The Relationship of Mobility, Child Characteristics and School Characteristics to the Academic Achievement of Third Grade Students in a Predominantly Latino District

John Christopher Hicks
Old Dominion University

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ABSTRACT

THE RELATIONSHIP OF MOBILITY, CHILD CHARACTERISTICS AND SCHOOL CHARACTERISTICS TO THE ACADEMIC ACHIEVEMENT OF THIRD GRADE STUDENTS IN A PREDOMINANTLY LATINO DISTRICT

John Christopher Hicks
Old Dominion University, 2014
Chair: Katharine Kersey

The high rates of mobility in the U.S. can produce negative consequences for children’s academic achievement. The purpose of this study was to determine relationships among math and reading academic achievement, mobility characteristics, student characteristics, and school characteristics in order to develop a model to predict achievement using these variables. Using such a model, educational stakeholders could identify students that are at risk for academic failure. The study included 523 third grade students from a high poverty, predominantly Latino, suburban district. Correlation analyses, factor analyses, ordered linear regression, and forward regression analyses were used to determine the relationships among variables as well as the power of variables to predict math and reading Transitional Colorado Assessment Program scale scores (TCAPSS).

In the correlation analyses, four predictor variables (including one mobility variable) had significant correlations with math TCAPSS, while six predictor variables (with no mobility variables) had significant correlations with reading TCAPSS. An initial factor analyses showed that the variables in the study had low proportion of variance that could be caused by underlying factors. A factor
analysis, therefore, was not considered useful for building a model, and was not conducted.

The single block and ordered two set block regression analyses revealed that student characteristics, as a block of variables, significantly predicts TCAPSS for both math and reading, while mobility characteristics did not.

A forward regression analysis was conducted to determine the best model for predicting TCAPSS. In the math regression, six variables (including two mobility characteristics) were accepted into the model, reaching a low predictive value (adjusted $R^2 = .21$). In the reading regression, four variables (with no mobility variables) were accepted into the model, also reaching a low predictive value (adjusted $R^2 = .26$).

The conclusions of this study are that most mobility characteristics are not useful as predictors of academic achievement for the population of this study when student characteristics are present or absent. However, two binary mobility variables, moving to a better school ($R^2$ change $= .006$) and moving between school years ($R^2$ change $= .008$), were accepted in the math forward regression model with small but significant predictive value.
This dissertation is dedicated to my brothers Van and Luke, whose resilience in times of trouble has been a source of inspiration for me, and who are such awesome and interesting characters that I am inspired to be one myself.
ACKNOWLEDGEMENTS

To Dr. Katharine Kersey for many reasons, among them for her unwavering belief, and for her wondrous example of how to be. To Dr. Dwight Allen, a master encourager and engaging thinker who started me on this path and who has been a friend and mentor ever since. To my committee, who deserve every bit of praise I can muster. To my family and friends, who were always fully supportive of me, even when I was, at times, absent and aloof with the rigor and travails of this pursuit. Finally, to my wife, Jennifer Stevenson, who was kindly peeping over my shoulder the whole way, and who shared with me the difficulties of this journey. Ich bin täglish dankbar für dich, schatzy!
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CHAPTER 1
INTRODUCTION TO THE STUDY

Student mobility is common throughout the world (Rumberger, 2003; Wasserman, 2001) and is predicted to expand and increase into the future (Schoen and Fusarelli, 2008). Many studies have determined that American students frequently change schools as well (Burkam, Lee, & Dwyer, 2009; Pribesh and Downey 1999; Rumberger, 2003; South and Haynie, 2004). Many studies have looked at the extent of mobility and found it to be very prevalent. Ligon and Paredes (1992) found that many districts in the United States have only 30-40% of the student population enrolled in a single school for the entire academic year. Rates of mobility can depend, however on location and demographics. For example, Rumberger (2003) found that mobility rates are high among large, urban, and predominantly minority districts. In addition, the U.S. Government Accountability Office (Ashby, 2010), found mobility to be highest among disadvantaged children at the elementary schools, and that schools in the South and West regions of the U.S. have high mobility in the highest percentage of schools. Ashby (2010) also found that, among a cohort of kindergarteners that were followed for eight years, 31% percent had changed schools once, 34% had changed twice, 18% had changed three times, and 13% had changed four or more times. The study also found that close to 11.5% of schools serving K through 8 have at least 10% of students leave during the year.
If mobility had no effect on student achievement or well being, it would not be worthy of study. However, the literature has shown that it does indeed have wide ranging and varied effects. Mehana and Reynolds (2004) estimated a 3-4 month performance disadvantage in math and reading for mobile students. Many other studies have confirmed that student mobility has a negative effect on student academic achievement with varying degrees of impact (e.g. Bruno & Isken, 1996; Temple & Reynolds, 1999; Heinlein & Shinn, 2000; Hanushek, Kain, & Rivkin, 2004; Scherrer, 2013). With high mobility rates and likely negative academic outcomes from mobility, educational stakeholders can use a greater understanding of its effects and how it relates to the child demographics.

Statement of the Problem

The prevalence of mobility in American schools poses serious problems not only for mobile students, but for their schools, teachers, and non-mobile peers (Fleming, Harachi, Catalano, Haggerty, & Abbot, 2001; Gasper, DeLuca, & Estacion, 2010, 2012; Kerbow, 1996, Parke & Kanyongo, 2012; Rumberger, 2003; Temple & Reynolds, 1999). In schools, high mobility promotes chaos, decreases teacher morale, and increases administrative burdens (Rumberger, 2003; Rumberger et al., 1999). Children in high mobility schools show weaker academic performance, higher dropout rates, and lower levels of school attachment (South, Haynie, & Bose, 2007). In the classroom, high mobility compromises long-term planning, and leads teachers to a more generic teaching
approach (Lash & Kirkpatrick, 1990). In addition, teachers review more and slow
the pace of instruction (Kerbow, 1996). Mobility effects are worse for minority
and poor students, which exacerbates the socioeconomic achievement gaps
(Hanushek et al, 2004). To make matters worse, reforms that are put into place
to overcome these gaps assume that students will stay for the reforms to take
effect, yet reform districts often have the highest rates of mobility (Kerbow, 1996).

The impact of many at-risk characteristics, including low social and
economic status and English Language Acquisition, has been the focus of
multiple studies. Mobility is one subcategory of risk factor that has been studied
more recently as well, but only as a single variable with few interacting
characteristics, very rarely looking at the varied influence of the multiple aspects
of mobility. The literature suggests that mobility has many aspects that have
varied and, at times, opposite effects on academic achievement.

For instance, earlier moves tend to have greater negative effects than
moves after third grade. Children who move during the first three years of school
are more likely to be negatively affected by mobility, with the negative impact of
mobility diminishing with increasing grade levels (Levine, Wesolowski, & Corbett,
1966; Ingersoll, Scamman & Eckerling, 1989; Schuler, 1990; Reynolds, 1991,

Moves during the school year (non-promotional moves) have negative
effects on student achievement while moves between school years (promotional
moves) do not produce the same effect (Hanushek, Kain, & Rivkin, 2004). Non-
promotional school changes have a stronger negative impact than promotional
school changes even when previous achievement and background characteristics are controlled (Xu et al, 2009; Rumberger, 2003:6; Rumberger & Larson, 1998; Mehana & Reynolds, 2004).

Moving to a better school can ameliorate the negative consequences of mobility (Judy & Arthur, n.d.). Cross-district moves, which are most often to better schools, are often “strategic moves” instigated by parents wishing for a better academic situation for their child, whereas school moves within a district (“reactive moves”) are related to low achievement scores (Wright, 1999; Hanushek, Kain, & Rivkin 2004; Rumberger, et al. 1999; Xu et al, 2009). In addition, multiple moves can have greater negative effects. Students that move frequently often fall further and further behind their peers (Alexander, Entwisie, & Dauber, 1996; Nelson, Simoni, & Adelman, 1996).

The impact of mobility can depend on the characteristics of the student and his/her family. Children who are part of an ethnic minority are more likely to be negatively affected by mobility (Hefner, 1994; Levine, Wesolowski, & Corbett, 1966; Astone & McLanahan, 1994; Ingersoll, Scamman & Eckerling, 1989; Schuler, 1990; Reynolds, 1991, 1992). Special education services can be interrupted or discontinued when a family moves (Cornille, Boyer & Smyth, 1983). Meanwhile, highly mobile students are more likely to be poor, more likely to be ethnic minorities, and more likely to be in a single-parent home (Titus, 2007). Xu et al (2009) also found that mobility rates between English learners and fluent English speakers varied from 7 (for a cohort in 2000) to 14 percentage points (for a cohort in 1997). The gender of the student can matter as well.
Some studies (Reynolds, 1991; Pillen et al, 1988) have found that mobility has very different effects on boys and girls.

The previous academic achievement of the student matters. Many studies have found that mobile students are likely to be low achieving, even before their mobility manifests (Alexander et al., 1996; Nelson et al, 1996). Controlling for previous academic effects and other covariates, studies have found mobility effects on academic achievement to be insignificant (Parr, 2010; Bollenbacher, 1962; Whalen & Fried, 1973), small but significant (Gasper, DeLuca, & Estacion, 2010; Strand & Demie, 2006; Temple & Reynolds, 1997; Paik & Philips, 2000) or significant (Herbers et al, 2012; Judy & Arthur, n.d.; Scherrer, 2013; Dunn et al, 2003).

The effects of mobility on reading and math scores can differ. Some studies have shown that mobility has a negative effect on both reading and math achievement (Engec, 2006; Hattie, 2009; Mehana & Reynolds, 2004; Strand & Demie, 2007; Temple & Reynolds, 1999). Some showed greater effects for reading (Juel, 1988; Vellutino, Scanlon, & Spearing, 1995). Still others showed greater effects for math achievement (Grigg, 2012; Kerbow, 1996).

All of these various aspects of mobility, in conjunction with student and school characteristics, can have an impact on student achievement, but until now have been rarely studied with a full range of student, school and mobility variables in the study. The nationwide emphasis placed on student academic achievement, as measured by each state’s standards-based assessment, makes
a study of the relationships among these very timely for addressing student needs that may have been overlooked until now.

**Purpose of the Study**

Because of the varied effects of the many covariates of mobility and related student characteristics, it is only possible to get an accurate picture of the effects of mobility by including these variables in a study to determine their relationships and to see what extent each one influences academic success. The mobility characteristics that have been shown to have significant effects, and that could be included in such a study are: the number of moves, the timing (how early in the academic career the moves were), whether the moves were during the school year (non-promotional) or between school years (promotional), and whether the move was to a better or worse school. Student characteristics that have been shown to have an effect on academic achievement via mobility are: poverty, special education, English language status, gender, race, and previous academic achievement. In addition, the effects on academics can differ between math and reading achievement.

This study proposes using the aforementioned variables in a single study to determine if certain mobility and student characteristics stand out from the rest. The statistical model from this study could be used by district stakeholders to “red flag” a student with the determining characteristics that make him more likely to fall behind academically. To this purpose, this study proposes to determine the significance of the effects, if any, of student mobility on academic
achievement (operationalized as standards-based scores), while including the numerous aspects of mobility and student variables that have been shown to have some explanatory power.

**District Demographics and Characteristics**

The district studied (known from this point on by the pseudonym *Jackson District*) is a small satellite district of a major city in Colorado, in which 84% of its students qualify for free and reduced lunch, 23% live below the poverty line, and 55% are English Language Learners. Thirty-one percent of the students are mobile and almost 10% are classified as homeless. Eighty-three percent (83%) of the students are Hispanic. The graduation rate is 52% (Adams 14, 2013), compared to a state average of 76.9% (CDE, 2013).

