the summer and four percent make a nonstructural move in the middle of the school year. Nonstructural moves are even more common for certain at-risk subpopulations of students. For example, as many as 14 percent of youth in foster care made nonstructural summer moves and 17 percent moved midyear, and among youth experiencing homelessness, 12 percent made a nonstructural move in the summer and nine percent moved midyear.

It is unclear to what extent all these school changes—whether structural or nonstructural—affect students' educational performance. School changes may have positive and negative consequences, depending on who initiated the move, the reason for the move, and the new circumstance (school and otherwise) to which the student must adapt. Numerous studies have documented a negative impact of mobility on student performance and the fact that moving schools appears to affect some groups of students more than others (e.g., ELs or low-income students) (Cohen et al., 2025; Min, 2022; Xu, Hannaway & D'Souza 2009; Gasper, DeLuca & Estacion, 2012; Haveman, Metzger et al., 2015; NRC, 2010; de la Torre & Gwynne, 2009; GAO, 1994; Kerbow, 1996; Ream, 2005; Fong et al., 2010). However, mobility could potentially be beneficial, particularly when students leave schools for ones that are a better fit (Schwartz, Steifel & Cordes, 2017; Rumberger, 2015). This includes finding schools that offer specialized services that the student needs or wants (e.g., bilingual education, special education) or give students access to better resources (higher teacher or leadership quality).

Our study investigates the impact of mobility on students' academic outcomes. Using data from several large California school districts over the period from 2016-17 to 2019-20, we address the following research questions:

1) To what extent do we see dips or boosts in achievement after school changes?
2) Does the type (structural or nonstructural) or timing of the move (mid-year vs. summer) impact its consequences?
3) Are there characteristics of schools that moderate the impact of mobility?
4) Does the impact of changing schools on achievement vary by grade?
5) Does moving to a higher achieving school affect the impact of moving on achievement?
6) Do subpopulations of students receiving special services—low income, English learners, special needs, foster, and homeless students—experience the effects of mobility differently?

Conceptual Framework

A theoretical framework to explain the varied causes and consequences of student mobility would involve social capital theory (Coleman, 1988, 1994) and the ecological systems model (Bronfenbrenner, 1979, 1994), both of which have been used as a predominant interpretive frame in prior research on the costs and benefits of student mobility (Welsh, 2017). Social capital and ecological systems are complementary insofar as both theories focus on the contextualized dimensions of social exchange, family processes, and human development. For social capital theorists, the interchangeability of resources depends significantly on social processes that are embedded (Granovetter, 1985; Small, 2009) within families, among peers, within the communities where students and their families reside, and—perhaps most notably—in schools (Coleman, 1988; Dika & Singh, 2002; Putnam, 2000).

Similarly, the ecological systems model holds that human development is deeply influenced by interconnected environmental systems, such as family, peers, schools and communities. Yet the stability of these social networks—which can be disrupted by student and residential mobility—also affects human development. While some child development theories posit that such disruptions can harm a child's social, emotional, and cognitive development by causing stress and insecurity (Bronfenbrenner, 1994; NRC, 2010; Sandstrom & Huerta, 2013; Wright & Masten, 2005), others show that strategic mobility can be beneficial—as in the case of the MTO policy or successful schools of choice—by exposing children to better resources and environments (Hanushek et al., 2004; Cordes, Schwartz, and Stiefel, 2019).

Our framework groups factors contributing to the causes and consequences of mobility into families and schools. Family factors might include socioeconomic status or changes in family circumstances, such as a residential move, change in job status, or a change in family structure.

Residential mobility, often prompted by economic considerations, such as changing jobs and home foreclosure, and by family disruptions, such as divorce, parental separation, or incarceration, sometimes drives school changes but it is not the only driver (Ryan et al., 2024). Early studies found that between 30 and 40 percent of student moves are not linked to changes in residence (Kerbow, 1996; Kerbow et al., 2003; Pribesh & Downey, 1999; Rumberger et al., 1999; Rumberger & Larson, 1998; Swanson & Schneider, 1999 cited in Welsh, 2017). More recently, using data similar to ours, Santibañez et al. (2025) found that 13%, 36% and 39% of those making a structural, nonstructural summer, and nonstructural midyear move, respectively, also changed residences.

Moreover, the timing of the move may be associated with higher or lower outcomes. Mid-year school changes, often driven by reactive circumstances rather than strategic planning, can negatively affect student outcomes. These transitions often disrupt academic progress due to a lack of curricular continuity, inefficient administrative processes like misplaced transcripts, and the general challenges students face when adjusting to a new environment (Ream, 2005).

Strategic choices on the part of families may also prompt a school change as they may elect to switch schools for a more suitable environment—one with better teachers, higher achieving peers, greater diversity, more resources, or specific programs such as a magnet program or a dual-language immersion program (Dauter & Fuller, 2011; Hanushek et al., 2004; Rumberger et al., 1999). These strategic moves are often an effort to find a better fit for the student. The characteristics of the new school, such as its quality, size, or charter school status, etc., can be key factors in understanding the impact of student mobility on academic achievement. Teibout (1956) posited a model of residential location to maximize the quality of public services, including education. When applied to school quality, the Tiebout-sorting perspective suggests that the benefits of a better-fitting school can eventually outweigh the disruption causes by the move if the new school more closely aligns with the students' educational needs (Hanushek et al., 2004; Welsh, 2017). Similarly, the fit between students and their schools may also motivate school switches. How well a student's race or achievement level matches that of the new school may play as much of a role as the quality of the school. Thus, it bears repeating that there may be an upside to mobility, particularly when students voluntarily leave schools with which they and their families are displeased for ones that are better fits (de la Torre & Gwynne, 2009; Rumberger, 2015). This includes finding schools that offer specialized services that the student needs or wants (i.e., bilingual education, special education) or when

students have access to better resources (higher teacher or leadership quality). Switching to a better school could offset the costs of adjusting to a new environment.

In this regard, school choice theory—that parents maximize their children's "utility" and educational benefit through control over the school their children can attend (Friedman, 1955)—is potentially a mechanism for producing positive consequences to mobility. However, research on the effects of school choice, such as attending charter schools or using vouchers, shows mixed results (see Berends, 2015, for a review of the literature and Betts & Tang, 2016, for a meta-analysis). Evidence shows that some charter schools or school systems like KIPP schools improve students' achievement and attainment (e.g., Tuttle et al., 2013), and studies based on lotteries for oversubscribed charter schools often show positive achievement effects for charters (e.g., Hoxby, Murarka, & Kang, 2009 and Abdulkadiroglu et al., 2009), but several lottery studies show negative effects (see the review of lottery studies by Chabrier, Cohodes, & Oreopoulos, 2016). A large scale matching study comparing charters with traditional public schools found positive achievement effects for charters in 16 states, negative effects in eight states, and no effects in three states (Cremata et al., 2013) and another study across seven states also found some positive and some negative results (Zimmer et al., 2012). A study of long-term outcomes like attainment and earnings showed positive outcomes for charters (Sass, Zimmer, Gill & Booker, 2016).[1] In summary, while there is some evidence that strategic school changes driven by parental choice can be beneficial, the positive effects aren't guaranteed (DeLuca &

[1] Vouchers programs also have shown mixed results. A recent study of the Louisiana Scholarship program showed that students who used vouchers to attend private schools initially saw negative academic effects, but these effects lessened over time (2 years) as students adjusted, suggesting that students or schools could adapt over time after a move to the new school (Mills & Wolf, 2017). Conversely, an evaluation of the Washington D.C. voucher system found positive achievement effects after three and four years (Wolf et al., 2013).

