RICE UNIVERSITY

Between-Year and Within-Year School Mobility: Different Effects by Race/Ethnicity

by

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ABSTRACT

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This paper investigates the effects of school mobility on the academic achievement of four cohorts of students in the Houston Independent School District (HISD). In this study I distinguish between within-year and between-year mobility, and accounts for all schools students have attended, also explores mobility effect differences by race/ethnicity. Using a multiple membership model (MMM), the findings suggest that within-year school mobility compromises students’ academic achievement more than between-year school mobility. Black students have the highest mobility rate both for between-year mobility and within-year mobility. In addition, although Asian-American students achieve higher reading and math scores on average than other groups, they experience a stronger negative impact from within-year school mobility than any other group. This finding suggests that Asian Americans are a diverse ethnic group in terms of socioeconomic status, a result contrary to the “model minority” image. The conclusion contains implications for policy making and suggestions for future research.
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Introduction

The United States is a country on the move—almost one in six households changes residence annually, a quarter of which are accompanied by school changes (Gasper et al. 2010). Many scholars have studied school mobility, especially its effects on student academic achievement. While there are a handful of scholars who find no relationship between school mobility and academic outcomes (Alexander et al. 1996; Heinlein and Shinn 2000), a majority of existing research has demonstrated that in general there is a negative association between school mobility and student academic achievement (Kerbow 1996; Hanushek et al. 2004; Engec 2006; Burkam et al. 2009; Grigg 2012). Admitting the generally adverse impacts of school mobility, some scholars find students could achieve better academic outcomes if they transfer to higher quality schools or schools that satisfy their special needs (Hanushek et al. 2004; Holme and Richards 2009; Xu et al. 2009; Schwartz and Stifel 2012).

Additionally, some researchers have identified the distinction between within-year (also called intra-year) school mobility and between-year (also called inter-year) mobility (Hanushek et al. 2004; Burkam et al. 2009; Grigg 2012). While within-year mobility refers to changing schools during the academic year, between-year mobility implies changing schools between academic years, which occurs during the summer. These scholars have also demonstrated that the timing of school mobility matters to children’s school outcomes as well (Hanushek et al. 2004; Grigg 2012). Specifically, school changes during the academic year tend to be “reactive moves” and hence are more likely to be disruptive to students’ studies than school mobility during the summer (Hanushek et al. 2004).
It is also important to note that not all racial/ethnic groups bear the burden of school mobility equally (Alexander et al. 1996; Hanushek et al. 2004). Research shows racial minority students, especially African Americans, have particularly high school mobility rates compared to white students. The incidence of school mobility for black students is often accompanied by parental divorce and financial problems (Rumberger 2003; Patrick 2015). To the best of my knowledge, the study by Hanushek et al. (2004) is the only one that has looked at the school mobility effects on students’ academic attainment with regard to the timing and race/ethnicity heterogeneity simultaneously. Acknowledging the contributions of Hanushek, Kain, and Rivkin’s (2004) study, we have to recognize that they have dismissed Asian Americans in their study, perhaps due to data limitation and not many surveys including Asian Americans in their sampling scope.

Using Houston Independent School District (HISD) data, I will first estimate which student-level characteristics are associated with a higher likelihood of school mobility. After that, using regression models and multiple membership models, this study aims to distinguish the effects of within-year school mobility from between-year mobility on students’ scores in the State of Texas Assessments of Academic Readiness (STAAR) reading and math tests, which are state-required for all students in grades 3-8. After identifying the timing distinction, different effects of within-year mobility and between-year mobility for students from various racial/ethnic groups will be teased apart.

My study contributes to previous work on school mobility in four ways. First, I provided a more accurate measure of mobility to identify the differences between inter-year and intra-year school mobility. Second, I used multiple membership models to account for all the schools
attended by mobile students, rather than solely considering the most recent school. Third, I included Asian American students—a group often neglected by scholars—and estimated whether the effects of each type of school mobility differ between racial and ethnic groups. Finally, I used data collected by Houston Independent School District (HISD), which is the seventh-largest school district (out of more than 14,000) with high student mobility rate in the United States but has rarely been studied. This research provides unique insights because HISD is dominated by minority students and hence might exhibit different patterns of academic performance as opposed to school districts dominated by white students.

**Literature**

*School Mobility*

School mobility occurs when a student moves to a different school. School changes can be classified as promotional or non-promotional school moves (Mao et al. 1997; Xu et al. 2009; Fiel et al. 2013). Promotional school moves are school changes required for all students, such as the transition from elementary school to middle school (Xu et al. 2009). In contrast, non-promotional moves occur when a student transfers school even though she/he has not yet reached the highest grade level. Students always experience promotional school changes with peers in the same grade level because promotional school moves are compulsory for all students (Xu et al. 2009). Unlike promotional transfers, students often experience non-promotional moves alone (Xu et al. 2009).

Non-promotional school mobility is a common phenomenon throughout the United States (Kerbow 1996; Rumberger et al. 1999; Hanushek et al. 2004; Xu et al. 2009; Gasper et al. 2010).
For instance, Xu et al. (2009) find that in North Carolina, the student turnover rate reached 33 percent in 2004. In Nashville, Tennessee, 8 to 15 percent of elementary and middle school students experienced non-promotional school mobility from 1998 to 2003 annually (Grigg 2012). In New Orleans, for public school students on grades 1-7, approximately 60 percent of students in 2004 and 67 percent in 2011 stayed in the same school (Maroulis et al. 2016). At the national level, 23 percent of middle and high school students changed schools between 1994 and 1996 (Metzger et al. 2015), and around 80 percent of 12-year-old students experienced at least one non-promotional school transfer from 1997 through 2004 (Gasper et al. 2010). Due to the prevalence of school mobility, it is a popular topic that has received substantial attention from scholars in sociology, education, and other social sciences (Alexander et al. 1996; Mao et al. 1997; Hanushek et al. 2004; Burkam et al. 2009).

**Mobility Reasons and Classification**

Students change schools for a variety of reasons (Rumberger et al. 1999; Hanushek et al. 2004; Xu et al. 2009; Burkam et al. 2009; Schwartz and Stiefel 2012). One common reason is that students move due to factors related to schools, such as troubles with teachers or peers in prior schools, desire for schools with higher quality or special programs, and school closures (Hanushek et al. 2004; Xu et al. 2009; Burkam et al. 2009). Students also change schools due to family reasons (e.g. parental divorce, parental job changes, financial issues), which are often accompanied by residential moves (Mao et al. 1997; Burkam et al. 2009). A school mobility study in Chicago in 1992 documents that, 40% of mobile students cited school-related reasons, around 30% changed schools because of a residential move, and the other 30% reported a combination of the two (Kerbow 1996). Based on his review of the U.S. Census reports,
Rumberger (2015), however, reveals that although school mobility reasons vary by time period and location, the majority of school transfers are related to family residential moves.