The proposed sample of study is the entire third grade cohort of students from the school year 2012-13 with a total sample number of third grade students of over 500 students. In the year 2012-13, the *Jackson District* as a whole was in the third year of an “Accredited with Turnaround Plan” status (Colorado Department of Education, 2012) with two high schools in year three of priority improvement / turnaround status, one middle school in year two of priority improvement / turnaround status, and one elementary school in year three of priority improvement / turnaround status (CDE, 2012).

Determining the effects of the many variables related to mobility can have a very real and immediate impact on how this district addresses the needs of
highly mobile students. Administrators can pinpoint severely at-risk students with outstanding needs based on their multiple mobility variable statuses and put policies into place that support those specific at-risk students.

**Research Questions**

Research Question 1: What are the relationships among mobility, student and school characteristics within a district to third grade *math* achievement?

Research Question 2: What are the relationships among mobility, student, and school characteristics within a district to third grade *reading* achievement?

**Hypotheses**

The first hypothesis is that moves to poorer academic schools, moves earlier in a child’s academic career, repeated moves, and non-promotional (during year) moves have a stronger negative relationship with student academic achievement.

The second hypothesis is that mobility has a stronger negative relationship with academic achievement when students are males, minority status, English language learners, or are in special education.
Design & Methods

Design

An ex post facto, correlational, quantitative design was used to investigate the relationships among academic achievement, student characteristics, mobility characteristics, and school characteristics in a largely Hispanic suburban school district. The study used existing data to investigate the research questions.

Analysis

Following binary coding for categorical variables, the following statistical analyses were conducted:

1. Pearson Correlation coefficients to investigate relationships among all variables
2. Factor analysis to describe variability among the predictor variables and to produce a lower number of factors for the regression analyses
3. Single linear (block entry) regression between mobility predictor sets and the academic achievement criterion variable
4. Ordered linear (block entry) regression method entering student characteristics first, and mobility characteristics second, then a
second ordered linear (block entry) regression entering mobility characteristics first, and student characteristics second.

5. Forward regression analysis in which the first variable entered was the one with the largest positive or negative correlation with the criterion variable (Math/Reading TCAPSS). Then, the next predictor variable entered has the largest partial correlation. This process continued until no variable is left that meets the stiff entry criterion, as computed using the Bonferroni method to avoid overfitting. In other words, variables were added to the model until none were left that improve the model.

**Measures**

Math and reading academic achievement were both measured using the state standards-based assessment, the Transitional Colorado Assessment Program (TCAP). The scale scores (TCAPSS) range from 150 to 795, and were used as a proxy for academic achievement. Student, school, and mobility characteristics were taken directly from the district database with coding processes described in detail in Chapter 3.

**Reliability and Validity**

The CDE technical report (2013) determined that the state wide TCAP tests had acceptable reliability and validity. The total test reliability coefficients
(Cronbach's alpha) for all state TCAP assessments ranged from .86 to .94, all above .80, and therefore were considered to be of sound reliability. In addition, several tests were run to ensure content and construct validity using various methods, including the Linn-Harnisch DIF Method, Item Local Independence (IRT) Models, and others.

Data collection

The school district supplied the requested student and mobility data in a single file, which was then used as a basis for coding the student and mobility variables. Data on school TCAP performance were collected from CDE (2013) records and out-of-state and international school performance comparisons were collected from the NCES reports (2012, 2013).

Limitations

This study did not attempt to determine effects beyond third grade test scores, focusing solely on mobility in the younger grades of elementary school.

The study did not seek to determine the specific individual reasons for student moves via questionnaires, a worthwhile qualitative study that is not the focus of this study.

The study focused on school mobility, not residential mobility.
School based comparisons used available data to determine school quality. However, accurate and thorough school comparisons are a very complicated pursuit in and of themselves, and, in absence of more exact procedures, this study used simplified methods for comparing schools that each student moved to and from. The coding for differences in quality of schools that a child move to and from uses school-based TCAP percentages of students who score proficient or advanced on the math or reading assessments. Comparing schools in such wise simplifies the assignment of a school with the label “better” or “worse” to a simple formula using only child performance on the state standardized tests as a measure. Thoroughly comparing the 125 state, 35 inter-state and 20 international schools that children moved from in this sample would be a study of immense scope, and is beyond the focus of the present study.

Previous academic achievement was not controlled for in this study. Instead, relationships were determined within each mobility and student characteristics and academic achievement, operationalized as TCAP scores.

Avoiding the “dummy variable” trap necessitated the omission of one variable in each of the binary variable sets. The variable excluded was chosen as least important to the study, though such a decision could vary depending on the focus and intent of a study.

No causal relationships can be determined from this correlational study.

The focus of this study is on a single district with high poverty, high English language acquisition, and a high percentage of Latino students, which cannot be generalizable to populations with different demographics.
Assumptions

The first assumption is that high mobility trends will continue in the United States, keeping the challenges related to mobility in the fore.

The second assumption is that an understanding of the combination of student and mobility characteristics could help school districts to address individual student needs and lead to greater academic achievement.

The third assumption is that high stakes standardized testing, begun by NCLB, will continue to be the law of the land throughout the United States and that at-risk characteristics will continue to be required in outcome reports.

The fourth assumption is that at-risk populations will continue to be singled out within high stakes testing for Annual Yearly Progress consideration.

The fifth assumption is that mobile students could be recognized in their own at-risk category within NCLB reporting if mobility was determined to have a significant individual effect, and therefore highlighting the difficulties that mobile students have and improving the likelihood of direct interventions to assist them to improve their academic achievement.

The sixth assumption is that the third grade Latino students in this study are representative of other Latino children living in the U.S.

The seventh assumption is that mobility in later school years (beyond the K-3 scope of this study) may have a very different relationship with academic achievement than mobility in the earlier years.
Significance

The strong emphases on academic achievement and standards-based assessments in the U.S. have caused public schools to search for ways to raise scores and improve achievement for all their students, regardless of race, gender, language, or special education status. A growing Hispanic and Spanish-speaking population (U.S. Department of Commerce, 2000a) within many schools has brought different challenges to schools striving to meet that goal. With high mobility rates a consistent reality as well, this study addressed the very real concerns that education stakeholders have by creating a model that can identify students that are at risk of academic failure beyond simple demographic descriptions.

Operational Terms

Mobility

For the uses of this study, mobility will be defined as a change in school enrollment from one school to another, and not a residential move.

During Year Move

A During Year Move is a non-promotional move to a different school during the school year.

Between Year Move
A Between Year move is a move to a different school between school years.

Transitional Colorado Assessment Program (TCAP)

TCAP is the standardized assessment that the Colorado Department of Education requires students in public schools to take to meet NCLB requirements.

Academic Achievement

TCAP math and reading scale scores (TCAPSS) are operationalized to be a proxy for academic achievement.
CHAPTER 2
LITERATURE REVIEW

Introduction

Student mobility has been an ongoing problem in the U.S., and is trending to continue so. Even so, it is not a one dimensional issue. Its effects can differ depending on a large host of factors, from the timing and direction of the move, to the students' characteristics, to the schools within which they study. This review will look at the most prevalent dimensions of mobility to get a clearer picture on the scope of the problem.

Prevalence of Mobility

As was stated in the introduction, many schools and districts in the U.S. have high rates of mobility (Rumberger, 2003; South & Haynie 2004). Some districts report that only 30% of their students remain their original school for the whole year (Ligon & Paredes, 1992). The problem is predicted to expand and increase into the future (Schoen & Fusarelli, 2008).

Mobility rates are highest among disadvantaged children (Ashby, 2010) and in large, urban, and predominantly minority districts (Rumberger, 2003). Mobility remains a very real problem for American schools to manage, with the
districts, schools and teachers with the lowest performing, poorest, and fewest native English-speaking students also dealing with the highest rate of mobility.

Many urban districts, like the one in this study, have extremely high mobility rates. The turnover rate (percent moving in or out during the school year) in the Los Angeles Unified School district in the 1990-91 school year exceeded 40% (LAUSD, 1991). In 1993-94, Chicago public schools had only 80% of its students remain in one school during a single year, while 46% remained in one school over four years (Bryk, Thum, Easton, & Luppescu, 1998). Mobility rates can vary widely. Among suburban and urban schools, they can range from a high of 60% to a low of 5% (Rumberger & Thomas, 2000). Even when a district has a high mobility rate overall, there can be considerable differences among individual schools (Kerbow, 1995).

Most moves by families are within the same school system, with a radius of five miles or less (Mantzicopoulos & Knutson, 2000). Inter-district moves do happen, though they are relatively rare compared to within-district moves, and are usually ‘strategic moves’ by more well-to-do families that are consciously choosing to move to better schools. Because of the beneficial nature of these inter-district ‘strategic moves’, the present study did not include such moves in its analysis.
NCLB and Districts with High Mobility

The No Child Left Behind Act (NCLB) (P.L. 107-110, 2002) calls for universal proficiency and competence for all children by 2014, and Adequate Yearly Progress (AYP) each year leading up to that goal. Because they are not reaching AYP, many districts find themselves labeled as “needing improvement” and are in danger of multiple state-imposed measures, including faculty and administrator replacement, chartering, and/or takeover by state departments of education (USDOE, 2003). Both large and small districts have been taken over by states or mayor’s offices, and yet the outcomes of these takeovers are not universally positive (Black, 2008).

About one-third of schools nationwide that did not make AYP goals did not do so for students of limited English proficiency (LEP) or for those with disabilities (Le Floch et al, 2007). In 2005, 13 percent of the nation’s schools were identified for improvement, and were more likely to high-poverty, high-minority, urban schools that have historically received Title I resources (Le Floch et al, 2007). As stated earlier, these high-poverty, high-minority districts and schools have much higher mobility rates than suburban, affluent, and majority white schools, giving added urgency to any study that addresses the difficulties of such high mobility districts.
Mobility’s Negative Effects on Schools

Mobility affects not only the individual who moved, but the students in the classroom where he moved. Impoverished schools tend to have higher mobility rates and negative correlations between mobility and achievement (Thompson et al, 2011) while schools with little or no student mobility tend to have higher achievement (Audette & Algozzine, 2000). Student transfers into the classroom can reduce teaching efficiency and lower scores on achievement measures (Rumberger, Larson, Ream, & Palardy, 1999). Many studies have found that high student mobility disrupts the learning environment in the school at large as well as the classroom (Lash & Kirkpatrick, 1990; Kerbow, 1996; Hanushek, Kain, & Rivkin, 2004; Rumberger, 2003, 1999; Smith, Smith, & Bryk, 1998; Heywood & Thomas, 1997). Scherrer (2011) suggests that student characteristics might lead to a school to have high mobility rates when achievement is dependent on higher percentages of its students being stable. Additionally, the pace of instruction in schools with high mobility is slower than schools with high stability (Smith, Smith, & Bryk, 1998). Mobility’s effects reach further than the single student, but to school functioning as a whole. Because these schools are also most often associated with low socio-economic status and the host of problems that come along with such status, studying the mobility problem within such schools is an important factor in alleviating the negative effects of mobility.