Dayton, 2009), and there is some suggestion that strategic moves may require time to produce positive results and overcome an initial negative impact.

All of the above factors motivating a school change may influence the academic outcomes of students after the move. In the next section, we review the research on the impact of mobility on achievement, to assess the prior evidence confirming or refuting the hypotheses stemming from this conceptual framework.

Prior Research

The effect of student mobility on academic achievement has been a longstanding focus of educational research with mixed findings that range from negative to null to positive (Welsh, 2017; Grigg, 2012; Schwartz, Steifel & Cordes, 2017). While many studies found detrimental impacts of student mobility on academic outcomes, others found that its effects can be neutral or positive under certain contexts, underscoring the need for more nuanced investigations into its influence on academic achievement.

A large body of literature using data from prior to the early 2000s found that student mobility had mostly negative effects on academic achievement (e.g., Bruno & Isken, 1996; Hanushek, Kain, & Rivkin, 2004; Temple & Reynolds, 1999; Ingersoll, Scamman, & Eckerling, 1989, Scherrer, 2013), although studies reported a varied range of effect sizes. Estimates of effect sizes ranged from around -0.2 in both reading and mathematics (see, for example, the meta-analysis conducted by Mehana and Reynolds, 2004) in correlational or associative studies to around -0.07 in studies that controlled for prior achievement (see, for example, the meta-analysis conducted by Reynolds, 2009). Hanushek, Kain, and Rivkin (2004), applied student fixed effects to a model that also controlled for prior achievement and lowered the effect size further to less than -0.02. Heinlein and Shinn (2000), in a small study using longitudinal data

from six-grade students during the 1996-97 school year in a school district in New York City, found null effects—the initially observed negative association between total student mobility (capturing all school changes regardless of type) and sixth-grade academic achievement was eliminated once they controlled for third grade prior achievement.

In addition to the simple estimation of achievement impacts, many studies delve into factors that influence the magnitude of these impacts. For example, Swanson and Schneider (1999), using the 1988-1994 years of National Education Longitudinal Study (NELS), found that students who changed schools early in high school (between Grades 8 and 10) showed no immediate effect on math achievement but demonstrated significantly improved academic achievement between 10th and 12th grade, suggesting long-term benefits of early school mobility. By comparison, students who transferred schools later in high school (between Grades 10 and 12) showed decreased math achievement.

Some of the early studies explored whether the impact of student mobility differs based on whether it occurs midyear, results from a grade-level transition (i.e., a promotional move), or both. For example, Griggs (2012), used 1998-2003 data from students in grades 3-8 in a large Tennessee district and found that both promotional moves and midyear non-compulsory transfers—those not resulting from disciplinary actions—were consistently associated with reduced growth in student achievement in mathematics and reading on the order of around a six percent decrease in expected learning growth. By comparison, he found that non-promotional summer transfers and midyear compulsory moves were linked to lower gains in mathematics but showed no statistically significant impact on English Language Arts.

The effect of school context in determining how student mobility affects academic achievement was touched upon by Hanushek et al. (2004), who, drawing on math test data from

fourth- to seventh-grade students in Texas public school districts, found that non-promotional moves within a district were more detrimental to student achievement than nonpromotional moves across districts. Their study pointed to the possibility that cross-district moves often led to enrollment in higher-quality schools, whereas within-district moves typically did not, and suggested that differences in the quality of receiving versus sending schools can differently shape the academic consequences of mobility.

One study focused on disentangling the impact of residential moves from school changes, Cordes, Schwartz, and Stiefel (2019), using data on students in grades 3-8 who moved to different rental housing units in New York City from 2004-2012, found contrasting effects based on move distance. Short-distance residential moves (under one mile) predicted improvements in academic achievement, but only when students remained in the same school. In contrast, long-distance moves (one mile or more) led to persistent declines in performance. Although changing schools partially explained these patterns, it did not fully account for them: the positive effect of short-distance residential moves depended on school continuity, while the negative impact of long-distance residential moves persisted regardless of whether students changed schools.

Moving schools also appears to affect some groups of students more than others. In the case of English Learners, frequent mobility is associated with delayed proficiency in English (Fong et al., 2010; Mitchell, Destino, & Karam, 1997). One study of 1,393 8th grade ELs in a large urban district found that mobile students had significantly lower test scores even after controlling for other student and classroom-level variables (Hofstetter, 1999). Homeless youth have much higher rates of student mobility than the general population, and this has been tied to lower test scores and grade point averages than low-income students (Cutuli et al., 2013; Miller, 2011).

Three somewhat more recent studies of school mobility use strong methodological approaches and share some analytic elements with our own study. We therefore discuss these in greater detail.

Schwartz et al. (2017) used longitudinal data from New York City (NYC) public elementary and middle schools from 2002 through 2010, using a highly constrained sample limited to students who lived in rental units and who entered the district by first grade and remained in the district through eighth grade, which allowed them to observe a complete mobility history. They employed student fixed effects and multiple instrumental variables to estimate the causal effects of student mobility on academic achievement. Their model with student fixed effects showed effects on ELA achievement of -0.10, -0.53, and null of structural, nonstructural summer, and midyear moves, respectively, and effects on mathematics achievement of -0.16, -0.08, and -0.08 of structural, nonstructural summer, and midyear moves, respectively. When they applied instrumental variables, the effects on ELA achievement became -0.11 and null for structural and nonstructural summer moves, respectively, and the effects on mathematics achievement become -0.20 and null for structural and nonstructural summer moves, respectively. To get at the effects of moves that are more strategic than reactive on the part of parents, they performed a second instrumental variable analysis (without student fixed effects) parsing nonstructural moves into moves that occur at the beginning of a school's grade span—what they term articulated effects that are more likely to be the result of strategic behavior—versus moves that occur in the middle of a school's grade span—what they term nonarticulated effects that are more likely to be in response to changes in circumstances. In these analyses, structural moves were consistently negative. Articulated nonstructural moves show positive effects on the order of 0.2 in ELA. They concluded that promotional moves negatively affected

both ELA and math achievement and effects of nonpromotional moves varied from negative to positive. Nonpromotional moves seen as strategic led to improved ELA performance.