**Figure 1. Mobility Classification**

[Diagram showing mobility classification]

Based on the aforementioned mobility reasons, scholars distinguish between two types of non-promotional school mobility—strategic moves and reactive moves (Rumberger et al. 1999; Hanushek et al. 2004; Burkam et al. 2009; Schwartz and Stiefel 2012). Strategic moves, also called “Tiebout type moves” by economists, are planned school changes through which students seek to attend higher-quality or better-fitting schools (Hanushek et al. 2004; Schwartz and Stiefel 2012). In contrast, reactive moves are often unplanned and occur due to unexpected family events or disciplinary actions (Rumberger et al. 1999; Grigg 2012). For example, if a student changes school because their parents suddenly divorce, it belongs to a family-related move.
(Rumberger et al. 1999). If a student is expelled by the school because of one’s behavioral problems, it is categorized as a disciplinary-related move (Grigg 2012).

School mobility can also be classified by the timing of its occurrence. In Texas public schools, an academic year can be divided into six 6-week cycles (Mao et al. 1997). School switches between the six cycles are identified as within-year school mobility, whereas school moves that do not fall into the six cycles but occur during the summer are named as between-year mobility. According to HISD transfer policies, students can change schools either in the summer before an academic year or during the school year. Even though both within-year mobility and between-year mobility can be reactive or strategic, moving during the summer is often planned by parents and tends to be strategic, whereas moving during the academic year tends to be reactive (Hanushek et al. 2004). Figure 1 is a graphic representation of the categorization of school mobility.

Confounders of School Mobility and Academic Attainment

Prior literature has documented that students who change schools frequently differ from students who are relatively stable along a number of lines, such as race and ethnicity, socioeconomic status, family structure, English language proficiency, and grade level (Scamman and Eckerling 1989; Alexander et al. 1996; Kerbow 1996; Rumberger et al. 1999; Burkam et al. 2009). Scholars have demonstrated that mobile students are more likely to be racial minorities, homeless, in low socioeconomic status, in lower grade levels, in single-parent families, and to have limited English proficiency (Alexander et al. 1996; Kerbow 1996; Hanushek et al. 2004; Burkam et al. 2009; Reynolds et al. 2009; Fong et al. 2010; Ashby 2010). Some relatively advantaged students also change schools, but they tend to move out of the school district to seek
better schools rather than moving within the school district (Alexander et al. 1996; Xu et al. 2009).

Substantial research has demonstrated that school mobility is associated with negative outcomes, such as achievement decline, grade retention, delinquency, drug use, and mental health problems (Alexander et al. 1996; Xu et al. 2009; Gasper et al. 2012). One crucial question surrounding school mobility is its effect on students’ school achievement. Since the aforementioned characteristics associated with high mobility rate are also causes of low academic performance, many scholars suggest that SES, race/ethnicity or family structures could be the underlying causes of both school mobility and academic achievement (Alexander et al. 1996; Heinlein and Shinn 2000). They argue that background characteristics that cause school mobility might also lead to lower academic performance. In this way, the observed effects of school mobility on school outcomes are predominantly explained by preexisting disparities such as SES and race/ethnicity.

The Independent Effects of School Mobility

With discovery of the confounding factors between mobility and academic attainment, the remaining question with regards to school mobility becomes whether mobility *per se* is harmful if background characteristics are held constant. A few scholars find a spurious relationship between school mobility and school achievement (Alexander et al. 1996; Heinlein and Shinn 2000). They demonstrate that the association between school mobility and academic achievement disappears after controlling for students’ demographic and background characteristics. A majority of existing research, however, has demonstrated that in general there is a negative association between school mobility and students’ academic outcomes (Hanushek et
The term “school mobility” in their works includes both between-year and within-year school mobility. As I have mentioned above, the negative association between school mobility and academic performance is predominantly elicited by preexisting disparities in family SES, race/ethnicity, or other issues (Alexander et al. 1996). However, because most scholars have found that there are remaining effects that cannot be explained by these preexisting disparities, school mobility in and of itself appears detrimental to school outcomes and is worth studying.

Previous scholars provide several mediators that might account for the independent effects of school mobility, such as social networks, peer influence, psychological wellbeing, and school engagement (Coleman 1990; South et al. 2007). According to Coleman (1990), social capital is the social ties embedded in families or communities. Switching Schools, however, might disrupt social networks between students and schools, which make students unfamiliar with the new school environment, new course content, new peers and teachers and eventually result in the decline of school performance (Astone and McLanahan 1994; Alexander et al. 1996; South et al. 2007). Peer effects refer to the influence of peers in schools. More mobile youths are more likely than those who are non-mobile or less mobile to be friends with peers who exhibit delinquency and have worse academic performance (South et al. 2007). Besides social networks and peer effects, there is a third explanation for the negative association between school mobility and worse outcomes for the youth—psychological wellbeing (South et al. 2007). South et al. (2007) argue that children and adolescents are experiencing two unique life stages, and school mobility might cause extra stress for them and threaten “their self-concept and self-esteem” (p.73). Another explanation is related to the third one, psychological wellbeing, which suggests that school mobility might distract students from their study and make them less likely to aspire
toward academic success (South et al. 2007). In an estimate of these mechanisms, South et al. (2007) find little support for the social capital and psychological wellbeing explanations. Rather, they find some differences between mobile and non-mobile students in terms of peer effects and school engagement. Previous literature has also indicated the frequency of school mobility matters. For example, Temple and Reynolds (1999) suggest that the negative effects on academic performance accumulate with each additional school transfer.

Even though many scholars accept the premise that school mobility negatively impacts academic outcomes in general, many argue that switching to higher-quality or better-fitting schools might benefit students’ academic attainment in the long run (Alexander et al. 1996; Hanushek et al. 2004). In other words, it is the resources associated with the new school that contributes to better academic outcomes, rather than the move per se. In this way, the negative-association argument and the positive-association argument are not in conflict, but actually complement each other. It should be noted, though, the positive association only applies to students who transfer to a better school and stay in that school long enough to recover from the transition (Hanushek et al. 2004). For those who move frequently, even if they transfer to better schools consistently, there seems to be not enough time for them to recover from the frequent mobility.