Mobility brings a host of problems that create both individual and collective challenges. Principals consider high student mobility one of the main obstacles
in applying high standards for all students (Smith, 2005). Thompson et al (2011) found that in schools that did not make AYP, the grade levels most affected by the requirements of AYP had stronger relationships between mobility and achievement. Many school factors also contribute to student mobility: class sizes, overcrowding, the academic climate of the school, and suspension and expulsion policies (Rumberger, 2002).

School and Residential Mobility

Changing schools and changing residences is not necessarily the same thing. Many studies have found school mobility to be associated with low academic achievement (Alvarez, 2006; Hinz, 2003; Kellam et al., 1975; Audette, Algozzine, & Warden, 1993; Leventhal & Newman, 2010; Obradovic et al., 2009). Moving from residence to residence also significantly impacts students' schools achievement (Kaase & Dulaney, 2005), while children who have moved residences three or more times with their families have much lower test scores than children whose families never moved (NAEP, 2002). Lesisko and Wright (2009) also found that native (non-moving) students had significantly higher scores than transient students in both math and reading scores from grades three to six. A rare advantage for mobile students appears in teacher ratings for social-emotional maturity. Reynolds (1991) found that children who have been in class longer have been shown to rate the "known" students harsher, giving mobile students higher marks for social-emotional maturity.
At times, moving residences can mean moving schools as well, but it is not a given. The present study looks at school mobility, not residential mobility, as it has been the focus of most studies in the literature.

Retention

In addition to lowering academic achievement, other studies have found that mobility increases grade retention (Alexander, Entwisle, & Dauber, 1996; Wood et al., 1993; GAO, 1994; Reynolds, Mavrogenes, Bezruczko, & Hagemann, 1996; U.S. General Accounting Office, 1994; Wood, Halfon, Scarlaia, Newacheck, & Nessim, 1993; Simpson & Fowler, 1994; Wood et al., 1993), and can even harm student health and nutrition (U.S. General Accounting Office, 1994; Wood, Halfon, Scarlaia, Newacheck, & Nessim, 1993). Students can suffer socially and psychologically from mobility as well (Rumberger, 1999).

Drop Out

Mobility can increase the likelihood of dropping out of school before graduation. Even when half the association between dropout and switching schools is explained by characteristics observed prior to the ninth grade (Gasper, DeLuca, & Estacion, 2012), switching schools still maintains an association with dropout. The loss of important social relationships contributes to the increased risk of dropping out of high school (Haveman, Wolfe, & Spaulding, 1991; Astone
and McLanahan 1994; Smith, Beaulieu, & Seraphine 1995; Hagan, MacMillan, & Wheaton 1996; Coleman, 1988). Rumberger et al (1999) found that for each time a child moved with his family to a new school and neighborhood, the likelihood of that child graduating high school was significantly reduced.

The timing of the moves has an effect on dropping out. Mobility between the first and eighth grades increases the likelihood of dropping out of high school even when controlling for eighth grade achievement and other factors (Rumberger & Larson, 1998; Swanson & Schneider, 1999; Teachman, Paasch, & Carver, 1996). Other studies (Voight et al, 2012; Haveman, Wolfe, & Spaulding, 1991) found that any mobility during the school years leads to a lower probability of graduation.

Moves during high school itself have negative consequences. Residentially mobile adolescents have higher rates of violent behavior than non-mobile students of the same age (Haynie, 2005). Friends' deviant behavior has the strongest impact of all the mechanisms used to explain the connection between mobility and violent behavior (Haynie, 2005). The difficulty in transferring credit when moving from high school to high school also poses problems for students (Weisman, 2012).

**Varied Effects on Reading and Math**

Some studies have shown that mobility has a negative but varied effect on both reading and math achievement (Engel, 2006; Hattie, 2009; Mehana &
Reynolds, 2004; Strand & Demie, 2007; Temple & Reynolds, 1999). Some show greater negative effects for reading (Juel, 1988; Vellutino, Scanlon, & Spearing, 1995). Others show greater negative effects for math achievement because of the greater likelihood for mobile students to experience gaps or repetitions in math instruction with each move due to greater sensitivity to curriculum sequencing (Grigg, 2012; Kerbow, 1996). Xu et al’s (2009) study found that mobility did not affect the mathematics performance of white students, but did hurt the math performance of both Black and Hispanic students, while mobility in general improved the reading performance of more advantaged and white students, but had no effect on minority students.

**Previous Academic Achievement**

Many studies have found that mobile students are likely to be low achieving, even before their mobility manifests (Alexander et al., 1996; Nelson et al, 1996; Wright, 1999; Cleveland, 1989; Mehana & Reynolds, 1995; Temple & Reynolds, 1999; Research Corner, 2005; Heinlein & Shinn, 2000; Levine, Wesolowski, & Corbett, 1966; Ingersoll, Scamman & Eckerling, 1989; Schuler, 1990; Reynolds, 1991, 1992; Astone & McLanahan, 1994; Hefner, 1994). Controlling for previous academic effects and other covariates, studies have found mobility effects on academic achievement to be **insignificant** (Parr, 2010; Alexander et al. 1996; Bollenbacher, 1962, Morris, Pestaner, & Nelson, 1967; Whalen & Fried, 1973), **small but significant** (Alexander et al. 1996; Association

One example of a study that controlled for previous academic achievement is Heinlein & Shinn’s study of third to sixth grade cohorts (2000). They focused on predominantly poor (95% Free/Reduced Lunch Program) students in New York City, studying the effects of mobility before or after third grade on sixth grade academic achievement, controlling for previous third grade achievement, SES and gender. Interestingly, all students receiving special education services were excluded from the study, as well as students that moved into the district after Kindergarten. The students were English speaking only, with no English language learners in the study. Students’ sixth grade achievement was largely predicted by their third grade achievement, with student scores taken from their grade-level California Achievement Tests, Fifth Edition (CTB/McGraw-Hill, 1992). When not controlling for third grade achievement, there was a strong association of high mobility with sixth grade achievement ($B= -3.80$, $SE=1.67$, $p<.05$ for math; $B= -5.47$, $SE=1.65$, $p<.01$ for reading). Similarly, there was a strong association between high mobility before third grade and third grade achievement ($B= -6.24$, $SE=1.59$, $p<.001$ for math; $B= -3.00$, $SE=1.46$, $p<.05$ for reading). Each move before the third grade was associated with a decrease of
2.4 percentile points in reading achievement and 1.4 percentile points in math achievement. In this highly cited study, early mobility was shown to have a strong correspondence to third grade achievement. Mobility during grades K-3 as well as grades 4-6 was also strongly associated with sixth grade achievement, but was not significant when controlling for third grade achievement. Some questions are left unanswered by this study. Is there a significant association between mobility in K-2 and third grade achievement when controlling for earlier (Kindergarten, grade 1, or grade 2) achievement? All students entering the system after Kindergarten were excluded from the sample. How did mobility affect their academic achievement? In addition, students receiving special education services were excluded from the study, and no English language learners were in the study.

Multiple Moves

Multiple school moves have been shown to have stronger effects on achievement than single moves. Students that move multiple times often fall further and further behind their peers (Alexander, Entwisie, & Dauber, 1996; Nelson, Simoni, & Adelmian, 1996). Mehana and Reynolds (2004) found the frequency of mobility to be one of the major predictors of effect size in academic achievement ($r = -0.33, P = 0.10$). Other studies found frequent school changes to be related to larger academic deficits (Hartman, 2002; Mehana & Reynolds, 1995; Kerbow, 1996, Xu et al, 2009; Rumberger & Larson, 1998; Heinlin &
Shinn, 2000; Popp et al., 2003; Sanderson, 2004; Skandera & Sousa, 2002; Wasserman, 2001). The Chicago Longitudinal Study (Judy & Arthur, n.d.) also found that frequent mobility increases the risk of academic underachievement over occasional mobility. Mantzicopoulous (2000) found that the frequency of early school changes had a significant association with second grade math and reading scores. Tucker, Marx, & Long (1998) found that one residential move does have an impact on behavior and academic achievement, but only among children not living with both biological parents. Coleman (1987) suggests that two-parent families have more “social capital” to help mitigate any negative effects related to moving residences.

**Strategic and Reactive Moves**

The effect of moves from one district to another differs from moves within a district. Cross-district moves tend to be “strategic moves” in which the families are proactively seeking a better educational or residential situation for their family, while within-district moves are more likely to be disruptive or “reactive moves” that a family takes not by choice but out of necessity (Rumberger et al, 1999; Wright, 1999; Hanushek, Kain, & Rivkin, 2004). Studies have found that low achievement scores are related to “reactive” moves, but not “strategic” moves. In addition, lower income students are more likely to make “reactive” moves, while higher income students are more likely to make “strategic” moves (Alexander et al, 1996). “Reactive” moves are found to be associated with
significant losses in learning (Xu et al, 2009). Similarly, other studies found that inter-city mobility is related to lower achievement while intra-city mobility is not (Long, 1975; Straits, 1987; Johnson & Lindblad, 1991). Higher income families tend to move to higher quality schools while lower income families tend to move to lower quality schools (Xu et al, 2009). The negative consequences of mobility are ameliorated by moving to better schools (Judy & Arthur, n.d.).

**Promotional/Non-promotional Moves**

School changes that happen during the school year are considered “non-promotional”. These non-promotional school changes have a stronger negative impact than promotional school changes, even when previous achievement and background characteristics are controlled (Hanushek, Kain, & Rivkin, 2004; Xu et al, 2009; Rumberger, 2003:6; Rumberger & Larson, 1998; Mehana and Reynolds, 2004). Other studies found that mid-year school changes have a greater impact than between-year moves (National Research Council and Institute of Medicine, 2010).

**Early Mobility**

Early mobility tends to have a greater impact than later mobility. Children who move during the first three years of school are more likely to be negatively affected by mobility, with the negative impact of mobility diminishing with

Heinlein and Shinn's study in 2000 found that students' sixth grade math and reading performance was largely predicted by their third grade performance, with no significant effects of mobility after third grade, controlling for SES and gender. Mobility prior to third grade was associated with a decrease of 1.4 percentile points in math achievement, and 2.4 percentile points in reading achievement. Voight et al (2012) found that mobility during years K-2 has negative effects on third grade test scores. Mantzicopoulos and Knutson (2000) found that frequent early school changes had a negative effect on second grade reading and math scores, even after controlling for previous academic achievement and the child's gender. The study also found that children who moved earlier tended to be rated lower in academic competence by their second grade teachers and had lower scores as well. The study also found that earlier grade movers had lower scores on the Peabody Picture Vocabulary Test-Revised, and the Woodcock-Johnson Tests of Achievement-Revised, and were rated lower in academic competence by their teachers.

Alexander, Entwisle, & Dauber (1996) found that there was a negative association between mobility during elementary school and grades, test scores, retention and referral to special education in fifth grade, though the correlation was found to be mostly insignificant once family characteristics and first grade academic performance were controlled. With so many studies pointing to
mobility having the largest impact in the earliest grades, further study is warranted.

**Student Characteristics**

The effects of mobility can vary by student characteristics, and student characteristics can predict rates of mobility as well. Families of different racial/ethnic backgrounds have different rates of school mobility. Xu et al (2009) found that Hispanic students are subject to higher rates of mobility than white students, though their rates of mobility have declined slightly over time. Highly mobile students are more likely to be poor, more likely to be ethnic minorities, and more likely to be in a single-parent home (Titus, 2007). In addition, children who are part of an ethnic minority are more likely to be negatively effected by mobility (Hefner, 1994; Levine, Wesolowski, & Corbett, 1966; Astone & McLanahan, 1994; Ingersoll, Scamman & Eckerling, 1989; Schuler, 1990; Reynolds, 1991, 1992).