Min (2022) examined students in grades 4, 5, 6, and 8 from a large school district during the 2011-2013 school years to compare the effects of within-year and between-year nonpromotional school mobility. The data set is highly constrained, eliminating all observations that include a promotional move and concentrating only on nonstructural summer and midyear movers only. She employs a multiple membership model (MMM), a variant of hierarchical linear modeling (HLM). The traditional HLM is used to address nested data structure and students are strictly nested within a single school (Level 1: student, Level 2: school). However, the MMM allows students to be nested within multiple schools. The author used the multiple membership weight by computing the proportion of days a student attended each school, thus accounting for students who may be affiliated with more than one school. By incorporating multiple school memberships into the model, Min's analytic strategy addresses the hierarchical nature of the data structure; however, as with HLM, this approach can fall short of establishing causal relationships. The study found that, overall, nonpromotional mid-year moves produced larger declines in math and reading scores than nonpromotional summer moves. It found negative effects of -0.03 in reading and -0.05 in mathematics for nonstructural summer movers versus -0.093 in reading and -0.182 in mathematics for midyear movers. It also reported that mid-year school changes had a disproportionately negative effect on Asian students' reading and mathematics achievement, while its effects were relatively similar among Hispanic, Black, and White students. Among students who did not move, Asian students exhibited the highest academic achievement scores, while among students who underwent midyear school changes, Asian students had the lowest predicted scores.

Cohen et al. (2025) studied the effects of midyear school mobility on achievement using more recent data from the 2009–10 to 2018–19 academic years for students in grades 3 through 8 across five counties in the St. Louis metropolitan area. Using a random effects model that included several school contextual variables, they estimated the effects of school transfers during the transfer year and the year that followed and found effects of midyear moves on the order of -0.09 for ELA and -0.11 for mathematics and the persistent effects into the following year on the order of -0.05 for ELA and -0.06 for mathematics. Additionally, they included a model that contained an interaction between midyear school transfers and the average achievement of the schools to which they transferred and found that, contrary to the academic advantages that might be predicted by Tiebout sorting, higher-performing schools were associated with lowered math achievement in the same academic year as the transfer, compared with students who did not change schools, and smaller but still negative effects persisted into the following year.

In summary, prior research indicates that mobility's impact may vary according to the type of move, its timing within a students' school year (Grigg, 2012; Min, 2022, Cohen et al., 2025), the grade in which a student changed schools (Swanson and Schneider (1999), student background characteristics like race-ethnicity (Min, 2022) or EL (Hofstetter, 1999) or homeless status (Cutuli et al., 2013; Miller, 2011), whether the school change coincides with a residential move (Cordes et al., 2019), and contextual factors related to schools (e.g., Hanushek et al., 2004). We build upon these valuable insights in structuring our analytic approach, and we extend prior findings, offering several contributions beyond those of the existing literature. Our panel data set, which encompasses several districts, is larger than those of other papers and rich in contextual variables. It enables us not only to estimate the effects of multiple types of student changes (e.g., structural moves, non-structural summer moves, and non-structural mid-year

moves) on the general population of students but also to parse out these effects by grade level, by differences in school achievement pre and post move, and by various subgroups of students who warrant special services due to disability, poverty, EL status, and homeless and foster status. We show the importance of a large set of contextual factors. In addition, we investigate effects of mobility after one year post move—i.e., "fade-out" effects. Our analytic strategy, described in detail below is strong, enabling us to infer impacts and their magnitudes that are more defensibly causal than those of most prior papers.

Data

We use longitudinal data beginning in 2016-17 and ending in 2019-20 for close to one million students from six moderate to large California districts from the CORE consortium. The CORE consortium of districts was founded in 2010 to engage in cooperative efforts to implement new academic standards, improve training for teachers and administrators, and pool data for policy research and information.[2] PACE, which stands for Policy Analysis for California Education, curates these data and connects the data to researchers with questions of importance to the districts. Data include test scores, student characteristics, disciplinary measures, school characteristics, and enrollment information.

Student characteristics include gender, race/ethnicity, and whether or not the student is free-and-reduced-price-lunch eligible, homeless, a foster student, and designated as having a disability or as an English Learner. We also have a variable that indicates that the student has undergone a residential move (which may or may not coincide with a school move).

We create several variables that characterize schools as well as the "fit" of students to their schools. School characteristics are enrollment size, a measure of diversity based on the

[2] See https://coredistricts.org/, accessed on 8/5/2025.

Blau index, charter school status, and a school quality index, updated annually, composed of the school's average achievement, rate of disciplinary actions, and the absenteeism rate. To measure students' fit with their schools, we compute the percentage of students in the school of the same race and the distance (in test score points) of student's achievement from average school achievement in the same grade. Finally, we examine the effect on achievement of differences between the new and former school, such as whether the new school has higher achievement, which would indicate that the student moved to a better school.

For the analysis, we keep only students in grades 4-8. We also exclude observations with missing school identifiers or grade-level data. Our resulting sample has 1.12 million observations representing close to 508,000 students.

Districts in our sample have higher proportions of students of color, low-income and linguistic minority students than the average in California. In our sample of districts, 71% of students are Latinx (vs. 56% in the state), 10% are African American (5% in the state), 10% are White (20% in the state), and 10% are Asian American (10% in the state). Seventy-one percent are eligible for free-and-reduced-price lunch (vs 56% in the state) and 22% are currently designated as ELs (vs 18% in the state).[3] Thus, our results can be interpreted to reflect large and medium urban, rural, and suburban districts with higher-than-average levels of racial/ethnic and language diversity and poverty rates.

Types of Student Moves

From the raw data on enrollment, we code three different types of moves: (1) *Structural moves* are those that happen when a student reaches the last grade offered in the school. These

[3] Source: Fingertip facts on education in California 2022/23 (https://www.cde.ca.gov/ds/ad/ceffingertipfacts.asp) and State profile of California Public Schools, by Ed Data Education Data Partnership. Available at: https://www.ed-data.org/state/CA.

are considered "promotional" moves and happen typically in 5th or 6th grade for elementary schools and 8th grade for middle schools. In a small set of cases, a move happens outside of a traditional promotional grade, but students must move because it is the last grade offered in a school with an unusual grade configuration. We categorize these promotional and compulsory moves as structural. (2) *Nonstructural summer moves* are moves that happen over the summer in a grade that is not the last grade offered in the school. (3) *Mid-year moves* happen in the middle of the school year at any grade level and are also considered nonstructural. We also carefully account for *attrition*, which represents students who leave any of the six districts in our sample. In our analyses we adjust mobility rates by attrition—i.e., when a student leaves our sample, we categorize that as a move, which may or may not be structural depending on the last grade in which the student is seen. Since all students leaving the districts are also moving schools, not adjusting for attrition would lead to undercounts in incidence estimates. Students who are categorized as "*stayers*" are those who remain in the same school the next year in our data.

Student and School-Level variables

For every year in our data, we have access to students' grade level (K-12) and school attended. Student demographic variables include gender (male/female) and race/ethnicity. Race is coded in five mutually exclusive categories: American Indian, Latinx, African American, White, and Asian American-Pacific Islander-Filipino (ASPIF). Program designations at the student level include English-learner designation (EL), student with disabilities (SWD), homeless (HL), foster youth (FST), and free-and-reduced price lunch eligible (FRPL). We have information on absences (days absent) and total numbers of suspensions and expulsions as well as an indicator summarizing any behavioral incident. We are able to measure residential mobility through a variable indicating whether the student had a change of address during the school year.