*The Timing of School Mobility*

The timing of changing schools adds more complexities to the effects of school mobility (Mao et al. 1997; Hanushek et al. 2004). Hanushek et al. (2004) states that, “the negative effect of mid-year entry is at least twice as large as the effect of entrants at the beginning of the school year (p.1742).” However, another study by Grigg (2012) suggests that there are no significant
differences between effects of school moves during the summer and those during the academic year. In Grigg’s study, he groups school mobility into four types: during-noncompulsory (voluntary within-year move), during-compulsary (mandatory within-year move, due to disciplinary actions), between-noncompulsory (nonpromotional between-year move), and between-compulsory (promotional between-year move). Grigg (2012) compares during-noncompulsory moves and between-noncompulsory moves, and equates it to the comparison between intra-year mobility and inter-year mobility. Yet, he does not recognize that there might be students who change schools during the summer because of disciplinary actions. In this way, he compares during-noncompulsory moves (include mandatory and voluntary moves) with between-noncompulsory moves (only voluntary moves), which probably narrows the gap between intra-year mobility and inter-year mobility.

*Heterogeneity across Racial/Ethnic Groups*

Although researchers have demonstrated that school transfer does influence youth development, not all students bear the burden of the transition costs equally. Some scholars have attempted to capture the heterogeneity of mobility effects among racial and ethnic groups. Alexander et al. (1996) suggest that school mobility is particularly harmful for racial minority and low SES students. Hanushek et al. (2004) find that, facing the same type of school mobility, black students experience larger academic slip compared to Hispanic and white students. Another mobility study in North Carolina, however, suggests that Hispanic students experience more harmful academic consequences than black students (Xu et al. 2009). Therefore, researchers have not yet reached consensus on which race/ethnic group is most impacted by school mobility.
Moreover, Asian-American students are often ignored by mobility researchers, perhaps because of the relatively small sample size compared to other race/ethnic groups. Even though Asian Americans only make up about 6% of the total U.S. population, they have been the fastest growing (in terms of percentage increase) group in the United States (Lee and Zhou 2015). Previous scholars have documented the academic success of Asian Americans over other race/ethnic groups (including whites), resulting in the “model minority” image (Lee and Zhou 2015). It is important to explore whether school mobility enlarges the achievement gaps among racial/ethnic groups, and whether Asian Americans’ academic advantage persists when they experience school mobility as well. Since prior scholars have not done an adequate job of measuring heterogeneity in mobility effects, the race/ethnic disparities need further investigation.

It should be a note of caution, however, of the limitations of treating Asians and Hispanics as homogenous groups. Previous literature has illuminated the socioeconomic, cultural, and educational diversity within these big categories (Mora 2014; Lee and Zhou 2015). For example, within the broad Hispanic group, Mexican youths exhibit higher rates of school dropout, worse academic performance, and lower college graduation rates relative to their counterparts of Cuban, Colombian, and Nicaraguan descents (Portes and Rumbaut 2001; Vernez and Mizell 2002; Gibson et al. 2004; Ream 2005). Similar situations occur to Asian Americans. While Asian immigrants from China and South Korea tend to have high education levels, professional skills, and ample financial resources, those who migrated to the United States as refugees, such as Vietnamese, do not possess the same advantaged human capital and resources (Lee and Zhou 2015). This demonstrates that even within the same broad race category, there can be very large academic achievement disparities.
Methodological Approaches

There are three major models to analyze the effects of school mobility on student academic achievements, two of which take a one-level (only individual-level) approach. First, some scholars use Ordinal Least-Square (OLS) regression models and only take individual characteristics into consideration (Alexander et al. 1996; Burkam et al. 2009). Second, other scholars realize that only controlling individual characteristics is not enough, since school contexts influence student academic performance. A substantial proportion of studies use fixed effects models (FEM) to control unobserved school characteristics (Hanushek et al. 2004; Grigg 2012; Scherrer 2012; Schwartz and Stiefel 2012). However, there are two main limitations associated with fixed effects models. First, the fixed effects model only controls characteristics that do not change over time, which is inconsistent with the fact that mobile students attend two or more schools. Second, the fixed effects model can only measure within-individual variance but not between-individual variance (Mao et al. 1997; Fiel et al. 2013). However, identifying the school-level factors would be more important for policy makers, since “it can produce policy-relevant estimates while allowing a wider range of research questions to be addressed” (Clarke et al. 2010: 1).

To address the second limitation of fixed effects models, later scholars have adopted a third approach—multilevel models. By using this analytic approach, scholars are able to explore policy-driven research questions and produce relevant suggestions for policy making. Nonetheless, traditional multilevel models cannot avoid the first limitation faced by fixed effects models, namely concerning only one school that students attend (Burkam et al. 2009). Leckie (2009) points out that school mobility studies ignoring the previous schools’ effects would
underestimate the school effects and prevent potential variables from being statistically significant, which eventually will result in inaccurate conclusions and incorrect inferences. As such, to measure the school effects finely, a more advanced model is needed.

A model that can take all the schools attended into consideration is the multiple membership model (MMM). The MMM data structure indicates a multiple membership relationship, that is, the lower-level units can belong to more than one higher-level unit (Leckie 2013). Multiple membership models were originally developed by Hill and Goldstein (1998) and then applied to various disciplines by later scholars (Browne et al. 2001; Chandola et al. 2005; Leckie 2009). For example, MMM has been used to study the illness conditions of patients taken care of by multiple nurses (Leckie 2013). The biggest strength of this model is that it can take all the higher-level units into consideration. More methodological debates can be found elsewhere (Luo and Kwok 2012; Leckie 2013; Rose 2013).

Given the importance and complexity of school mobility, a re-estimation of within-year and between-year school mobility effects is crucial. This study focuses on the Houston Independent School District (HISD), which is one of the biggest school districts in the United States. HISD has a higher average school mobility rate (20.2 percent) than the state (18.2 percent) (Eyewitness News 2012) and especially the nation (10.5 percent) (Rumberger 2015). In particular, there are 13 elementary schools in HISD with extremely high student turnover rates, in which around 40 percent of students change schools throughout the academic year due to family financial reasons (Patrick 2015). Moreover, HISD allows students to attend non-zoned schools, which leads to higher student mobility because the availability of school choice increases school mobility (Fiel et al. 2013). As such, it is important to study HISD and investigate the effects of school mobility
on student academic achievement in this specific site. This study might have significant meaning beyond Houston, since the number of school choice districts has been increasing in recent years (Burkam et al. 2009). In sum, this study mainly seeks to address two research questions:

1. Do the effects of between-year and within-year school mobility on student academic achievement differ? Specifically, do they differ when applying a different model (MMM) to data from a school choice district?