Children in special education programs have been shown to have their services interrupted or discontinued (Cornille, Boyer & Smyth, 1983), though the study predates electronically shared files.

Gender has been shown to be a factor in how children handle moving to a new school. Early adaptational outcomes have associations with gender (Masten et al., 1988, Reynolds, 1989a). Boys, aged 8-13, when exposed to higher stress situations are less socially competent than girls, and are less protected in their
school competence by positive family qualities (Master et al., 1988). Reynolds (1989a) found that school mobility in kindergarten had a greater effect on boys' socio-emotional maturity.

English language learners and immigrant students have above-average mobility rates, and mobility is associated with taking longer to achieve English proficiency (Ashby, 2010; Fong et al., 2010; Mitchell, Destino, & Karam, 1997). When families engage in cross district “strategic” moves, English language learners do not benefit from these moves, while white students do (Xu et al, 2009). Xu et al (2009) also found that the gap in mobility rates between proficient English-speakers and non proficient speakers can range from 7 to 14 percentage points.

Latino Population

By 2020, the Latino population in the U.S. is projected to reach 60 million, almost one quarter of the U.S. population. By 2025, one quarter of all U.S. K-12 students will be of Spanish Speaking origin (U.S. Department of Commerce, Bureau of the Census, 2000a). In addition, Latinos are the largest and fastest growing minority in the United States (Tienda, 2001).

Double digit disparities between the high school completion rates of Latino and non-Latino White students have remained, while those between non-Latino and White students have narrowed significantly in the last 30 years (U.S. Department of Education, 2004). Among the subcategories of Latinos, Mexican
Americans students are experiencing the greatest difficulties achieving school success. Youth of Mexican descent score significantly lower on Stanford achievement tests than Nicaraguan, Columbian, and Cuban Americans (Portes & Rumbaut, 2001) and are dropping out of school at twice the rate of students of Cuban descent (U.S. Department of Commerce, Bureau of the Census, 2000b). Latinos of Mexican origin also have the lowest college completion rate among all Latino sub-groups living in the U.S. (Chapa & Valencia 1993; Vernez & Mizell, 2002).

Varying theories attempt to explain these gaps. Often teachers of Latino students do not share the students’ ethnic background and have limited knowledge of their students’ culture, leading to alienation and student disengagement from school (Matute-Bianchi, 1986; Valenzuela, 1999). Latino students are also often at a socioeconomic disadvantage, a well-researched contributor to the gap. In addition, inferior facilities and inequitable schooling exacerbate the problem (Gándara et al. 2003).

One important study that addressed multiple student characteristics (such as race) and mobility was Xu et al’s 2009 study that focused on the mobility effects on cohorts of children from third grade to eighth grade. The study used a fixed effects model to determine how mobility affected year by year academic gains, as measured by end-of-year standardized tests in math and reading. It compared student achievement gains after a move to the expected gain if the same student did not move. The study found schools with higher percentages of students performing at or above grade level tend have turnover (mobility) rates
that are 10 to 15 percentage points lower than schools with higher minority or FRPL populations (26% versus 15%). Rates of mobility for students of limited English or who received special education services were consistently higher than those who were not. Higher parent education was associated with declines in school mobility rates. Students with parents with more education (some college or higher) tend to move to a better school, while students with parents with no college tended to move to a lower quality school. Cross-district (strategic) moves benefit all students, but the benefit is larger for white students ($SD = 0.05$).

Mobile students generally saw declines in math and held steady or saw improvement in reading. Mobility did not affect the mathematics performance of white students, but did hurt the math performance of both Black and Hispanic students. Mobility, in general, improved the reading performance of more advantaged and white students, but had no effect on minority students.

They found that, on average, mobility harms black and Hispanic students' academic performance but has no effect on white students, and that poor, ELL and special education students do not benefit from cross-district moves, while more advantaged peers (English speakers, non special education, non-poor) do benefit. For multiple movers, students saw a 2.2 percent decline in math score gains, with no losses in potential gains for the second or third move. However, the fifth move sees them lose another 4.7 percent of possible gain. Cumulatively, a student with five moves loses 7.7 percent in math learning. This study showed the variability of the effects of mobility and student characteristics. Variables included gender, race, ELL, special education status, and looked at multiple
moves. It did not, however, look at the effects of earlier moves or control for earlier academic achievement.

**Mechanisms of Mobility**

Many studies have sought to understand the mechanisms that might link mobility and academic performance. Haour-Knipe (1989) showed that maltreated children had higher mobility rates than non-maltreated children. Fantuzzo et al (2012) found that school mobility was related to classroom engagement and that absenteeism partially mediated relations between mobility, homelessness, and task engagement. Mehana and Reynolds (2004) used Bronfenbrenner's ecological systems theory (1975) to explain how the change in learning environments adversely affects learning because of the child's need for stability, predictability, and consistency. They also found that mobility's effects on achievement can be explained by three factors: it is a byproduct of family economic hardships, it disrupts student instruction, and it disrupts peer relationships. Voight (2007) found that disruption of social ties and disruption of routines have detrimental effects on children's learning.

Multiple factors can influence why a child moves from school to school, including a new residence, parental preference, custodial and parental rights changes, gang activity, school suspension, violence, and other reasons. Students may also move because parents want to place them in a better
performing school or district, which can often happen in suburban schools bordering large cities (Dillon, 2006).

There are many challenges for a student who has experienced mobility. The student must adjust to a new school environment socially, psychologically and academically. Multiple moves can compound the challenge, and lead to the student experiencing isolation, which can affect attendance and academic performance (Rumberger et al., 1999). With multiple moves the adjustment period extends over many years (Kerbow, Azcoitia, & Buell, 2003). The number of school switches can be associated with many school-related factors, such as class size reduction, safety, overcrowding, academic policies, and suspension/expulsion policies (Kerbow, Azcoitia, & Buell 2003; Rumberger, 2003)

**Summary**

The present study addressed the gaps in the literature by focusing on the earliest grades by including the frequency and timing of mobility, by including the student characteristics that have been shown to have some effect on academic outcomes, and by including the comparison of schools that children moved to and from. The poverty variable, however, was not studied. The vast majority of students in the school district to be studied (84%) are eligible for Free/Reduced Lunch, reducing the sample number of non-poor students to a number that is too small to draw meaningful conclusions. By studying a district with high poverty
and high numbers of English language learners, this study essentially controlled for Socio-Economic Status, producing a model for determining if mobility and student factors have an impact in districts with like populations.
CHAPTER 3
METHODOLOGY

Introduction

This study used data from a single district to determine relationships among academic performance, mobility, student characteristics and school characteristics. Most data were not available in a ready-made coded file, and therefore extensive recoding had to be conducted to have accurate and clean data. The intent of this study is to find a model that may help education stakeholders identify students in need of additional support by using varied mobility, student and school characteristics.

Collection of data

The data was mined from the school district online system from the Jackson District online student tracking system. Mobility data, student characteristics, school characteristics and Transitional Colorado Assessment Program (TCAP) assessment data was mined from this source. Permission was requested and granted to gain access to all pertinent information in the system from the district Research Review Committee. In addition, the researcher received approval (Approved Application Number: 201401104) from the ODU Institutional Review Board for Exempt Research.
The data for student characteristics and individual TCAP scores existed in student records on an online website that tracks student grades, assessment scores, movement between schools, attendance, and other student characteristics. General School TCAP score averages were mined from the state department of education yearly report (CDE, 2013). In addition, out-of-state standardized test score averages for math and reading (NCES, 2013) and out-of-country schools PISA (NCES, 2012) score averages were compared with Colorado score averages to determine the most accurate coding for PV4 (School Quality).

Once the data was received, initial classification codes of third grade students into mobility categories (between year/during year, timing of move, timing of move in academic career, number of moves, move to better or worse school), and student characteristic categories (gender, English language learner status, special education status, and race), had to be determined.

**Research Questions**

Research Question 1: What are the relationships among mobility, student and school characteristics within a district to third grade math achievement?

Research Question 2: What are the relationships among mobility, student, and school characteristics within a district to third grade reading achievement?
Variable Coding

Because many of the predictor variables in this study are categorical, they had to be recoded into binary (dummy) variables in order to input them into the regression model (Cohen et al, 2003). To avoid multicollinearity, caused when all binary variables are included in each category, the coding system for each categorical variable in the regression used one less variable group in each category or g-1, where g represents the number of groups in each variable (Hardy, 1993). Leaving one group out within each categorical variable was necessary to run the regression analyses, so a group of least interest within each category was chosen. Binary coding strategies for each categorical variable are shown below. For variables such as gender (PV6) and IEP status (PV7), where the number of groups in each variable is already two, binary coding is unnecessary. The Number of Moves (PV2) is an interval variable, and therefore need not be recoded.

For each predictor variable recoded as a binary variable, a table is shown that demonstrates how each variable was coded as binary, with the variable category of least interest placed on the at the top of the table. That variable of least interest was coded 0 for each binary recoding.

Mobility Characteristics

Predictor Variable 1 (PV1): Academic Timing of Move
If the student moved more than once, the earliest school year move is recorded. The categories for (PV1) are by academic year (Kindergarten, first grade, second grade, third grade). Table 3.1 shows the dummy coding with first grade as the control group (group of least interest), and C1, C2, and C3 respectively the codes for Kindergarten, second grade and third grade. Since the binary coding for PV1 includes a category for no moves, other predictor variables using no moves can exclude this category within the binary code because the analysis of PV1 will determine its effects and relationships with other variables.

Table 3.1

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>First Grade</td>
<td>Kinder/No</td>
<td>Second/No</td>
<td>Third/No</td>
</tr>
<tr>
<td>First Grade</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Kindergarten</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Second Grade</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Third Grade</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>No moves</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Predictor Variable 2 (PV2): Number of Moves

PV2 is an interval variable with numbers of moves recorded as such. One move is 1, two moves is 2, etc.

Predictor Variable 3 (PV3): Time of Year Move (Between, During)
Table 3.2 shows the dummy coding with no moves as the control group (group of least interest), and C1 and C2, respectively, the codes for during the school year and between school years.

Table 3.2  
Binary Coding for Time of Year Move  

<table>
<thead>
<tr>
<th>Code 1: During</th>
<th>Code 2: Between</th>
</tr>
</thead>
<tbody>
<tr>
<td>No moves</td>
<td>0</td>
</tr>
<tr>
<td>During School Year</td>
<td>1</td>
</tr>
<tr>
<td>Between School Years</td>
<td>0</td>
</tr>
</tbody>
</table>

Predictor Variable 4 (PV4): School Quality

For PV4, a system had to be created to determine the quality of schools that were moved to and from. For the 125 schools within Colorado, the 2013 TCAP report (CDE, 2013) was used to determine the percentage of students who scored proficient or advanced. For a student moving from one school to another, the percentages of each were compared and the move was assigned a code, as seen in Table 3.3.