At the school level we created two variables: a school diversity index and a variable showing the percentage of students in the school that match the student's own race. The school diversity index is based on the Blau index, a measure of racial/ethnic diversity that equal to 0 if there is no racial diversity inside a school (i.e., all enrollment is from one racial/ethnic group only) and equals 1 if all racial/ethnic groups are equally balanced. In our data this index is 0.37 on average, suggesting low diversity. The percent same race variable is 1 when 100% of students in the school match the student's own race, and 0% when nobody matches the student's own race. The average in our sample is 74.5%.

Methods

As a baseline, we estimate the association of our different types of mobility indicators with achievement outcomes (either ELA or mathematics), controlling only for a set of basic demographic characteristics, and grade and year fixed effects, and using OLS. The baseline equation is as follows:

(Model 1 - Baseline) $$y_{it} = \alpha + M_{it}\mu + X_{it}\beta + g_{it} + t_{it} + \varepsilon_{it},$$

where y_{it} is the dependent variable for student i at time t—e.g., ELA or mathematics test scores. M_{it} represents the vector of mobility indicators for student i at time t—structural move, nonstructural summer move, nonstructural midyear move—and μ is the vector of associated mobility coefficients. X_{it} is a vector of demographic characteristics—gender, race/ethnicity, and indicators for free-and-reduced-price-lunch eligibility, disability, English Learner, homeless, and foster status—and β is the vector of associated coefficients. The grade and year fixed effects are denoted by g_{it} and t_{it}, respectively.

We then move in the direction of establishing a stronger causal link between different types of moves and outcomes by adding student fixed effects to the equation, represented by γ_i in

equation (2). The addition of student fixed effects controls for any time-invariant characteristics of students—e.g., a persistent ability trait—and removes these unknowns from the error term.[4]

(Model 2 – Fixed Effects) $$y_{it} = \alpha + M_{it}\mu + X_{it}\beta + g_{it} + t_{it} + \gamma_i + \varepsilon_{it},$$

In a third model—what we consider the "full" model—we retain the student fixed effects and include additional controls for a number of potentially important contextual variables, represented by the vector *S*. These contextual variables comprise a set of characteristics of the receiving school (quality, size, diversity, and charter status), two "fit" variables measuring the closeness of the student's characteristics to the receiving school's characteristics (similarity of achievement and the percent of students of the same race), a set of measures showing the difference between student's new school and old school (difference in school quality, size, average achievement, percent of students of the same race), a variable indicating that the student has moved from a non-charter to a charter school, and a variable indicating that the student experienced a residential move concomitant with the school move. The expanded model is as follows:

(Model 3 - Full) $$y_{it} = \alpha + M_{it}\mu + X_{it}\beta + S_{it}\sigma + g_{it} + t_{it} + \gamma_i + \varepsilon_{it}.$$

We further examine the effect of changing schools on outcomes by including lagged mobility indicators in the full model, which allow us to look at the degree to which achievement effects brought about by changing schools lasts through a second year. This "fade-out" model is as follows:

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[4] In this second model, the time-invariant demographic characteristics, gender and race/ethnicity—are absorbed in γ_i., so the X_{it} vector contains fewer variables.

(Model 4 – Fade-out)

$$y_{it} = \alpha + M_{it}\mu + M_{it-1}\mu_{it-1} + X_{it}\beta + S_{it}\sigma + g_{it} + t_{it} + \gamma_i + \varepsilon_{it}.$$

Results

Table 1 shows the coefficients from regressions of standardized *ELA achievement* scores on our mobility variables using the baseline model, the student fixed effects model, the fixed effects model containing the contextual variables, and the fade-out model. Stayers (i.e., non-movers) represent the reference category.[5]

In the baseline model for ELA achievement shown in column 1, with controls limited to demographic and grade-year indicators, all three types of moves are negative and statistically significant. Mid-year movers experience the largest penalty (-0.419 SD), roughly four times that of structural movers (-0.072 SD) and more than three times that of nonstructural summer movers (-0.118 SD). The magnitude is consistent with conventional expectations that disruptions occurring in the middle of the academic year are most damaging, whereas moves timed to the summer or coinciding with the terminal grade carry smaller but still meaningful losses. However, this model does not control for a host of factors related to success after a move and is therefore not defensible as a causal model.

Once student fixed effects are introduced in Model 2, all mobility coefficients shrink sharply. This is evidence that a sizable share of the gaps in the baseline model reflected pre-existing differences across students rather than the moves themselves. However, the relative ordering of the penalties now places structural movers at the top (-0.067 SD), followed by mid-year movers (-0.050 SD), with nonstructural summer movers showing the smallest within-

[5] We present the coefficients of interest to the study in our main tables. Full regression results are presented in the Appendix.

student loss (-0.029 SD). In other words, after netting out stable individual traits, the largest remaining achievement dip is associated with promotional-grade moves (elementary to middle), not mid-year moves. One plausible explanation is that structural moves entail transitions to new school configurations, bringing with them curricular discontinuities and unfamiliar peer groups that may disrupt performance even after accounting for fixed student attributes. Mid-year moves immediately disrupt performance due to the change of environment when individual heterogeneity is purged, although they may not bring about as many curricular discontinuities. By contrast, nonstructural summer moves appear least harmful in this within-student frame, which suggests that these movers may experience less of a new environment shock (compared with mid-year movers) and fewer curricular discontinuities (compared with structural movers).

Model 3 adds the contextual variables to the student fixed effect model and nearly eliminates the deficits for structural (from –0.067 SD to –0.006 SD) and nonstructural summer movers (from –0.029 SD to –0.003 SD). Moreover, coefficients for the latter group barely retain significance. This suggests that the detrimental effects of these orderly moves may be associated with the school-level conditions. In contrast, the coefficient for mid-year movers deepens slightly (from –0.050 SD to –0.073 SD), suggesting that factors associated with the mid-year disruption itself drive the achievement loss, rather than the observable school context. In other words, while school-level covariates explain away much of the deficit associated with summer moves, they cannot account for the effect of mid-year moves.

Model 4 augments the full model with one-year-lagged mobility indicators in addition to the current-year indicators—what we term a “fade-out” model—which looks at not just the immediate effect of a move but also effects one year after a move. The immediate effects remain unaltered for structural movers and lose all significance for nonstructural summer movers, and

the midyear move coefficients become slightly more negative (from –0.073 SD in Model 3 to -0.090 SD in Model 4).

The one-year lagged effect is small, negative, and significant for structural movers. There appear to be no significant lagged effects for nonstructural movers, whether they are summer or midyear movers. It's possible that the achievement penalty for a midyear move dissipates once the student is able to attend a school for a full year following the move because the disruptive effects of moving midstream are outweighed by families securing better matches for their children and because students benefit from entering at the natural start of the instructional cycle.