2. Do effects of either type of school mobility vary by race/ethnicity? Specifically, how do they differ for Asian Americans?

Data

I used a combination of four datasets: PEIMS (Public Education Information Management System) data, ADA (Attendance) data, CCD (Common Core of Data), and STAAR (the State of Texas Assessments of Academic Readiness) data provided by Houston Independent School District (HISD). HISD is the seventh-largest school district (out of more than 14,000) in the United States and the largest one in Texas. HISD enrolls 215,000 students in 10 early childhood schools, 153 elementary schools, 37 middle schools, 40 high schools, and 43 combined/other schools (HISD website). The PEIMS data contain student-level demographic characteristics and other background information such as race/ethnicity, gender, date of birth, and grade level. The ADA data involve all the campus IDs that students have attended and how many days they have been enrolled in each school, which allows me to identify whether students have changed schools during the academic year or in the summer. The CCD contains school-level characteristics, such as proportion of students eligible for free/reduced price lunch and total student population. The STAAR data include students’ scores in the STAAR test, which is a
state-required test that replaced the Texas Assessment of Knowledge and Skills (TAKS) in the 2011-2012 academic year. Students have to take the reading and math tests annually from grade 3 to grade 8, take the writing test in grades 4 and 7, science in grades 5 and 8, and social studies in grade 8. In addition, the STAAR test has an English version and a Spanish version. To ensure the continuity of dependent variables, I focused on students who take the English version tests.

Since promotional school transition refers to changing schools with an entire cohort, it is not viewed as between-year mobility (Mao et al. 1997; Xu et al. 2009). For this reason, I dropped students who transitioned from elementary school to middle school, namely, from grade 5 to grade 6. As such, I focused on four cohorts of students who had taken the STAAR tests both in the 2011-2012 and 2012-2013 academic year. In the 2012-2013 school year, these cohorts were grades 4, 5, 7, and 8. In the CCD data, there are some schools without corresponding information, probably due to school closure or other disclosed reasons. With respect to the missing data, I have examined the characteristics of missingness and there don’t appear to be any, thus I assume that there is no significant selection bias in my sample. After addressing all the concerns mentioned above, the total student sample size is 34,299, nested within 202 elementary and middle schools.

**Variables**

The dependent variables in this study are students’ reading and math scale scores in the STAAR test in the 2012-2013 academic year. Potochinick and Mooney (2015) articulate the importance of using reading and math scores as indicators for student achievement, which contain two parts. First, states mainly rely on reading and math scores to estimate students’ school performance; second, reading and math performance are crucial predictors of students’
future labor market outcomes. Additionally, there are two versions of the outcomes of the STAAR test—raw scores and scale scores. While raw scores only estimate how many questions a student has answered correctly, scale scores account for the difficulty level of each test (TEA 2016). Based on this, the STAAR designers proclaim that scale scores are comparable across different tests. For the same reason, I used scale scores instead of raw scores in my analysis. I also used students’ reading and math scores in the 2011-2012 school year as independent variables, in order to control their prior academic performance. To better understand the extent of mobility effects, I standardized the scale scores both in the 2011-2012 and 2012-2013 academic years. Table 1 provides a descriptive summary of the original scale scores and scores after standardization in the 2012-2013 school year.

As Table 1 shows, the average math scale score is slightly higher than the average reading scale score. The math scores also have a larger range and standard deviation relative to the reading scores. After standardization, we can more clearly see that math scores have more variation. For example, the maximum math scale score is around 14 standard deviations higher than the average math scale score.

Table 1. Standardized Reading and Math Scale Scores in the 2012-2013 academic year

<table>
<thead>
<tr>
<th>STAAR test</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reading scale scores</td>
<td>1571</td>
<td>134.6</td>
<td>811</td>
<td>2141</td>
</tr>
<tr>
<td>Math scale scores</td>
<td>1596</td>
<td>157.0</td>
<td>867</td>
<td>3784</td>
</tr>
<tr>
<td>Standardized reading scores</td>
<td>-3.59e-09</td>
<td>1</td>
<td>-5.65</td>
<td>4.23</td>
</tr>
<tr>
<td>Standardized math scores</td>
<td>-1.47e-09</td>
<td>1</td>
<td>-4.64</td>
<td>13.93</td>
</tr>
</tbody>
</table>

My key independent variable is type of school mobility, which includes three categories (1=no school change, 2=between-year school mobility, and 3=within-year school mobility). To construct this variable, first I generated two dummy variables, one for between-year school
change, and the other for within-year school change. The between-year school mobility is identified by comparing the campus ID that the student attended in the last day of the 2011-2012 academic year and the campus ID the student attended in the first day of 2012-2013 academic year. If the campus IDs are different, the variable is coded as 1, indicating the student has changed school during the summer before next academic year, otherwise it is coded as 0. Similarly, the within-year school mobility is identified by comparing the campus ID that students attended in the first day of the 2012-2013 academic year and the campus ID they attended in the last of this school year. If the IDs are different, the student has changed schools during the school year, otherwise not.

Next, I created a categorical variable of school mobility by using the two dichotomous variables. Specifically, I classified students who neither change schools during the summer nor within the 2012-2013 school year as no change, students who only change schools during the summer as between-year changers, and those who only change schools during the academic year as within-year changers.¹

Previous scholars argue the frequency of school mobility also matters, that is, students who change schools more often tend to have worse academic outcomes than those who change occasionally (Xu et al. 2009). The ADA data document all the schools that each student has enrolled in, allowing me to identify the number of school transfers students have experienced.

¹ Note that some students do not only move during the summer, but also move during academic year. This population is relatively small (less than 1%) and the effects of experiencing both types of mobility on student achievements are mainly driven by within-year mobility based on my supplemental analysis. Therefore, I dropped these cases from the sample and leave three major categories (no change, only between-year change, and only within-year change) for the mobility type variable.
According to the data, there are ten reporting periods within one academic year. In each reporting period, the campus ID that students attended and attendance days in that school were recorded. Technically, the school district allows each student to transfer at most ten times within one school year. But no student in my research sample has transferred that many yet, and the maximum number that a student has moved during the 2012-2013 school year is three times, as table 2 shows. Since I have already dropped students who change schools both in the summer and during the academic year, only around 20 students have moved twice or more. Therefore, I did not include the frequency of mobility in my analysis. My other independent variables include race/ethnicity, gender, economic disadvantage status, grade level, limited English proficiency, gifted/talented program and special education status.  