Additionally, Appendix A and B show the tables created to compare TCAP proficient and advanced percentages among schools within Colorado and the Jackson District schools. If a student moved more than once, the data from the school most recent move was used.
Table 3.3

Initial Coding for School TCAP Score Comparisons

<table>
<thead>
<tr>
<th>Percentage of students score Adv./Prof.</th>
<th>Much Worse -15% or more</th>
<th>Worse -4 to -15%</th>
<th>Equivalent -4 to +4% or same school</th>
<th>Better +4 to +15%</th>
<th>Much Better +15% or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coding</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
</tbody>
</table>

For the sample of students, 12 individual students who were taking the math TCAP and 11 individual students taking the reading TCAP moved from Mexico to the Jackson district. Instead of eliminating those students out of the data set, a general comparison of U.S. and Mexican primary school data was used to determine coding for PV4 “Better or Worse” school. The NCES (2012) reported that on the reading literacy scale section of the Program for International Student Assessment (PISA), 27.9 percent of students in the United States received scores in the highest levels (levels four, five and six) of the reading literacy test, while only 4.9 percent of students in Mexico reached the highest levels. Similarly, on the mathematics literacy section of the PISA, 24.6 percent of students in the United States received scores in levels four, five, and six, while only 4.3 percent of students in Mexico did so. In light of this a usually generalization can be reached that in mathematics and reading achievement, the U.S. has far superior outcomes, and even though individual schools have different levels of achievement, the likelihood of a school in Mexico outperforming one in the United States, especially schools that the impoverished population of Jackson district are likely to have attended, is very low. In light of this
information, students in the Jackson district had the Independent Variable 4 (Better or Worse school) imputed/coded as a 5 (much better school) for all schools entered. This decision is supported by the fact that the students coming from Mexico are more likely to have strong Spanish skills and weaker English skills, and, though the Mexican school they were attending might have taught reading and mathematical skills well for testing in Spanish, the TCAP in Colorado is given in English. Those Spanish skills that would support higher test scores for reading and math are thus non-transferable to a test in another language. Therefore the schools any child might have attended in Mexico could be seen as “much worse” in the confining definition on how well the children in that (Spanish only) school would have performed on an English TCAP test.

Fifty (50) students in each data set (math and reading) came to the Jackson District from schools outside of Colorado. To determine what code to use for children moving to Colorado from non-Colorado schools, the NCES Report (2013) on statewide Mathematics and Reading Assessments were used to determine if, overall, Colorado as a state has a higher percentage of students scoring proficient or higher on mathematics and reading NAEP assessments. Though this process of coding ‘better’ or ‘worse’ schools is not optimal, it is a better alternative than leaving over 50 individual students, 10% of the sample, out of the data set. The NCES report assigns each state with one of three labels for percentage of students scoring proficient or higher: 1) higher percentage than the nation, 2) percentage not significantly different from the nation, 3) lower percentage than the nation. With three categories, and with Colorado a state
that is ranked “higher than the nation”, there is a possibility of coding a school from another state as ‘equivalent’ (3) if the state has a “higher” rating, ‘better’ (4) if the state has a “no significant difference rating” in comparison with the national scores, or ‘much better’ (5) if the state has a “lower percentage” rating. Sixteen students, in both the math and reading sample, had no information about what school they moved from when they came to Jackson District. Because of this, those sixteen students had to be deleted from the data set.

After the initial categorical coding for better or worse schools, the PV4 data was then binary coded, as seen in Table 3.4.

Table 3.4
Binary Coding for School Quality

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalent</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Much Worse</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Worse</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Better</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Much Better</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Student Characteristics

Predictor Variable 5 (PV5): Level of English Language Learner

Initial coding for this categorical variable was as follows: (Not English Proficient, (1), LEP (Limited English Proficiency, 2), English Speaker, (N/A [Not
Applicable] 3), FEP (Fluent English Proficient, 4). After the initial categorical coding for Level of English Language Learner, the PV4 data was then binary coded, as seen in Table 3.5.

Table 3.5

<table>
<thead>
<tr>
<th>Code 1: NEP/No</th>
<th>Code 2: LEP/No</th>
<th>Code 3: FEP/No</th>
</tr>
</thead>
<tbody>
<tr>
<td>English Speaker</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>NEP</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>LEP</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>FEP</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Predictor Variable 6 (PV6): Special Education Status

The variable was coded as no (0) and yes (1). This status was taken from the students' third grade status.

Predictor Variable 7 (PV7): Gender

This will be coded male (0) and female (1).

Predictor Variable 8 (PV8): Race. The nominal racial categories of Black, Hispanic, and White, will be used in the statistical analysis. The racial categories of Multiple Races, American Indian/Alaska Native, Asian and Native Hawaiian/Pacific Islander will not be included in this study, as very few or no representatives of these categories exist in the Jackson School district. The PV8 data was then binary coded, as seen in Table 3.6.
Table 3.6

*Binary Coding for Race*

<table>
<thead>
<tr>
<th></th>
<th>Code 1: Hispanic/No</th>
<th>Code 2: Black/No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Hispanic/Non-Black</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>Black</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Criterion Variables**

1) Third grade Mathematics TCAP scale scores (Math TCAPSS) from 2012-13 school year (Range: 150-795)

2) Third grade Reading TCAP scale scores (Reading TCAPSS) from 2012-13 school year (Range: 150-795)

**Treatment of the data**

This study intended to be a model that school districts could use to predict TCAP scores using student and mobility categorical data in order to identify children at academic risk, beyond the usual risk categories, so that interventions could be put into place.

Before correlation or regression analyses were run, the data was screened for outliers and evidence of linear relationships between the predictor
variables (and blocks of predictor variables) and the criterion variable by examining a mean graph of each of the data points.

Then, a factor analysis was conducted to identify a relatively small number of dimensions, or factors, from a relatively large set of variables by distinguishing sets of variables that have more in common than other sets. The smaller set of factors would then be used in the regression analysis.

The following analyses were conducted for both the Math and Reading samples. First, Pearson product-moment correlation coefficients between single predictor variables and the criterion variables were determined for the full sample set. Then, a single block regression was run with each set of mobility characteristics. Next, an ordered, two set linear regression was run with the student characteristics block entered first, and the mobility characteristics block entered second. Then, the two set linear regression was run flipping the order, with mobility characteristics being entered first, then the student characteristics next.

Finally, for the forward stepwise regression model, the variable with the largest negative or positive correlation was considered for entry into the model. This model started with no variables, then tested each variable following a model comparison criterion. The Bonferroni correction method was used to adjust the study's test for significant effects when repeated analyses were being done (eg. forward linear regression). To use the Bonferroni correction when p<.05, the desired p value is divided by the number of hypotheses being conducted. In this study, seventeen predictors were entered into the forward linear regression so
the p value desired was .05 divided by 17 (.05/17=0.00714), the quotient being 0.0029. The new threshold of significance was $p<0.0029$ (99.71% confidence interval) to maintain the 95% confidence for the data set.

After the first variable was entered into the forward regression, the next predictor variable (or block of variables) with the largest partial correlations was entered next. The regression model continued in this manner until there were no predictor variables (or block of binary predictor variables) left that meet the criterion for entry. That is, no variables remained that improve the model.

**Protection of Participant Rights**

Existing data, mined from an online system, was placed into a digital file with each student assigned a study code, and had no identifying student data beyond a student identification number. At no time did the researcher have access to student names, nor did he have a key to determine what identification number was associated with any given student. The spreadsheet and statistical package files used in the study were encrypted and stored on a single password access computer in a locked location. Only the primary investigator knew the computer entry password and encryption password for excel and SPSS files. The use of this archived data posed no risk to study participants.
CHAPTER 4
DATA ANALYSIS & FINDINGS

Introduction

The full sample sizes of each set (math and reading) were reduced from the original set when missing data was discovered among the data. After determining the school quality of each move, from in-state, inter-state, and international moves, it was discovered that 16 entries had no mention of the school of origin at all, and therefore had to be removed from each sample.

As has been mentioned before, slight discrepancies exist between math and reading data sets, even when they are pulled from the same population. This is explained by the differing number of students taking each TCAP assessment. For unknown reasons, a certain small number of children did not take the reading assessment that did take the math assessment, and vice versa. That said, the full sample size (N=523) is the same for both math and reading, though it is reflective of a slightly different population. Table 4.1 below shows the number of students and percentages in each of the predictor variable categories of this study. Some of the individual variables within some sets had to be excluded from the correlation and regression analyses to avoid the “dummy variable” trap, where perfect multicollinearity (and false outcomes) is achieved. These variables, as well as the number of moves variable, are included in this table for discussion,
though they are excluded, for reasons explained later in this chapter, from later analyses.

Table 4.1

<table>
<thead>
<tr>
<th></th>
<th>Math</th>
<th></th>
<th></th>
<th>Reading</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number</td>
<td>Percentage</td>
<td>Number</td>
<td>Percentage</td>
<td></td>
</tr>
<tr>
<td>PV1. Kindergarten Move</td>
<td>87</td>
<td>16.6</td>
<td>88</td>
<td>16.8</td>
<td></td>
</tr>
<tr>
<td>PV1. First Grade Move</td>
<td>77</td>
<td>14.7</td>
<td>77</td>
<td>14.7</td>
<td></td>
</tr>
<tr>
<td>PV1. Second Grade Move</td>
<td>88</td>
<td>16.8</td>
<td>88</td>
<td>16.8</td>
<td></td>
</tr>
<tr>
<td>PV1. Third Grade Move</td>
<td>33</td>
<td>6.3</td>
<td>31</td>
<td>5.9</td>
<td></td>
</tr>
<tr>
<td>PV1. No Move</td>
<td>238</td>
<td>45.5</td>
<td>239</td>
<td>45.7</td>
<td></td>
</tr>
<tr>
<td>PV1. At least one move</td>
<td>285</td>
<td>54.5</td>
<td>284</td>
<td>54.3</td>
<td></td>
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<tr>
<td>PV2. One move</td>
<td>194</td>
<td>37.1</td>
<td>191</td>
<td>36.5</td>
<td></td>
</tr>
<tr>
<td>PV2. Two moves</td>
<td>58</td>
<td>11.1</td>
<td>61</td>
<td>11.7</td>
<td></td>
</tr>
<tr>
<td>PV2. Three moves</td>
<td>21</td>
<td>4.0</td>
<td>21</td>
<td>4.0</td>
<td></td>
</tr>
<tr>
<td>PV2. Four moves</td>
<td>11</td>
<td>2.1</td>
<td>11</td>
<td>2.1</td>
<td></td>
</tr>
<tr>
<td>PV3. During School Year</td>
<td>149</td>
<td>28.5</td>
<td>150</td>
<td>28.7</td>
<td></td>
</tr>
<tr>
<td>PV3. Between School Year</td>
<td>135</td>
<td>25.8</td>
<td>134</td>
<td>25.6</td>
<td></td>
</tr>
<tr>
<td>PV4. Much Worse School</td>
<td>92</td>
<td>17.6</td>
<td>55</td>
<td>10.5</td>
<td></td>
</tr>
<tr>
<td>PV4. Worse School</td>
<td>50</td>
<td>9.6</td>
<td>49</td>
<td>9.4</td>
<td></td>
</tr>
<tr>
<td>PV4. Equivalent School</td>
<td>36</td>
<td>6.9</td>
<td>48</td>
<td>9.2</td>
<td></td>
</tr>
<tr>
<td>PV4. Better School</td>
<td>56</td>
<td>10.7</td>
<td>63</td>
<td>12.1</td>
<td></td>
</tr>
<tr>
<td>PV4. Much Better School</td>
<td>50</td>
<td>9.6</td>
<td>69</td>
<td>13.2</td>
<td></td>
</tr>
<tr>
<td>PV5. NEP</td>
<td>44</td>
<td>8.4</td>
<td>42</td>
<td>8.0</td>
<td></td>
</tr>
<tr>
<td>PV5. LEP</td>
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<td>50.1</td>
<td>263</td>
<td>50.3</td>
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</tr>
<tr>
<td>PV5. FEP</td>
<td>22</td>
<td>4.2</td>
<td>22</td>
<td>4.2</td>
<td></td>
</tr>
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<td>PV5. English-speaking</td>
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<td>37.3</td>
<td>196</td>
<td>37.5</td>
<td></td>
</tr>
<tr>
<td>PV6. SPED Status</td>
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<td>13.6</td>
<td>71</td>
<td>13.6</td>
<td></td>
</tr>
<tr>
<td>PV7. Female</td>
<td>267</td>
<td>51.1</td>
<td>268</td>
<td>51.2</td>
<td></td>
</tr>
<tr>
<td>PV7. Male</td>
<td>256</td>
<td>49.0</td>
<td>255</td>
<td>48.8</td>
<td></td>
</tr>
<tr>
<td>PV8. Hispanic</td>
<td>428</td>
<td>81.8</td>
<td>428</td>
<td>81.8</td>
<td></td>
</tr>
<tr>
<td>PV8. Black</td>
<td>12</td>
<td>2.3</td>
<td>14</td>
<td>2.7</td>
<td></td>
</tr>
<tr>
<td>PV. White</td>
<td>76</td>
<td>14.5</td>
<td>74</td>
<td>14.2</td>
<td></td>
</tr>
</tbody>
</table>