One caveat pertinent to the results for lagged effects is that the regression sample loses observations due to attrition from the longitudinal sample when we include a lagged year. The number of observations in the supporting sample decreases from more than a million to a little over 600,000, thus by around 40 percent. Therefore, we lose many students from the sample who have moved out of their districts or moved out of the public school system. These students may be different from those who remain in the public school districts for which we have data in some qualitative way that can affect the findings, and the results of Model 4 are not entirely comparable to those of Model 3.

Table 1. Coefficients from regressing achievement in ELA on student mobility

	(1)	(2)	(3)	(4)
VARIABLES	Baseline	FE	Full	Full w/ Fade out
Structural mover	-0.072***	-0.067***	-0.006***	-0.006***
	(0.003)	(0.002)	(0.001)	(0.002)
Non-structural summer mover	-0.118***	-0.029***	-0.003*	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)
Mid-year mover	-0.419***	-0.050***	-0.073***	-0.090***
	(0.005)	(0.004)	(0.005)	(0.009)

Lagged structural mover				-0.009***
				(0.002)
Lagged non-structural summer mover				0.001
				(0.003)
Lagged mid-year mover				0.007
				(0.006)
Constant	0.865***	0.144***	-0.001	-0.037
	(0.003)	(0.009)	(0.008)	(0.042)
Observations	1,116,331	1,117,040	1,033,216	615,098
Unique Student IDs		507,891	476,376	344,825
R-squared	0.359	0.006	0.647	0.617
Grade FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Individual FE		YES	YES	YES
Contextual controls			YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
See appendix for full regression results

The results for *mathematics achievement* are very similar to those of ELA for all model specifications. In the baseline specification with no student fixed effects, mid-year movers experience the largest penalty in mathematics (-0.449 SD), nearly four times the size of the hit for nonstructural summer movers (-0.122 SD), and more than seven times that for structural movers (-0.060 SD).

Introducing student fixed effects in Model 2 reduces all coefficients and greatly reduces the coefficients on nonstructural moves, showing that much of the baseline gap fails to account for reactions to school moves related to time-invariant differences among students. After this adjustment, mid-year moves still carry the largest within-student deficit (-0.057 SD), followed closely by structural movers (-0.053 SD), while nonstructural summer moves carry the smallest effect (-0.023 SD). Unlike the ELA results (where structural moves show a bigger impact), mid-

year moves seem to hurt mathematics performance a little more than structural moves. And nonstructural summer moves remain the least harmful.

The addition of school-level covariates in Model 3 further reshapes the picture. For structural movers, the coefficient not only shrinks to almost nothing but actually turns slightly positive (+0.003 SD), and for nonstructural summer movers it effectively reaches zero (-0.000 SD). These patterns imply that whatever math deficits accompanied orderly, start-of-year moves were fully explained through school-context factors; once differences in school conditions are held constant, the moves themselves exert no residual harm. By contrast, the penalty for mid-year movers deepens to -0.083 SD, suggesting that the impact of entering a new mathematics classroom in the middle of a school year cannot be explained away by observable school conditions. This evidence indicates that disruptive timing drives the achievement loss, rather than the quality of the receiving school, while deficits seen for nonstructural summer or structural transitions are almost entirely mediated by the characteristics of the new learning environment.

The fadeout model (Table 2 - Model 4) shows how mathematics achievement responds to school mobility when both contemporaneous and one-year-lagged mover indicators are introduced. The nearly null contemporaneous effects of structural and summer nonstructural movers remain unchanged, but the contemporaneous negative effect of midyear moves increases (from -0.082 to -0.103 SD). A small but significant lagged effect of structural moves appears (-0.009 SD), but no lagged effects are found for both types of nonstructural moves. Thus, our finding that midyear moves harm mathematics achievement more than other types of moves is reinforced in this model with lags.

Table 2. Coefficients from regressing achievement in mathematics on student mobility

	(1)	(2)	(3)	(4)

VARIABLES	Baseline	FE	Full	Full w/ Fade out
Structural mover	-0.060***	-0.053***	0.003***	0.005***
	(0.003)	(0.002)	(0.001)	(0.002)
Non-structural summer mover	-0.122***	-0.023***	-0.000	-0.000
	(0.004)	(0.002)	(0.002)	(0.003)
Mid-year mover	-0.449***	-0.057***	-0.083***	-0.103***
	(0.005)	(0.004)	(0.005)	(0.008)
Lagged structural mover				0.009***
				(0.002)
Lagged non-structural summer mover				0.001
				(0.002)
Lagged mid-year mover				0.008
				(0.005)
Constant	0.963***	0.140***	-0.026***	0.034
	(0.003)	(0.008)	(0.008)	(0.042)
Observations	1,124,077	1,124,933	1,033,316	615,067
Unique Student IDs		512,068	476,491	344,857
R-squared	0.327	0.005	0.631	0.636
Grade FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Individual FE		YES	YES	YES
Contextual controls			YES	YES

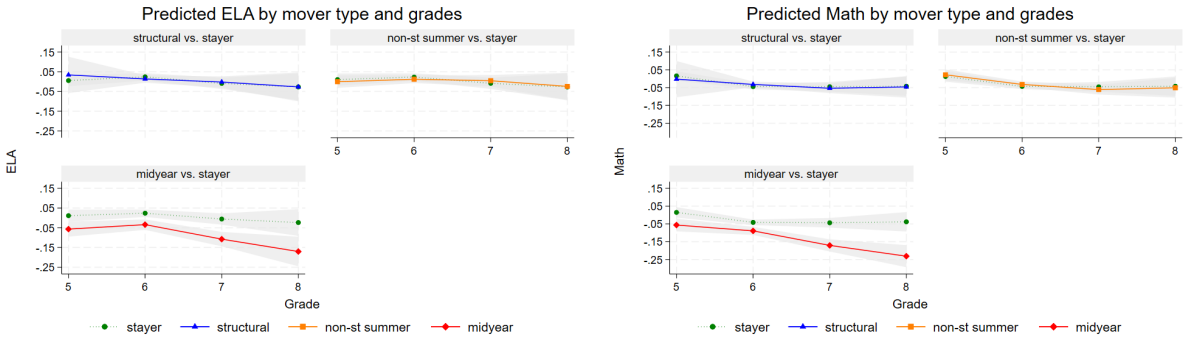
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
See appendix for full regression results

Patterns by grade

Figure 1 shows the predicted ELA and mathematics across grades 5 through 8, using Model 3—the full model. For both ELA and mathematics, the achievement trajectories of structural and nonstructural summer movers are nearly indistinguishable from their stayer peers, with their 95% confidence intervals consistently overlapping, as would be expected given the results reported above for all grades.

In contrast, midyear movers exhibit a distinct and concerning pattern. They begin with slightly lower ELA scores in elementary school, and this achievement gap widens considerably through middle school, with their predicted scores declining sharply from grade 6 to grade 8 relative to stayers. The results are similar for mathematics, as midyear movers experience a steep and continuous decline in achievement as they advance through the grades. By grade 7, their performance falls significantly below that of stayers, and this gap widens substantially by grade 8, indicating a significant negative academic trajectory in mathematics for students who move during the school year. In both cases, the middle school years seem to be where divergence in post-move achievement starts to show. A statistically significant gap between stayers and midyear movers starts to appear in 6th grade for ELA and in 7th grade for mathematics.