Besides student-level variables, I also controlled for school-level variables, which include percentage of students eligible for free/reduced price and student-teacher ratio. The student-teacher ratios and percentage of free/reduced price lunch eligible students also appear to be

2 Race/ethnicity is documented based on the race identity that the student reported (1=white, 2=black, 3=Hispanic, 4=Asian). Gender is coded as a dummy variable (1=female). Economic disadvantage status and limited English proficiency are also dummy variables. The economic disadvantage category includes students who are eligible for reduced-price lunch, free lunch, and classified as poverty status. The classification of each of these categories is based on the students’ family income (whether below the federal poverty line). A student who satisfies any of the three categories is classified as economically disadvantaged (1=economically disadvantaged). More information regarding how it is calculated can be seen from elsewhere (http://kinder.rice.edu/uploadedFiles/Kinder_Institute_for_Urban_Research/Programs/HERC/PEIMS20Variables%20-%20Table%20of%20Contents.pdf). Grade level is counted by the grade that the student attended, which includes grades 4, 5, 7 and 8. Gifted/talented program indicates whether a student is involved in a gifted/talented program. Special education is for students who have cognitive disabilities.  

3 Originally I also controlled percentage of minority students, but found that it is highly correlated to the percentage of free/reduced price lunch. So I did not include percentage of minority students in my later analyses. The racial composition is similar in most schools, in which Hispanic and black students dominate the student body, and whites and Asians only make up a small proportion.
similar in most schools. In HISD, the percentages of students receiving subsidized lunch are relatively high in most schools. For example, more than 75% of schools have a proportion of free/reduced price lunch eligible students of higher than 85%. Another school variable, student-teacher ratio, is approximately normally distributed and does not have as much variation as the percentage of subsidized lunch eligible students does.

Methodology

In this study, I chose a multiple membership model (MMM) for two reasons. First, each school may have a distinct impact on students, so we cannot assume that each student is randomly selected and thus an independent observation as OLS modeling does. Therefore, it is necessary to take account of effects from different schools. Second, MMM is used in cross-classified data in which lower-level units belong to more than one higher-level unit (Leckie 2013). In this study, higher-level unit implies one or more schools student have attended.

One crucial feature of the multiple membership data structure is that “the degree to which each lower level unit belongs to each higher level unit will often vary across those higher level units (Leckie 2013: 3).” In addition, the degrees often represent different weights of the higher-level units. According to Leckie (2013), there are four ways to define multiple membership weights. First, assigning equal weights to all higher-level units; second, assigning complete weights to one higher-level unit and no weights to other units; third, assigning more weights to certain higher-level units and less weights to other units; and last, assigning weights based on the role played by each higher-level unit. Using different ways to assign weights and then fitting these weights into the multilevel models might result in completely different results. Particularly,
simply assigning weights to just one higher-level unit is what the traditional multilevel model does, which overlooks other higher-level units and would result in misleading conclusions.

In this study, the multiple membership weight is defined as the proportion of days students spent in each school, because I assume that the more time one student has spent in one school, the larger influences the school might have on this student. If a student has not changed schools, it means he/she attends one school for the entire of the 2012-2013 academic year. Therefore, I assigned value 1 to that school for this student. Take another example, a student who has changed school once in the 2012-2013 school year. The student had enrolled in the first school (“A”) for 54 days and in the second school (“B”) for 126 days, the multiple membership weights would be 0.3 (54 days divided by the total enrollment days, which is 180 days) for school A and 0.7 (126 days divided by the total enrollment days) for school B.

Based on the classification notation introduced by Leckie (2013: 45), the multiple membership model can be written as:

\[
y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 \sum_{j \in \text{school}(i)} w_{ji}^{(2)} x_{ji}^{(2)} + \sum_{j \in \text{school}(i)} w_{ji}^{(2)} u_j^{(2)} + e_i
\]

\[
u_j^{(2)} \sim N(0, \sigma_{u(2)}^2)
\]

\[e_i \sim N(0, \sigma_e^2)
\]

In this case, \(i (i = 1, 2, \ldots, 34299)\) represents the student population and \(j (j = 1, 2, \ldots, 202)\) measures the number of schools. Each student or school has its distinct ID number. Where \(y_i\) is the STAAR reading/math score for student \(i\), \(\beta_0\) is the average reading/math score for the entire population. For the \(\beta_1 x_{1i}\), \(x_{1i}\) is the student-level variable with a slope coefficient \(\beta_1\). The fixed part \(\sum_{j \in \text{school}(i)} w_{ji}^{(2)} u_j^{(2)}\) represents the degree student \(i\) belongs
to school $j$ with an associated effect of $u_{j}^{(2)} \cdot \sum_{i \text{school}} w_{j,i}^{(2)} x_{2j}^{(2)}$ is the weighted sum of school-level variables, with a slope of $\beta_{2}$. $e_{i}$ is the residual error, which is the difference between a student’s real score and the predicted score by using the full equation. In addition, $\sigma^{2}_{u(2)}$ is the school variance, which captures the differences between schools once the predictor variables are already controlled. As such, it can also be understood as the school-level residual. $\sigma^{2}_{e}$ is the student variance, which measures how students vary from each other within the same school.

For specific analysis, I followed the common approach used by Burkam et al. (2009: 22), which contain three steps. First, to investigate the “unadjusted achievement differences” between groups, I ran OLS regressions by including the types of school mobility as the single predictor. Second, I used multiple membership models to measure the “adjusted achievement differences” by controlling for student-level and school-level factors related to academic achievement. Third, I estimated the potential different effects of school changes by adding interactions between type of school mobility and race/ethnicity.

**Results**

*Descriptive Findings*

The descriptive analyses of independent variables are shown in Table 2. The sample is dominated by Hispanic students (61.36%), and then followed by blacks (25.97%), whites (8.33%), Asians (3.41%), and others (0.93%). Four out of five students are classified as economically disadvantaged, either living in poverty or receiving a lunch subsidy. Approximately 3 in 10 have limited English proficiency, and 1 in 5 are in a gifted/talented program. As for student mobility rates, around 8.41% of students only changed schools during
the summer before the 2012-2013 academic year, and 1.76% of students only switched schools during this school year. The overall mobility rate (around 10%) in this study is lower than the mobility rate (20.2%) reported by HISD (Eyewitness 2012), that’s because the data I used only include information of students enrolled in HISD. That is to say, information of students who transfer out of HISD is not covered by HISD data.