As seen in Table 4.1, 54.5% of children taking the Math TCAP in third grade and 54.3% of children taking the Reading TCAP had moved at least once.
Predictor variable one (PV1) for each test (math/reading) shows substantial percentages of children who moved in each grade: Kindergarten (16.6/16.8), first grade (14.7/14.7), second grade (16.8/16.8), third grade (6.3/5.9). Predictor variable two (PV2) shows that the highest percentage of movers (among all children) only moved once (37.1/36.5), and that as the number of moves increases, the percentage decreases: two moves (11.1/11.7), three moves (4.0/4.0), and four moves (2.1/2.1). With predictor variable 3 (PV3), the percentage of those who moved is nearly evenly split between moving during the school year (28.5/28.7) and moving between school years (25.8/25.6). The final predictor variable (PV4), quality of school moved to, shows that the greatest percentage moved to a much worse school for the math sample (17.6), but for the reading sample, the greatest percentage moved to a much better school (13.2). The differences in percentages in this variable highlight the variability in quality of reading and math instruction for the schools compared in this study.

Other student characteristics percentages of note include Hispanic (81.8/81.8), LEP (50.1/50.3), and English-speaking (37.3/37.5). These statistical frequencies establish the framework of understanding of the mobility and student characteristic predictor variables for the statistical analyses that were conducted.
Data analysis

Linearity

Student characteristic predictor variables and mobility characteristic variables were tested for linearity with the Math TCAPSS, using the full sample set. Scattergram graphs were created to determine if a linear relationship with the Math TCAPSS exists, in order to determine if each variable can be inserted in the regression analysis. All variables except for PV2 (Number of moves) were shown to have the linear relationship. Figure 1 shows a graph of PV2 on the x axis and TCAPSS on the y axis. At first glance it seems to be a noticeable downward slope. However, on closer examination of the means, this does not bear out. The mean Math TCAPSS for each number of moves is reported: zero moves (403.5), one move (401.8), two moves (410.9), three moves (419.1), and four moves (356.6). A slight decrease between zero moves and one move, a substantial increase between one move and two moves, a substantial increase between two moves and three moves, and a substantial decrease between three moves and four moves suggests a non-linear relationship. In a statistical analysis where multiple predictors are present, variable transformation to achieve linearity confounds the pairwise relationships of other variables in the model. Therefore, PV2 (Number of Moves) was not entered into the correlation or regression analysis for math.
Using the reading sample set as well, all variables were checked for linearity before being put into the regression equation. Only one, PV2 (Number of Moves) suggested a non-linear relationship. As shown in Figure 2, the Reading TCAP seems to decrease with each successive number of moves. However, on closer examination of the means, this does not bear out. The mean Reading TCAP Scale Score for each number of moves is reported: zero moves (524.8), one move (517.1), two moves (515.5), three moves (528.0), and four moves (469.3). A slight decrease between zero moves and one move, a slight
decrease between one move and two moves, a substantial increase between two moves and three moves, and a substantial decrease between three moves and four moves suggests a non-linear relationship. Therefore PV2 (Number of Moves) was not entered into the correlation or regression analysis for reading.

Figure 2. Graph of mean reading TCAP scale scores by number of moves.
Factor Analysis

This study intended to use the principal component factor extraction method form uncorrelated linear combinations of the predictor variables. However, when initial factor analyses were conducted, both the math and reading sample were shown to be unfit for a factor analysis. A Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's Test of Sphericity were conducted for both samples. The KMO indicated the proportion of variance in the variables of the sample that could be caused by underlying factors. High values (0.8-1.0) are considered superb and indicated that a factor analysis would be useful with the data (Hutcheson & Sofroniou, 1999). Some statisticians (Hair et al., 2010) consider 0.7 the low threshold for confirmatory analysis while others (Kaiser, 1970, 1974) recommend accepting values of .5 or above. In the present study, the KMO values for the math (.346) and reading (.361) were far below the acceptable threshold to pursue a useful factor analysis study. The Bartlett’s tests did show significant values ($p<.00$) for both the math and reading variable sets, indicating that the variables may be suitable for structure detection and that the strength of the relationship among variables is strong. It also indicated that the variable correlation matrix was not an identity matrix. However the low KMO values lead to the conclusion that the results of a factor analysis would not be useful for neither the math nor reading sample.
Bivariate Correlations

The results of the correlation analysis for the full math and reading samples (N=523) are shown in correlation matrices in Table 4.2 and Table 4.3. Correlation coefficients were computed among the Math TCAPSS/Reading TCAPSS and the seventeen predictor variables, including dummy coded sub-variables for some predictor variables.

Math Correlation

Table 4.2 shows that only 4 out of 17 predictors were significantly correlated to the Math TCAPSS. To facilitate understanding of the correlational matrix, boxed borders were placed around each of the dummy variable sets. Many variables were binary coded into several "dummy" codes, and within each of those variable sets, there is, understandably, significant correlation among the variables since they originate from one variable and so are aspects of that variable. For example, all sub-variables of Predictor Variable 1 (Academic Timing of Move) are significantly correlated with one another, but the significance is devoid of meaning because they are dummy codes of a single variable. In addition, Predictor Variable 1d (No moves), is significantly correlated with all mobility characteristics by virtue of defining whether a student has moved or not. For all the other mobility characteristics, which define what type of move, they are automatically significantly negatively correlated with 1d by virtue of the variable being a move. This correlation of binary-coded variables has no
Table 4.2

Pearson Correlation Matrix of Math TCAPPSS and Predictor Variables (N-2=521)

<table>
<thead>
<tr>
<th></th>
<th>SD</th>
<th>0</th>
<th>1a</th>
<th>1b</th>
<th>1c</th>
<th>1d</th>
<th>3a</th>
<th>3b</th>
</tr>
</thead>
<tbody>
<tr>
<td>0. Math TCAPSS</td>
<td>(78.203)</td>
<td>.024</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1a. Kindergarten Move</td>
<td>(.373)</td>
<td>-0.001</td>
<td>.219&quot;</td>
<td>.090&quot;</td>
<td>.394&quot;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1b. Second Grade Move</td>
<td>(.374)</td>
<td>.031</td>
<td>.241&quot;</td>
<td>.365&quot;</td>
<td>-0.135&quot;</td>
<td>.187&quot;</td>
<td>.290&quot;</td>
<td></td>
</tr>
<tr>
<td>1c. Third Grade Move</td>
<td>(.243)</td>
<td>.031</td>
<td>.221&quot;</td>
<td>.097&quot;</td>
<td>-0.031</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1d. No Move</td>
<td>(.498)</td>
<td>.050</td>
<td>-0.106&quot;</td>
<td>.061</td>
<td>.142&quot;</td>
<td>.114&quot;</td>
<td>.165&quot;</td>
<td>.177&quot;</td>
</tr>
<tr>
<td>3a. During Year Move</td>
<td>(.452)</td>
<td>.020</td>
<td>.117&quot;</td>
<td>.275&quot;</td>
<td>.087&quot;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3b. Between Year Move</td>
<td>(.438)</td>
<td>.134&quot;</td>
<td>.097&quot;</td>
<td>.023</td>
<td>.155&quot;</td>
<td>.150&quot;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4a. Much Worse School</td>
<td>(.381)</td>
<td>.050</td>
<td>.045</td>
<td>.124&quot;</td>
<td>-0.071</td>
<td>.121&quot;</td>
<td>-0.116&quot;</td>
<td>-0.014</td>
</tr>
<tr>
<td>4b. Worse School</td>
<td>(.294)</td>
<td>.196&quot;</td>
<td>.042</td>
<td>.043</td>
<td>.054</td>
<td>.095&quot;</td>
<td>-0.048</td>
<td>-0.058</td>
</tr>
<tr>
<td>4c. Better School</td>
<td>(.310)</td>
<td>.331&quot;</td>
<td>.072</td>
<td>.075</td>
<td>.012</td>
<td>.048</td>
<td>.059</td>
<td>.004</td>
</tr>
<tr>
<td>4d. Much Better School</td>
<td>(.294)</td>
<td>.081</td>
<td>.035</td>
<td>.031</td>
<td>.065</td>
<td>.027</td>
<td>.084</td>
<td>.052</td>
</tr>
<tr>
<td>5a. NEP</td>
<td>(.278)</td>
<td>-0.312&quot;</td>
<td>.013</td>
<td>.103</td>
<td>-.022</td>
<td>-.139&quot;</td>
<td>.068</td>
<td>.089</td>
</tr>
<tr>
<td>5b. LEP</td>
<td>(.500)</td>
<td>.050</td>
<td>.045</td>
<td>-.124&quot;</td>
<td>-.071</td>
<td>.121&quot;</td>
<td>-0.116&quot;</td>
<td>-0.014</td>
</tr>
<tr>
<td>5c. FEP</td>
<td>(.201)</td>
<td>.196&quot;</td>
<td>-.042</td>
<td>-.043</td>
<td>-.054</td>
<td>.095&quot;</td>
<td>-0.048</td>
<td>-0.058</td>
</tr>
<tr>
<td>6. SPED</td>
<td>(.343)</td>
<td>.331&quot;</td>
<td>.072</td>
<td>.075</td>
<td>.012</td>
<td>.048</td>
<td>.059</td>
<td>.004</td>
</tr>
<tr>
<td>7. Gender</td>
<td>(.500)</td>
<td>.050</td>
<td>.035</td>
<td>.031</td>
<td>.065</td>
<td>.027</td>
<td>.084</td>
<td>.052</td>
</tr>
<tr>
<td>8a. Hispanic</td>
<td>(.386)</td>
<td>.081</td>
<td>-.016</td>
<td>-.013</td>
<td>-.061</td>
<td>.052</td>
<td>-.043</td>
<td>-.017</td>
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<tr>
<td>8b. Black</td>
<td>(.150)</td>
<td>.050</td>
<td>-.034</td>
<td>.102&quot;</td>
<td>-.040</td>
<td>-.063</td>
<td>-.012</td>
<td>.085</td>
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</table>