Figure 1. Predicted ELA and mathematics outcomes by mover type over grade levels



Patterns by differences in the achievement level of the receiving school

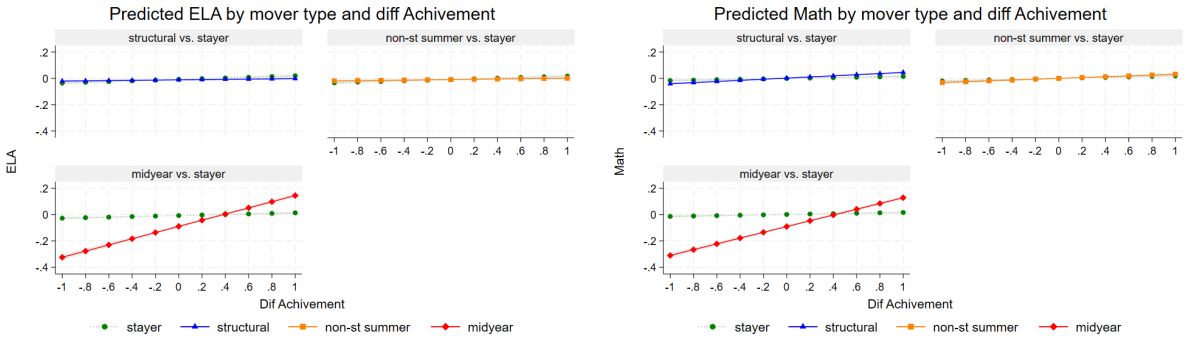
A final set of plots (Fig. 2) examines how the achievement of movers is moderated by moving to a school with a different performance level, as measured by the differences in achievement between the old and new school (negative values mean moving to a worse school, while positive values mean moving to a better school). For structural and nonstructural summer movers, the academic performance of the receiving school has no discernible association with

their predicted outcomes in either subject; their performance remains stable and closely aligned with that of their stayer peers.

However, the achievement of midyear movers is strongly linked to the difference in achievement for both ELA and mathematics. A strong, positive, and linear relationship is evident across both subjects: moving to a lower-performing school is associated with a severe drop in scores. Conversely, moving to a higher-performing school corresponds with a substantial boost in predicted achievement.

This effect is particularly noteworthy for midyear movers because not only does this show that the achievement gap with stayers closes when moving to a top-tier school, but also the receiving school needs to be at least half a standard deviation (dif_ach=0.5) better in performance than the sending school. The boost is so significant that it allows these same students to surpass the average achievement levels of their stayer peers, highlighting the critical role that the receiving school's academic environment plays for midyear movers. It is also interesting but not surprising that moving to a comparable school (where dif_ach=0) predicts lower achievement in both ELA and mathematics (-0.1)

Figure 2. Predicted ELA and mathematics outcomes by mover type over differences in school achievement between sending and receiving schools



Results for special populations

Lastly, we investigate the differential impact that different types of moves may have on populations of students receiving special services. Table 3 shows the coefficients and standard deviations for interactions of indicators of various program designations with the move variables.

We see that structural moves display small positive interaction effects on ELA achievement for students with disabilities, homeless, and EL students. Mathematics achievement, however, suffers for these same groups of students. One explanation for these findings is that the curricular transitions from elementary to middle school are relatively easy for students with these particular special circumstances in ELA and relatively difficult in mathematics. A very small negative impact is also seen in ELA for low-income students.

Nonstructural summer movers show virtually no interaction effects with the special groups of students we study, but the picture for midyear movers is quite different. We see substantive negative interaction effects of midyear moves on ELA for students with disabilities, EL students, and low-income students. And, for mathematics, the effects are as bad or worse for these students and include homeless students as well.

Table 3. Coefficients from regressing achievement in mathematics on interactions of student mobility and special categories

VARIABLES	(1) Full - ELA	(2) Full - Math
Structural mover	-0.004**	0.014***
	(0.002)	(0.002)
Non-structural summer mover	-0.007*	0.007*
	(0.004)	(0.004)
Mid-year mover	-0.023***	-0.028***
	(0.007)	(0.007)
SWD	-0.003	0.010**
	(0.004)	(0.004)
Homeless	-0.004	0.004
	(0.004)	(0.004)
Foster youth	0.008	0.005
	(0.008)	(0.008)
EL	- 0.015***	0.024***
	(0.002)	(0.002)
FRPL	-0.001	0.005***
	(0.002)	(0.002)
ST mover x SWD	0.012***	-0.019***
	(0.003)	(0.002)
ST mover x HL	0.008*	-0.010**
	(0.005)	(0.004)
ST mover x FST	-0.002	-0.001
	(0.014)	(0.013)
ST mover x EL	0.020***	-0.034***
	(0.003)	(0.002)
ST mover x FRPL	-0.008***	-0.002
	(0.002)	(0.002)
NST summer mover x SWD	0.009*	-0.008
	(0.005)	(0.005)
NST summer mover x HL	-0.003	-0.001
	(0.008)	(0.008)
NST summer mover x FST	0.000	0.005
	(0.017)	(0.017)
NST summer mover x EL	0.008	-0.009*
	(0.005)	(0.005)
NST summer mover x FRPL	0.001	-0.005
	(0.004)	(0.004)
Midyr mover x SWD	-0.022***	-0.038***
	(0.008)	(0.008)
Midyr mover x HL	0.003	-0.023**
	(0.011)	(0.010)
Midyr mover x FST	-0.033	-0.015
	(0.034)	(0.033)
Midyr mover x EL	-0.047***	-0.045***

	(0.007)	(0.007)
Midyr mover x FRPL	-0.053***	-0.054***
	(0.007)	(0.007)
Constant	-0.005	-0.033***
	(0.008)	(0.008)
Observations	1,033,216	1,033,316
Unique Student IDs	476,376	476,491
R-squared	0.648	0.631
Grade FE	YES	YES
Year FE	YES	YES
Individual FE	YES	YES
Contextual controls	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
See appendix for full regression results

Discussion

Our study produces some key observations regarding the modeling of mobility. First, the baseline model, which more or less reflects conventional expectations and shows strong negative relationships between all forms of mobility and test scores, is naïve. The use of a student fixed effect, which carries us much further toward a causal model, greatly reduces the observed negative impacts of a move. Moreover, when we use our data to measure and introduce several important observable contextual factors, the impacts are further modified. This "full model" approach produces the most defensible coefficients in terms of a causal interpretation.

Our study has some limitations. Despite the fact that our data permit us to move close to a causal model, it is still possible that unobserved time-varying factors, such as a divorce or a loss or change of employment on the part of parents in the family, could cause a change of schools for the student and exert an effect on student outcomes that is independent of the school change. Our data do not record these types of events or reactions to them, so it is impossible for us to control for them. One could argue, however, that divorce rates or unemployment shocks are at

least somewhat correlated with factors we do control for, such as poverty, race, residential moves, etc.