Table 2: Descriptive Statistics (by type of school mobility)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values</th>
<th>All youth (N=34,299)</th>
<th>Between-year mobility (N=2,883)</th>
<th>Within-year mobility (N=604)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ethnicity</td>
<td>White</td>
<td>8.33</td>
<td>3.82</td>
<td>3.15</td>
</tr>
<tr>
<td></td>
<td>Black</td>
<td>25.97</td>
<td>35.73</td>
<td>44.37</td>
</tr>
<tr>
<td></td>
<td>Hispanic</td>
<td>61.36</td>
<td>57.2</td>
<td>48.34</td>
</tr>
<tr>
<td></td>
<td>Asian/PI</td>
<td>3.41</td>
<td>2.6</td>
<td>3.31</td>
</tr>
<tr>
<td></td>
<td>Other</td>
<td>0.93</td>
<td>.66</td>
<td>0.83</td>
</tr>
<tr>
<td>Economically disadvantaged</td>
<td>Non-disadvantaged</td>
<td>20.09</td>
<td>12.04</td>
<td>8.44</td>
</tr>
<tr>
<td></td>
<td>Disadvantaged</td>
<td>79.91</td>
<td>87.96</td>
<td>91.56</td>
</tr>
<tr>
<td>Gender</td>
<td>Male</td>
<td>49.78</td>
<td>50.71</td>
<td>52.48</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>50.22</td>
<td>49.29</td>
<td>47.52</td>
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<tr>
<td>Grade level</td>
<td>4</td>
<td>25.27</td>
<td>25.18</td>
<td>31.29</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>29.34</td>
<td>27.61</td>
<td>28.18</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>26.06</td>
<td>28.58</td>
<td>23.84</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>19.33</td>
<td>18.63</td>
<td>16.72</td>
</tr>
<tr>
<td>Limited English</td>
<td>No</td>
<td>68.34</td>
<td>68.26</td>
<td>74.83</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>31.66</td>
<td>31.74</td>
<td>25.17</td>
</tr>
<tr>
<td>Gifted/talented Program</td>
<td>No</td>
<td>79.59</td>
<td>87.96</td>
<td>93.38</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>20.41</td>
<td>12.04</td>
<td>6.62</td>
</tr>
<tr>
<td>Special Education</td>
<td>No</td>
<td>96.25</td>
<td>96.36</td>
<td>95.7</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>3.75</td>
<td>3.64</td>
<td>4.3</td>
</tr>
</tbody>
</table>
As Table 2 shows, I also examined how school mobility varies by students’ attributes. With regard to race/ethnicity, black students have the highest mobility rates, followed by Hispanics, whites, and Asians. For example, among within-year mobile students, 44.37% are blacks, which is much higher than their representation (25.97%) in the overall student population. Students who are economically disadvantaged (including being eligible for free/reduced lunch or in poverty status) display a higher tendency to move, as are students not in gifted/talented programs.

Furthermore, students who have limited English proficiency (LEP) do not display higher mobility rates relative to non-LEP students, which is not consistent with prior findings that LEP students tend to move more often (Malmgren and Gagnon 2005; Xu et al. 2009). All these differences by characteristics survive proportional significance tests except for gender and special education, indicating that there are not obvious mobility discrepancies by gender and special education. Overall, the between-year mobility rates are higher compared to within-year mobility rates across various characteristics, which reflects that parents tend to make their children change schools following the academic calendar to minimize the disruption to their normal study paces.

*Unadjusted Achievement Differences*

Before adding other control variables, I ran two regression models to estimate the effects of school mobility on standardized reading and math scores. In Table 3, as we can see in Model 1, between-year school changers have a reading score .239 standard deviations lower than the reading score of non-mobile students, and within-year school changers’ reading scores are .545 standard deviations lower than students who do not change schools. The effects of school
mobility on math follow the same pattern as reading scores, as shown in Model 4. Between-year school changers have a math score .234 standard deviations lower than non-mobile students, within-year changers’ math scores are .556 standard deviations lower than students who stay in previous schools. By comparing the decline of standard deviations in Model 1 and Model 4, we can know that mobility affects students’ math achievement more than reading. In sum, within-year changers have the lowest reading and math achievement relative to between-year changers and stable students. In other words, within-year school mobility negatively affects students’ academic outcomes more than between-year mobility.

Adjusted Achievement Differences

After the regression analyses, I ran two multiple membership models, one for reading and the other for math. As we can see in Model 2 and Model 5, with individual-level and school-level factors controlled, school mobility still negatively impacts student academic achievement. In Model 2, between-year changers have a reading score .031 standard deviations lower than students who do not change schools, and within-year changers’ reading scores are .093 standard deviations lower than stayers. In Model 5, the decreased magnitude of math scores is also larger for within-year school changers than for between-year changers, with other variables controlled. As such, we can conclude that changing schools during the academic year is more harmful to student academic performance than changing schools during the summer.
Table 3: Results from OLS Regression and Multiple Membership Models  
(on Standardized Reading and Math Scores)