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).
Table 4.2 (continued)

Pearson Correlation Matrix of Math TCAPSS and Predictor Variables (N=521)

<table>
<thead>
<tr>
<th></th>
<th>SD</th>
<th>4a</th>
<th>4b</th>
<th>4c</th>
<th>4d</th>
<th>5a</th>
<th>5b</th>
<th>5c</th>
<th>6</th>
<th>7</th>
<th>8a</th>
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<tbody>
<tr>
<td>4b. Worse</td>
<td>(.294)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>4c. Better</td>
<td>(.310)</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>4d. Much</td>
<td>(.294)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Better</td>
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<td>5a. NEP</td>
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<td>-.013</td>
<td>.065</td>
<td>.029</td>
<td>.159</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
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<td>-.027</td>
<td>-.013</td>
<td>-.105</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>5c. FEP</td>
<td>(.201)</td>
<td>.028</td>
<td>-.068</td>
<td>-.073</td>
<td>-.036</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>6. SPED</td>
<td>(.343)</td>
<td>-.022</td>
<td>-.034</td>
<td>.043</td>
<td>.061</td>
<td>.202</td>
<td>-.207</td>
<td>-.055</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Gender</td>
<td>(.500)</td>
<td>.030</td>
<td>.045</td>
<td>-.057</td>
<td>.032</td>
<td>.007</td>
<td>-.075</td>
<td>-.043</td>
<td>-.148**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8a. Hispanic</td>
<td>(.386)</td>
<td>-.017</td>
<td>.052</td>
<td>.003</td>
<td>-.083</td>
<td>.107</td>
<td>.403**</td>
<td>.099</td>
<td>.045</td>
<td>-.104</td>
<td></td>
</tr>
<tr>
<td>8b. Black</td>
<td>(.150)</td>
<td>.063</td>
<td>-.006</td>
<td>.030</td>
<td>.037</td>
<td>-.046</td>
<td>-.102**</td>
<td>-.032</td>
<td>-.088**</td>
<td>-.029</td>
<td>-.325**</td>
</tr>
</tbody>
</table>

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

meaning within this study. These correlations that fall under this ‘meaningless’ understanding are highlighted gray in the correlation matrix Table 4.2.

The correlation between ‘Better School’ and Math TCAPSS was statistically significant, \( r(521) = -.106, p < .05 \). Other significant correlations with Math TCAPSS were with NEP, \( r(521) = -.312, p < .05 \), FEP, \( r(521) = .196, p < .05 \), and SPED, \( r(521) = -.331, p < .05 \). Other interesting significant correlations exist between many of the mobility and student characteristic variables. Predictor Variable 3a (During Year Move) correlates with Third Grade Move, \( r(521) = .394, p < .01 \). This indicates that among moves in all grades, third grade is likely to have more moves that are during the school year, rather than between the academic
school years. In fact, 32 of 33 third grade moves (97%) were during the school year, with only one happening between the second and third grade school year. Predictor Variable 3b (Between Year Move) correlates with Second Grade Move, $r(521)=.365, p<.01$, indicating that moves during second grade were likely to be moves between the academic school year. In fact, 54 of 88 (61%) second grade moves were between school years. There is a significant correlation between moving to a much worse school (4a) and moving between school years, $r(521)=-.290, p<.01$, suggesting that the moves between school years, though highly likely to be less reactive and more organized than a move during the school year, are still more likely to be to a much worse school.

The highest correlation among the English Language Learner Status (PV5a-c) and Academic Timing of Move (PV1a-d) variables was the negative correlation between NEP and no moves, $r(521)= -.139, p<.01$, indicating that to a moderate extent, children who are Not English Proficient, are more likely to move. Additionally, NEP had significant correlations with between year moves, $r(521)= .089, p<.05$, and moving to a much better school, $r(521)= .159, p<.01$, suggesting that NEP students are likely to begin at subpar schools but are also likely to move between years or move to much better schools if they do move. LEP students had a significant negative correlations with moving during the year ($r(521)= .116, p<.01$), and moving to a much better school, $r(521)= .105, p<.01$. This suggests that LEP students are not likely to move during the year, nor are they likely to move to a much better school. Special Education status was positively correlated with NEP status, $r(521)= .202, p<.01$, negatively correlated
with LEP status, $r(521) = -.207, p < .01$, and was negatively correlated with Gender (female), $r(521) = -.148, p < .01$.

Finally, the Race predictors (PV8a,b) showed some significant correlations as well. As per expectations, Hispanic status was correlated with all English Language Learner statuses: NEP, $r(521) = .107, p < .05$, LEP, $r(521) = .403, p < .01$, and FEP, $r(521) = .099, p < .05$. Black status was negatively correlated with LEP status ($r(521) = -.102, p < .05$) and was positively correlated with Special Ed. Status, $r(521) = .088, p < .05$.

**Reading Correlation**

Table 4.3 shows a correlation matrix of the Reading TCAPPS and 17 predictor variables. Similar to the math correlation matrix, boxed borders were again placed around each of the dummy variable sets to facilitate understanding. The 'meaningless' correlations within dummy variables sets are highlighted gray as well.

The matrix shows that only six out of seventeen predictors were significantly correlated to the Reading TCAPSS, none of which are mobility predictor variables. Of these six predictors, the highest correlation coefficient was with Special Education Status, $r(521) = -.411, p < .01$. All three of the binary variables in the English Language Learner variable category were significantly correlated with Reading TCAPSS, with the Non English Proficient (NEP) having the highest correlation coefficient, $r(521) = -.333, p < .01$. LEP, $r(521) = .090, p < .05$, FEP, $r(521) = -.174, p < .01$, Gender (female coded as 1), $r(521) = .102, p < .05$, and Hispanic status, $r(521) = -.104, p < .05$, were also significant.
Table 4.3

Pearson Correlation Matrix of Reading TCAPPSS and Predictor Variables (N-2=521)

<table>
<thead>
<tr>
<th></th>
<th>SD</th>
<th>0</th>
<th>1a</th>
<th>1b</th>
<th>1c</th>
<th>1d</th>
<th>3a</th>
<th>3b</th>
</tr>
</thead>
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<td></td>
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<td>Move</td>
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<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
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<td></td>
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<tr>
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<td></td>
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<td></td>
</tr>
<tr>
<td>1c. Third Grade</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Move</td>
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<td></td>
<td></td>
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<td>1d. No Move</td>
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</tr>
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<td>3a. During Year</td>
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<tr>
<td>Move</td>
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<td></td>
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</tr>
<tr>
<td>3b. Between year</td>
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<td>-0.022</td>
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<td></td>
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<tr>
<td>move</td>
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</tr>
<tr>
<td>4a. Much Worse</td>
<td>.307</td>
<td>.056</td>
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<tr>
<td>School</td>
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<td></td>
</tr>
<tr>
<td>4b. Worse School</td>
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<td></td>
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</tr>
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<td></td>
<td></td>
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<td></td>
</tr>
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<td>4d. Much Better</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>School</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5a. NEP</td>
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<td>-0.333</td>
<td>.018</td>
<td>.093</td>
<td>-0.044</td>
<td>-0.129</td>
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<tr>
<td>5b. LEP</td>
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<td>.049</td>
<td>-0.125</td>
<td>-0.058</td>
<td>.118</td>
<td>-1.14</td>
<td>-0.012</td>
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<td>.174</td>
<td>-0.043</td>
<td>-0.043</td>
<td>-0.053</td>
<td>.055</td>
<td>-0.049</td>
<td>-0.058</td>
</tr>
<tr>
<td>6. SPED</td>
<td>.343</td>
<td>-0.411</td>
<td>-0.074</td>
<td>.075</td>
<td>.019</td>
<td>-0.048</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Gender</td>
<td>.500</td>
<td>.102</td>
<td>-0.032</td>
<td>.030</td>
<td>.067</td>
<td>-0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8a. Hispanic</td>
<td>.386</td>
<td>-0.104</td>
<td>-0.013</td>
<td>-0.013</td>
<td>-0.050</td>
<td>.052</td>
<td>-0.041</td>
<td>-0.019</td>
</tr>
<tr>
<td>8b. Black</td>
<td>.162</td>
<td>-0.026</td>
<td>-0.043</td>
<td>.084</td>
<td>.009</td>
<td>-0.080</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).
Table 4.3 (continued)

Pearson Correlation Matrix of Reading TCAPPSS and Predictor Variables (N=521)

|                  | SD  | 4a  | 4b  | 4c  | 4d  | 5a  | 5b  | 5c  | 6   | 7   | 8a  |
|------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 4b. Worse School | .292|     |     |     |     |     |     |     |     |     |     |     |
| 4c. Better School| .326|     |     |     |     |     |     |     |     |     |     |     |
| 4d. Much Better School | .339|     |     |     |     |     |     |     |     |     |     |     |
| 5a. NEP          | .272| -.078| .026| .042| .155**|     |     |     |     |     |     |     |
| 5b. LEP          | .500| .029| .005| -.008|     | .155**|     |     |     |     |     |     |
| 5c. FEP          | .201| .052| -.035| .078| -.025|     |     |     |     |     |     |     |
| 6. SPED          | .343| -.063| -.032| .059| .076| .212**| -.209**| -.055|     |     |     |     |
| 7. Gender        | .500| .023| -.015| -.050| .041| .007| -.067| -.043| -.149**|     |     |     |
| 8a. Hispanic     | .386| .032| -.019| -.008| -.080| .103| .404**| .099**| -.045| -.102**|     |     |
| 8b. Black        | .162| .059| .069| -.025| .040| -.049| -.119**| -.035| .073| .028| -.352**|     |

* Correlation is significant at the 0.05 level (2-tailed). ** Correlation is significant at the 0.01 level (2-tailed).

There are many significant correlation coefficients among the predictor variables. The fifteen significant correlations between predictor variables the Academic Timing of Move binary variables had mostly low coefficients. The highest were between Kindergarten move and moving during the school year, \( r(521) = .223, p < .01 \), Kindergarten year and between year moves \( r(521) = .239, p < .01 \), and second grade moves and between year moves, \( r(521) = .357, p < .01 \).
Nine predictor variables had significant correlations with the Time of Year Move binary variables. The variables for During School Year Move and Much Better School, $r(521) = -0.215, p<0.01$, were negatively correlated, while Between Year Move and Better School, $r(521) = 0.227, p<0.01$, and Between Year move and Much Worse School, $r(521) = 0.199, p<0.01$, had a positive correlation. NEP had a significant positive correlation with Much Better School, $r(521) = 0.155, p<0.01$, while LEP had a significant negative correlation with Much Better School, $r(521) = -0.155, p<0.01$. Special Education status was positively correlated with NEP, $r(521) = 0.212, p<0.01$, but negatively correlated with LEP, $r(521) = -0.209, p<0.01$. Gender (female) had a mild positive correlation with Special Education Status, $r(521) = 0.149, p<0.01$. The second highest correlation coefficient value of the matrix was between Hispanic and LEP, $r(521) = 0.404, p<0.01$.

Math Ordered Two Set Regression Analyses

In order to evaluate whether Math TCAPSS was predicted by student characteristics as well as whether mobility characteristics after controlling for the effects of student characteristics, an ordered multiple regression analysis was conducted.