To situate our findings in the context of other recent research on mobility, we find effects of changing schools that differ from those reported by other studies. For example, our fixed effects model augmented with contextual variables produces very small effects of around -0.006 in ELA and 0.003 in mathematics for structural moves. Contrast this with the relatively large negative effects of structural moves reported in Schwartz et al. (2017), namely -0.10 in ELA and -0.16 in mathematics in their fixed effects models with even more strongly negative findings in their instrumental variables models. With regard to nonstructural summer moves, we find negligible effects, whereas Schwartz et al. find strong negative effects, namely -0.053 for ELA and -0.076 for mathematics. With regard to midyear moves, we find strong effects of around -0.073 for ELA and around -0.083 for mathematics, and Schwartz et al. find a similar effect of -0.078 for mathematics but no effect for ELA. Their instrumental variables models find no effects for nonstructural moves. We attribute these differences to factors related to modeling and sample context. Our fixed effects models without the addition of contextual variables are a bit closer to theirs, particularly with respect to structural moves but when we add a strong set of contextual variables we diverge further. The addition of a strong set of contextual variables to our models makes them more defensible. Moreover, the constraints on the sample used in Schwartz et al. (2017)—i.e., students living in rental units who remain in the district for all years of elementary school—renders their results less generalizable to the full population of students than our results.

Min (2022), who focuses only on nonstructural movers only and uses a random effects type of model finds larger negative effects of both summer and midyear moves than we do. In

fact, her findings for summer moves are 10 or more times larger than ours. Again, modeling choices and the constrained sample used in her study are likely the reasons for the differences.

Cohen (2025) focus only on midyear moves and find negative and significant effects that are more or less within the same range as ours. Their persistence effects are more strongly negative than ours, however. They use the full population of a large five-county data set, which is likely the reason why our results are more closely matched with theirs than with those of Schwartz et al. (2017) and Min (2022). Differences in our results may stem from our choice of a fixed versus random effects approach and the fact that we include all types of mobility in our models.

Conclusions

There are several important takeaways from our findings. We show persuasive evidence that changing schools, particularly in the middle of the school year, produces some—mostly negative—effects on student achievement, but they are generally smaller than previously thought. We also show that the timing of a move in a student's trajectory through elementary and middle school matters, and that midyear moves in middle school are particularly harmful to achievement. We also find that persistent negative effects of moves are fairly negligible. Moreover, we show definitively that characteristics of schools and the student-to-school fit matter in determining the effects of a move, and that more potentially beneficial moves, such as to schools with higher overall achievement, can mitigate the negative effects of moving on achievement. Also, we show that the impact of a move, depending on its timing, affects special populations of students in different and important ways. All these findings point to the fact that specific strategic choices on the part of parents can help outweigh some of the negative

achievement effects of disrupting their children's school environment and that school environments can do much to affect the achievement performance of students after a move.

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Appendix Table 1 Coefficients from regressing achievement in ELA on student mobility (full specification)

VARIABLES	(1) Baseline	(2) FE	(3) Full	(4) Full w/ Fade out
Structural mover	-0.072***	-0.067***	-0.006***	-0.006***
	(0.003)	(0.002)	(0.001)	(0.002)
Non-structural summer mover	-0.118***	-0.029***	-0.003*	-0.001
	(0.004)	(0.003)	(0.002)	(0.003)
Mid-year mover	-0.419***	-0.050***	-0.073***	-0.090***
	(0.005)	(0.004)	(0.005)	(0.009)
Lagged structural mover				-0.009***
				(0.002)
Lagged non-structural summer mover				0.001
				(0.003)
Lagged mid-year mover				0.007
				(0.006)
Female	0.193***			
	(0.002)			
Hispanic	-0.419***			
	(0.003)			
Black	-0.765***			
	(0.004)			
Asian/PI	0.148***			
	(0.004)			
American Indian/Alaska Native	-0.460***			
	(0.019)			
Other	-0.112***			
	(0.007)			
SWD	-0.701***	-0.002	-0.001	0.004
	(0.002)	(0.007)	(0.004)	(0.007)
Homeless	-0.132***	0.001	-0.003	-0.008
	(0.004)	(0.006)	(0.004)	(0.006)
Foster youth	-0.271***	0.012	0.006	0.007
	(0.011)	(0.011)	(0.007)	(0.013)
EL	-0.908***	-0.117***	-0.012***	-0.007*
	(0.002)	(0.004)	(0.002)	(0.004)
FRPL	-0.350***	0.010***	-0.006***	-0.010***
	(0.002)	(0.003)	(0.002)	(0.002)
School Quality Index (SQI)			0.114***	0.105***
			(0.001)	(0.002)
School total students			-0.000***	-0.000***
			(0.000)	(0.000)
School Div Index			0.004	0.008
			(0.007)	(0.009)
Charter			-0.000	0.004
			(0.003)	(0.004)
Fit achievement			-0.978***	-0.966***

			(0.001)	(0.002)
Percent same race			-0.030***	-0.026**
			(0.007)	(0.010)
Diff in SQI			-0.003***	-0.003**
			(0.001)	(0.001)
Diff in achievement			0.011***	0.006*
			(0.002)	(0.003)
Diff in school size			0.000	0.000
			(0.000)	(0.000)
Diff in pct same race			0.009*	0.004
			(0.005)	(0.007)
Non-charter to charter			0.017***	0.019***
			(0.004)	(0.005)
At least one residential move			0.001	-0.001
			(0.001)	(0.002)
Year 2017	-0.007***	0.258***	-0.007	
	(0.002)	(0.021)	(0.013)	
Year 2018	-0.014***	0.543***	-0.012	0.001
	(0.002)	(0.042)	(0.025)	(0.026)
Year 2019	-0.017***	0.821***	0.001	0.019
	(0.002)	(0.063)	(0.038)	(0.053)
5th Grade	-0.037***	-0.282***	0.017	0.052
	(0.002)	(0.021)	(0.013)	(0.032)
6th Grade	-0.025***	-0.530***	0.037	0.068
	(0.003)	(0.042)	(0.026)	(0.056)
7th Grade	-0.078***	-0.842***	0.048	0.080
	(0.002)	(0.063)	(0.038)	(0.081)
8th Grade	-0.111***	-1.133***	0.065	0.087
	(0.002)	(0.085)	(0.051)	(0.107)
Constant	0.865***	0.144***	-0.001	-0.037
	(0.003)	(0.009)	(0.008)	(0.042)
Observations	1,116,331	1,117,040	1,033,216	615,098
Unique Student IDs		507,891	476,376	344,825
R-squared	0.359	0.006	0.647	0.617
Grade FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Individual FE		YES	YES	YES
Contextual controls			YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2 Coefficients from regressing achievement in mathematics on student mobility (full specification)