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Model 1 Coef</th>
<th>Model 2 Coef</th>
<th>Model 3 Coef</th>
<th>Model 4 Coef</th>
<th>Model 5 Coef</th>
<th>Model 6 Coef</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Constant)</td>
<td>.034</td>
<td>.247</td>
<td>.234</td>
<td>.034</td>
<td>.044</td>
<td>.023</td>
</tr>
<tr>
<td>Female</td>
<td>.021***</td>
<td>.021***</td>
<td>-.014*</td>
<td>-.014*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Hispanic)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>white</td>
<td>.055***</td>
<td>.054***</td>
<td>.066***</td>
<td>.066***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black</td>
<td>-.05***</td>
<td>-.048***</td>
<td>-.036***</td>
<td>-.039***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>.166***</td>
<td>.17***</td>
<td>.277***</td>
<td>.284***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other ethnic group</td>
<td>.023</td>
<td>.021</td>
<td>.149***</td>
<td>.153***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Limited English Proficiency</td>
<td>-.102***</td>
<td>-.101***</td>
<td>-.058***</td>
<td>-.057***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Economically Disadvantaged</td>
<td>-.067***</td>
<td>-.067***</td>
<td>-.042***</td>
<td>-.042***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gifted/Talented Program</td>
<td>.232***</td>
<td>.232***</td>
<td>.332***</td>
<td>.332***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Special Education</td>
<td>-.179***</td>
<td>-.179***</td>
<td>.028</td>
<td>.028</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scores in the Prior Year</td>
<td>.697***</td>
<td>.697***</td>
<td>.611***</td>
<td>.61***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Grade 4)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade 5</td>
<td>-.106***</td>
<td>-.106***</td>
<td>-.011</td>
<td>-.011</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade 7</td>
<td>.189***</td>
<td>.187***</td>
<td>.05**</td>
<td>.046*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade 8</td>
<td>.216***</td>
<td>.215***</td>
<td>.32***</td>
<td>.316***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(no change)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between-year change</td>
<td>-.239***</td>
<td>-.031**</td>
<td>-.032**</td>
<td>-.234***</td>
<td>-.047***</td>
<td>-.047***</td>
</tr>
<tr>
<td>Within-year change</td>
<td>-.545***</td>
<td>-.093***</td>
<td>-.068**</td>
<td>-.556***</td>
<td>-.159***</td>
<td>-.182***</td>
</tr>
<tr>
<td>Percentage of free/reduced lunch</td>
<td>-.003***</td>
<td>-.003***</td>
<td>-.002***</td>
<td>-.002***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Student-teacher ratio</td>
<td>-.003</td>
<td>-.003</td>
<td>.003</td>
<td>.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Hispanic × within-year)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White × within-year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.197</td>
<td>.012</td>
</tr>
<tr>
<td>Black × within-year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.053</td>
<td>.083</td>
</tr>
<tr>
<td>Asian × within-year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.299**</td>
<td>-.396**</td>
</tr>
<tr>
<td>Other × within-year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-.124</td>
<td>-.242</td>
</tr>
<tr>
<td>Between school variance</td>
<td>.011</td>
<td>.011</td>
<td>.036</td>
<td>.035</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Between individual variance</td>
<td>.297</td>
<td>.297</td>
<td>.427</td>
<td>.427</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note: * p< .1, ** p< .05, *** p< .005
The effects of other predictors are almost consistent with previous literature. Females tend to have higher reading scores (around .021 standard deviations higher) and slightly lower math scores (around .014 standard deviations lower) than males given that other variables in the model are held constant. Compared to Hispanic students, blacks have lower reading and math scores, while whites and Asians have higher scores. For reading performance, black students have an average reading score that is .05 standard deviations lower than Hispanics, white students’ average score is .055 standard deviations higher, and Asian students is around .166 standard deviations higher than Hispanic students. For math scores, black students’ average score is .036 standard deviations lower, white students’ score is about .066 standard deviations higher, and Asian students’ math score is .277 standard deviations higher than Hispanic students. Therefore, in HISD schools, black students have the lowest average reading and math scores, whereas Asian students have the highest.

Not surprisingly, limited English proficiency, special education status and economic disadvantage are all negatively associated with reading and math performance, and gifted/talented program status is positively related to both reading and math scores. Limited English proficiency reduces reading scores by .102 standard deviations and math scores by .058 standard deviations compared with non-LEP students. It indicates that limited English proficiency yields more harmful impacts on students’ reading performance than math. Being in a gifted/talented program increases reading scores by .232 standard deviations and math score by about .332 standard deviations relative to non-gifted/talented students. Thus being in a gifted/talented program is more beneficial for math than for reading. Moreover, the average reading score of students who are economically disadvantaged is about .067 standard deviations lower, and the average math score is about .042 standard deviations lower than those who are not
economically disadvantaged. Additionally, the reading and math scores of the prior year are strongly and positively associated with scores in the current year.

I also looked at the score differences between grade levels. While Grade 7 and Grade 8 are positively related to both reading and math scores (especially for Grade 8), Grade 5 is negatively associated with reading scores compared to Grade 4. Based on this finding, we can conclude that on average middle school students have better academic performance than elementary students. As for students in Grade 5 who have worse reading performance (.104 standard deviations lower) than those in Grade 4, it seems difficult to find relevant explanations from prior research.

As for school-level predictors, the percentage of free/reduced price lunch eligible students is negatively associated with student academic achievement. If the proportion of students receiving subsidized lunch increases by 1 percent, the reading scale score decreases by .003 standard deviations and math score decreases by .002 standard deviations. Although the decreased magnitude seems to be small with one percent increase of subsidized lunch eligible students, this could make a large difference when the discrepancy between two schools is large. The student-teacher ratio is not significant both in Model 2 and Model 4, which might be due to the lack of variation in ratios across schools.

Effects of School Mobility by Race/Ethnicity

Burkam et al. (2009) note that “pooling results across settings with positive, negative, and neutral outcomes will often lead to very little overall differences” (p.8). As such, it is necessary to explore how the effects of school mobility vary by different types of groups, rather than focusing on the main effects of school mobility. To estimate whether the effects of school
changes on student academic performance differ along racial lines, I added interaction terms between types of school mobility and race group into the original multiple membership models. Following the rule of model parsimony (Aiken et al. 1991), I eliminated interaction terms that are not statistically significant. The remaining interaction terms include within-year school mobility and race/ethnicity, indicating the harmful effects of between-year school mobility do not vary across race groups.

In Model 3, the interaction term between Asian and within-year change is negative and significant at the .05 level, indicating that within-year school mobility reduces the reading scores more for Asian students relative to Hispanic students. The interaction terms between white or black and within-year mobility are not significant, revealing that within-year mobility affects Hispanics, blacks, and whites to similar degrees. In Model 6, the interaction term between Asian and within-year school change is also negative and significant, suggesting that within-year change impacts Asians’ math performance more relative to Hispanic students. The interaction terms are not significant for whites and blacks, indicating the harmful effects of within-year mobility are almost the same for Hispanic, black, and white students.

To reveal the disparities of academic performance among race and ethnic groups more clearly, I plot the predicted scores based on the full models (Model 3 for predicted reading scores and Model 6 for predicted math scores). Figure 2 presents the predicted reading scores by types of school mobility across race/ethnicity. Among stayers, Asian American students have the highest academic performance. But once Asians experience intra-year mobility, their academic achievement is most impaired. Other racial/ethnic groups are not negatively affected by within-
year mobility as much as Asians. Similar patterns can be observed in Figure 3, which reflects the predicted math scores across racial/ethnic groups.

**Figure 2. Predicted Reading Scores (by type of school mobility and race)**

![Graph showing predicted reading scores by type of school mobility and race.](image)

**Figure 3. Predicted Math Scores (by type of school mobility and race)**

![Graph showing predicted math scores by type of school mobility and race.](image)
**Discussion and Conclusion**

Consistent with Hanushek, Kain, and Rivkin’s (2004) findings, this study demonstrates that both within-year and between-year school mobility are harmful to students’ reading and math scores, but the former yields more detrimental effects than the latter. In addition, I found that while the effects of within-year school mobility vary across race/ethnic groups, the effects of between-year mobility do not. Furthermore, even though black students have the highest mobility rate, within-year school mobility has similarly negative effects on academic attainment for Hispanic and black students.