VARIABLES	(1) Baseline	(2) FE	(3) Full	(4) Full w/ Fade out
Structural mover	-0.060***	-0.053***	0.003***	0.005***
	(0.003)	(0.002)	(0.001)	(0.002)
Non-structural summer mover	-0.122***	-0.023***	-0.000	-0.000
	(0.004)	(0.002)	(0.002)	(0.003)
Mid-year mover	-0.449***	-0.057***	-0.083***	-0.103***
	(0.005)	(0.004)	(0.005)	(0.008)
Lagged structural mover				0.009***
				(0.002)
Lagged non-structural summer mover				0.001
				(0.002)
Lagged mid-year mover				0.008
				(0.005)
Female	-0.030***			
	(0.002)			
Hispanic	-0.461***			
	(0.003)			
Black	-0.831***			
	(0.004)			
Asian/PI	0.231***			
	(0.004)			
American Indian/Alaska Native	-0.514***			
	(0.019)			
Other	-0.125***			
	(0.007)			
SWD	-0.727***	-0.004	0.003	-0.003
	(0.003)	(0.006)	(0.004)	(0.007)
Homeless	-0.113***	0.005	-0.000	0.002
	(0.004)	(0.006)	(0.004)	(0.005)
Foster youth	-0.268***	0.011	0.006	0.005
	(0.011)	(0.011)	(0.007)	(0.012)
EL	-0.787***	-0.081***	0.018***	0.009**
	(0.002)	(0.003)	(0.002)	(0.003)
FRPL	-0.324***	0.022***	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
School Quality Index (SQI)			0.102***	0.099***
			(0.001)	(0.002)
School total students			0.000***	0.000***
			(0.000)	(0.000)
School Div Index			-0.017***	-0.010
			(0.006)	(0.009)
Charter			0.000	-0.001
			(0.003)	(0.004)
Fit achievement			-0.915***	-0.933***

			(0.001)	(0.002)
Percent same race			0.023***	0.023**
			(0.007)	(0.010)
Diff in SQI			-0.002**	-0.002
			(0.001)	(0.001)
Diff in achievement			0.030***	0.018***
			(0.002)	(0.003)
Diff in school size			-0.000	0.000
			(0.000)	(0.000)
Diff in pct same race			-0.015***	-0.011*
			(0.005)	(0.006)
Non-charter to charter			-0.014***	-0.015***
			(0.004)	(0.005)
At least one residential move			-0.000	0.002
			(0.001)	(0.002)
Year 2017	-0.008***	0.290***	0.038***	
	(0.002)	(0.019)	(0.013)	
Year 2018	-0.016***	0.596***	0.068**	0.018
	(0.002)	(0.039)	(0.027)	(0.025)
Year 2019	-0.019***	0.904***	0.123***	0.058
	(0.002)	(0.058)	(0.040)	(0.051)
5th Grade	-0.033***	-0.309***	-0.029**	-0.059*
	(0.002)	(0.019)	(0.014)	(0.032)
6th Grade	-0.023***	-0.594***	-0.063**	-0.084
	(0.003)	(0.039)	(0.027)	(0.055)
7th Grade	-0.069***	-0.926***	-0.090**	-0.104
	(0.002)	(0.058)	(0.040)	(0.079)
8th Grade	-0.099***	-1.246***	-0.120**	-0.115
	(0.002)	(0.077)	(0.054)	(0.103)
Constant	0.963***	0.140***	-0.026***	0.034
	(0.003)	(0.008)	(0.008)	(0.042)
Observations	1,124,077	1,124,933	1,033,316	615,067
Unique Student IDs		512,068	476,491	344,857
R-squared	0.327	0.005	0.631	0.636
Grade FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Individual FE		YES	YES	YES
Contextual controls			YES	YES

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 3 Coefficients from regressing achievement in mathematics on interactions of student mobility and vulnerable categories (full specification)

VARIABLES	(1) Full - ELA	(2) Full - Math
Structural mover	-0.004**	0.014***
	(0.002)	(0.002)
Non-structural summer mover	-0.007*	0.007*
	(0.004)	(0.004)
Mid-year mover	-0.023***	-0.028***
	(0.007)	(0.007)
SWD	-0.003	0.010**
	(0.004)	(0.004)
Homeless	-0.004	0.004
	(0.004)	(0.004)
Foster youth	0.008	0.005
	(0.008)	(0.008)
EL	-0.015***	0.024***
	(0.002)	(0.002)
FRPL	-0.001	0.005***
	(0.002)	(0.002)
ST mover x SWD	0.012***	-0.019***
	(0.003)	(0.002)
ST mover x HL	0.008*	-0.010**
	(0.005)	(0.004)
ST mover x FST	-0.002	-0.001
	(0.014)	(0.013)
ST mover x EL	0.020***	-0.034***
	(0.003)	(0.002)
ST mover x FRPL	-0.008***	-0.002
	(0.002)	(0.002)
NST summer mover x SWD	0.009*	-0.008
	(0.005)	(0.005)
NST summer mover x HL	-0.003	-0.001
	(0.008)	(0.008)
NST summer mover x FST	0.000	0.005
	(0.017)	(0.017)
NST summer mover x EL	0.008	-0.009*
	(0.005)	(0.005)
NST summer mover x FRPL	0.001	-0.005
	(0.004)	(0.004)
Midyr mover x SWD	-0.022***	-0.038***
	(0.008)	(0.008)
Midyr mover x HL	0.003	-0.023**
	(0.011)	(0.010)
Midyr mover x FST	-0.033	-0.015
	(0.034)	(0.033)
Midyr mover x EL	-0.047***	-0.045***

	(0.007)	(0.007)
Midyr mover x FRPL	-0.053***	-0.054***
	(0.007)	(0.007)
School Quality Index (SQI)	0.113***	0.101***
	(0.001)	(0.001)
School total students	-0.000***	0.000***
	(0.000)	(0.000)
School Div Index	0.005	-0.017**
	(0.007)	(0.006)
Charter	-0.001	0.001
	(0.003)	(0.003)
Fit achievement	-0.978***	-0.915***
	(0.001)	(0.001)
Percent same race	-0.029***	0.024***
	(0.007)	(0.007)
At least one residential move	0.001	-0.000
	(0.001)	(0.001)
Diff in SQI	-0.003***	-0.002***
	(0.001)	(0.001)
Diff in achievement	0.012***	0.031***
	(0.002)	(0.002)
Diff in school size	0.000	-0.000*
	(0.000)	(0.000)
Diff in pct same race	0.008*	-0.013***
	(0.005)	(0.005)
Non-charter to charter	0.017***	-0.017***
	(0.004)	(0.004)
5th Grade	0.018	-0.028**
	(0.013)	(0.014)
6th Grade	0.038	-0.061**
	(0.025)	(0.027)
7th Grade	0.051	-0.087**
	(0.038)	(0.041)
8th Grade	0.069	-0.116**
	(0.051)	(0.054)
Year 2017	-0.008	0.037***
	(0.013)	(0.014)
Year 2018	-0.014	0.067**
	(0.025)	(0.027)
Year 2019	-0.003	0.120***
	(0.038)	(0.041)
Constant	-0.005	-0.033***
	(0.008)	(0.008)
Observations	1,033,216	1,033,316
Unique Student IDs	476,376	476,491
R-squared	0.648	0.631
Grade FE	YES	YES
Year FE	YES	YES

Individual FE	YES	YES
Contextual controls	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, *
p<0.1