An unexpected finding in this study is that Asian students are set back most by within-year school mobility. To gain a sense of the mechanisms behind this finding, I took a closer look at the attributes of Asian students who change schools during the academic year. There are two possible explanations for this phenomenon. First, I found Asian students have the highest percentage of being foreign-born among all within-year mobile students. After I added immigration status into the models as a control variable, the negative effects of within-year school change decrease slightly for Asians. For this reason, I suggest that immigration status exacerbates the negative effects of school mobility. Immigrant children probably have more difficulty adjusting to new school environments due to language barriers and cultural differences. Second, it is possible that mobile Asian students tend to be lower performing and from lower-SES backgrounds, since there is significant difference among Asian subgroups (Lee and Zhou 2015). While the average academic performance for Asians is high, a small number of Asian students are relatively mobile and do not possess the same advantages as their non-mobile counterparts.
Another finding is that reading and math scores are compromised unequally by school mobility. Specifically, students’ math performances are impacted more by school mobility than their reading performance. Previous scholars (Kerbow 1996; Swanson and Schneider 1999) suggest that learning mathematics is a cumulative process and thus more sensitive to disruption of course instruction, while literacy instruction is relatively flexible. This evidence probably explains why school changes yield more negative effects on students’ math performance than reading.

Since the data only include information of students enrolled in Houston Independent School District, I am not able to examine students not in HISD before the 2012-2013 academic year and those who moved out of HISD during the 2012-2013 school year. In other words, this study only estimates intra-district school mobility and does not concern between-district mobility. On the one hand, we can conclude that even changing schools within the same school district, mobile students do have lower achievements in state-required tests. These findings echo Fitchen’s (1994) contention that “even a short-distance move may take a child into another school district with fundamentally different teaching approaches, methodology, and basal texts (p.427).” On the other hand, we should be cautious to generalize these findings to between-district or long-distance school transfers.

There are several limitations in this study, which also serve as suggestions for future studies on school mobility. First, since the 2012-2013 academic year is the sole year that both ADA data

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4 By comparing the students IDs in the end of the prior academic year and student IDs in the beginning of the 2012-2013 academic year, I found almost 12 percent of the students left Houston Independent School District during the summer before the 2012-2013 academic year.
and STAAR data are available, this study only examines the short-term effects of school mobility. Previous scholars have demonstrated that the negative effects from mobility might diminish with more accommodation to the new environment, and in the long term students would recover from school changes (Mao et al. 1997; Hanushek et al. 2004). Kain and O’Brien (1999) also state that even strategic moves would appear costly if researchers only examined achievement right after the move. It is quite likely that the negative mobility effects dampen over time for students in this study. Therefore, we can only conclude that changing schools has immediate effects on test scores following the move, and the longer-term effects need further investigation once more waves of data are available. Second, for the same reason, non-mobile students in this sample might have changed schools the year earlier, which mitigates the discrepancy between mobile students and non-mobile students in the study.

Third, prior researchers state that school changes are often accompanied by residential moves (Alexander et al. 1996; Swanson and Schneider 1999; Gasper et al. 2010). The two types of mobility involve different adjustments, one is to schools and the other is to neighborhoods. As such, they attempt to distinguish school mobility from residential mobility and find that the two types of mobility have different impacts on children. Due to the difficulty of identifying whether students in my sample have changed residence, the neighborhood effects and residential mobility effects are beyond the scope of this study.

Last but not least, according to previous research, family factors are strong predictors of student academic achievement and school mobility (Gasper et al. 2010). For example, mobile children are more likely to change schools due to family reasons rather than school reasons (Burkam et al. 2009). However, there is not enough family information in HISD data, except for
the economic disadvantage predictor, which is not a good proxy for socioeconomic status. As a result, I am not able to control family factors in this study. Therefore, future educational research using HISD data could consider incorporating other data sources that include family-related factors, such as parent occupation and family structure.

Implications

Overall, this study has practical implications for both parents and policy makers. Since within-year school mobility is more harmful, policy makers should implement strategies to reduce within-year school mobility or mitigate its negative effects. If school mobility is unavoidable, such as when a student experiences eviction and thus has to move to somewhere else, the only thing schools could do is to alleviate its disadvantageous outcomes. For example, districts could establish standardized curriculum across all schools or provide proper adjustment programs for mobile students (Nelson et al. 1996; Hanushek et al. 2004).

If a school move is avoidable, schools should put more effective strategies in place to address school mobility. Given the more severe consequences of within-year school mobility, the policies should target students who change schools during the academic year specifically. The Home Field Advantage program, active since May 2014, is such an initiative to reduce within-year school transfers, which was implemented in 13 HISD elementary schools with high student turnover rates. This program allows students who change residence during the academic year to stay in their original schools and assists them with transportation if their new address is more than two miles from the campus. The program has been documented to reduce the student turnover rates from more than 30 percent to around 20 percent on average (HISD News Blog 2015). The effectiveness of the HFA program, however, remains uncertain. Specifically, did
mobility rates also decrease for other schools not implementing the HFA program? Was the reduction of school mobility rates of these 13 schools due to the program *per se* or larger context changes? If school mobility rates also declined in other schools, it is hard to conclude that the HFA program creates educational stability for students. As such, to adequately measure the role of the HFA program, a more thorough investigation of whether this program helps to reduce school mobility needs to be done.

Additionally, the question of whether the program mitigates the negative effects of within-year school mobility requires further inquiry. Previous studies have paid attention to whether similar programs reduce school mobility (Fiel et al. 2013), but research has rarely been conducted on whether these programs produce positive effects on student academic achievement. Scholars have found that high mobility rates not only directly affect the mobile students, but also bring negative consequences to their non-mobile peers, teachers, and the school environment at large (Burkam et al. 2009). Therefore, future research following up this study could focus on the effects of the HFA program on student academic performance, besides its direct influence on school mobility. By having a better understanding of the HFA program, policy makers can decide whether to continue this program or extend it to other schools in the district.

Finally, one other thing to note is that schools alone cannot resolve the school mobility issue. As I have mentioned, some students may change schools because they have experienced an eviction. In this case, school mobility is unavoidable and the aforementioned strategies would not achieve their purposive goals. Therefore, school districts could consider collaborating with the city government or housing market agents to establish relevant housing policies that benefit families with school-age children. For example, leasing should be a year so that families would
not get evicted during the middle of the academic year. In sum, given the negative impact of school mobility, policy makers should work together at all levels to address this issue.
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