The results present an evaluation on how well the Math TCAPSS is predicted by student characteristics (Set 1), and how well the set of mobility characteristics (Set 2) predicts Math TCAPSS over and above student characteristics. The first set of predictors, race, gender, ELL status, and SPED status, accounted for a significant amount of variability, $R^2 = 0.21, (7, 515) = 20.12,$
The eleven mobility characteristics (binary variables from three block variables) did not account for a significant proportion of Math TCAPPSS variance after controlling for the effects of student characteristics, $R^2$ change = .03, (10, 505) = 1.63.

A second ordered block analysis was conducted in order to evaluate whether Math TCAPSS is predicted by mobility characteristics after controlling for the effects of student characteristics.

The results present an evaluation on how well the Math TCAPSS is predicted by mobility characteristics (Set 1), and how well the set of student characteristics (Set 2) predicts Math TCAPSS over and above mobility characteristics. The first set of predictors, three mobility characteristics (expressed as eleven binary variables), did not account for a significant amount of variability, $R^2 = .15$, (10, 512) = 1.25. The four student characteristics (expressed as 7 binary variables), accounted for a significant proportion of Math TCAPSS variance after controlling for the mobility characteristics, $R^2$ change = .22, (7, 505) = 20.34, $p < .01$.

**Math Block Regression Analyses of Mobility Variable Sets**

In order to evaluate whether Math TCAPSS is predicted by single mobility characteristic sets, a single block regression analysis was conducted with each of the linear mobility characteristic sets in this study: Academic Timing of Move, Time of Year Move, and School Quality.
The results present an evaluation on how well the Math TCAPPSS was predicted by the mobility characteristics sets. The first set of predictors, Academic Timing of Move, did not account for a significant proportion of Math TCAPPSS variance, $R^2 = .00$, $(4, 518) = .44$, $p > .01$. The second set of predictors, Time of Year Move, also did not account for a significant proportion of Math TCAPPSS variance, $R^2 = .00$, $(2, 520) = .96$, $p > .01$. Finally, the third set of predictors, School Quality, did not account for a significant proportion of Math TCAPPSS variance, $R^2 = .01$, $(4, 518) = 1.60$, $p > .01$.

Math Forward Regression

Forward multiple regression analyses were conducted to predict the Math TCAPSS by first entering the predictor variable with the largest (positive or negative) correlation with the Math TCAPSS criterion variable. The Bonferroni method was used to establish the entry criterion for variables to be entered into the analyses.

In both the math and reading forward regression, 17 (binary included) predictor variables were entered, therefore the desired $p$ value of .05 was divided by 17 (.05/17), the quotient being 0.0029. The new threshold of significance was $p < 0.0029$ (99.71% confidence interval) to maintain the 95% confidence for the data set.

As Table 4.4 shows, the predictor variable identified with the highest correlation with math was SPED. It shows the SPED zero order correlation coefficient ($r = -.333$), while Table 4.5 shows that this initial variable explains 11%
Table 4.4

Summary of Forward Regression Analysis for Variables Predicting Math TCAPSS

<table>
<thead>
<tr>
<th>Step</th>
<th>Variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
<th>Zero-order</th>
<th>Partial</th>
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<td>-.331</td>
<td>-.331</td>
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<td>-.291</td>
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<td>7.008</td>
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<td>.050</td>
<td>.088</td>
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Table 4.5

*Model Summary of Forward Regression Analysis for Variables Predicting Math TCAPSS*

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<th>Variable</th>
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<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>R Square Change</th>
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<td>.007</td>
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</tr>
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</table>

---

a. Predictors: (Constant), SPED, b. Predictors: (Constant), SPED, NEP, c. Predictors: (Constant), SPED, NEP, FEP, d. Predictors: (Constant), SPED, NEP, FEP, Hispanic, e. Predictors: (Constant), SPED, NEP, FEP, Hispanic, Between, f. SPED, NEP, FEP, Hispanic, Between, Better

of the variance in math scores, $R^2 = .11$, $(1, 521) = 64.16, p<.00$. The next predictor variable selected for the model, NEP, had a moderate zero order correlation coefficient ($r = -.312$), and partial correlation coefficient ($r = -.265$). With the two predictors the amount of explained variance increased, $R^2 = .17$, $(1, 520) = 39.37$. The adjusted $R^2$ is an adjustment for the number of terms relative to data points. With the first two variables are entered, the adjusted $R^2 = .17$.

When all six predictor variables are in the equation, a low but significant level of variance remains explained by the model (adjusted $R^2 = .21$). The partial correlations column (Table 4.4) shows SPED ($r = -.288$) and NEP ($r = -.257$) with the greatest correlation with the math scores, controlling for the other variables in the set.
Reading Ordered Two Set Regression Analyses

In order to evaluate whether Reading TCAPSS was predicted by student characteristics, controlling for the effects of mobility characteristics an ordered two set regression analysis was conducted.

The results present an evaluation on how well the Reading TCAPSS is predicted by student characteristics (Set 1), and how well the set of mobility characteristics (Set 2) predicted Reading TCAPSS over and above student characteristics. The first set of predictors, race, gender, ELL status, and SPED status, accounted for a significant amount of variability, $R^2 = .27$, $(7, 515)= 27.08$, $p<.01$. The eleven mobility characteristics (binary variables from three block variables) did not account for a significant proportion of Reading TCAPSS variance after controlling for the effects of student characteristics, $R^2$ change$= .00$, $(10, 505)= 0.14$, $p>.01$.

Another regression, with the opposite order on entry was conducted to evaluate whether Reading TCAPSS was predicted by student characteristics after controlling for the effects of mobility characteristics.

The results present an evaluation on how well the Reading TCAPSS was predicted by mobility characteristics (Set 1), and how well the set of student characteristics (Set 2) predicts Reading TCAPSS over and above mobility characteristics. The first set of predictors, three mobility characteristics (expressed as eleven binary variables), did not account for a significant amount
of variability, $R^2 = .01$, (10, 512) = .72. The four student characteristics (expressed as 7 binary variables), accounted for a significant proportion of Reading TCAPPSS variance after controlling for the mobility characteristics, $R^2\text{ change} = .26$, (7, 505) = 25.45, $p < .01$.

**Reading Block Regression Analyses of Mobility Variable Sets**

In order to evaluate whether Reading TCAPSS was predicted by single mobility characteristic sets, a single block regression analysis was conducted with each of the linear mobility characteristic sets in this study: Academic Timing of Move, Time of Year Move, and School Quality.

The results present an evaluation on how well the Reading TCAPPSS is predicted by the single mobility characteristics sets. The first set of predictors, Academic Timing of Move, did not account for a significant proportion of Reading TCAPPSS variance, $R^2 = .01$, (4, 518) = .88, $p > .01$. The second set of predictors, Time of Year Move, also did not account for a significant proportion of Reading TCAPPSS variance, $R^2 = .00$, (2, 520) = .92, $p > .01$.

Finally, the third set of predictors, School Quality, did not account for a significant proportion of Reading TCAPPSS variance, $R^2 = .01$, (4, 518) = .93, $p > .01$.

**Reading Forward Regression**

Forward multiple regression analyses were conducted to predict the Reading TCAPSS by entering the predictor variable with the largest (positive or
negative) correlation with the Reading TCAPSS criterion variable. Similar to the math forward regression, a new confidence interval was established at 99.71% using the Bonferroni method to maintain the 95% confidence for the data set.

The predictor variable identified with the highest partial correlation with math was the SPED predictor variable. Table 4.6 shows the SPED zero order correlation coefficient (r = -.411), while Table 4.7 shows that this initial variable explains 17% of the variance in reading scores, $R^2 = .17, (1, 521) = 106.19, p < .01$.

The next predictor variable selected for the model, NEP, had the next largest correlation (r = -.333), and a partial correlation (r = -.277). With the two predictors the amount of explained variance increases, $R^2 = .23, (1, 520) = 43.08$. The adjusted $R$ square is an adjustment for the number of terms relative to data points. With the first two variables are entered, the adjusted $R^2 = .23$. When all four predictor variables are in the equation, the adjusted $R$ square is at its greatest (adjusted $R^2 = .26$) explaining 26% of variance in the criterion, while the partial correlations column shows SPED (r = .377) and NEP (r = .259) with the greatest correlation controlling for the other variables in the set.
Table 4.6

Summary of Forward Regression Analysis for Variables Predicting Reading TCAPSS

<table>
<thead>
<tr>
<th>Variable</th>
<th>B</th>
<th>SE B</th>
<th>β</th>
<th>Correlations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Zero-order</td>
</tr>
<tr>
<td>Step 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Constant)</td>
<td>532.546</td>
<td>3.341</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPED</td>
<td>-93.434</td>
<td>9.067</td>
<td>-.411</td>
<td>-.411</td>
</tr>
<tr>
<td>Step 2</td>
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<td>(Constant)</td>
<td>536.793</td>
<td>3.278</td>
<td></td>
<td></td>
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<tr>
<td>SPED</td>
<td>-81.044</td>
<td>8.924</td>
<td>-.357</td>
<td>-.411</td>
</tr>
<tr>
<td>NEP</td>
<td>-73.824</td>
<td>11.247</td>
<td>-.258</td>
<td>-.333</td>
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<tr>
<td>Step 3</td>
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<td></td>
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</tr>
<tr>
<td>(Constant)</td>
<td>534.175</td>
<td>3.319</td>
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<td></td>
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<tr>
<td>SPED</td>
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<td>8.828</td>
<td>-.351</td>
<td>-.411</td>
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<tr>
<td>NEP</td>
<td>-71.735</td>
<td>11.131</td>
<td>-.251</td>
<td>-.333</td>
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<tr>
<td>FEP</td>
<td>53.764</td>
<td>14.752</td>
<td>.139</td>
<td>.174</td>
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<tr>
<td>Step 4</td>
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<td>(Constant)</td>
<td>552.087</td>
<td>7.030</td>
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<td></td>
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<td>SPED</td>
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<td>-.358</td>
<td>-.411</td>
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<td>NEP</td>
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<td>11.135</td>
<td>-.237</td>
<td>-.333</td>
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<tr>
<td>FEP</td>
<td>58.149</td>
<td>14.727</td>
<td>.150</td>
<td>.174</td>
</tr>
<tr>
<td>Hispanic</td>
<td>-22.223</td>
<td>7.705</td>
<td>-.110</td>
<td>-.104</td>
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</table>

Table 4.7

Model Summary of Forward Regression Analysis for Variables Predicting Reading TCAPSS

<table>
<thead>
<tr>
<th>Variable</th>
<th>R</th>
<th>R Square</th>
<th>Adjusted R Square</th>
<th>Std. Error of the Estimate</th>
<th>R Square Change</th>
</tr>
</thead>
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<tr>
<td>Step 1a</td>
<td>.411a</td>
<td>.169</td>
<td>.168</td>
<td>71.026</td>
<td>.169</td>
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<tr>
<td>Step 2b</td>
<td>.483b</td>
<td>.233</td>
<td>.230</td>
<td>68.320</td>
<td>.064</td>
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<td>Step 3c</td>
<td>.502c</td>
<td>.252</td>
<td>.248</td>
<td>67.527</td>
<td>.019</td>
</tr>
<tr>
<td>Step 4d</td>
<td>.514d</td>
<td>.264</td>
<td>.258</td>
<td>67.056</td>
<td>.012</td>
</tr>
</tbody>
</table>

a. Predictors: (Constant), SPED, b. Predictors: (Constant), SPED, NEP, c. Predictors: (Constant), SPED, NEP, FEP d. Predictors: (Constant), SPED, NEP, FEP, Hispanic
Summary

This study sought to answer two research questions: 1) what are the relationships among mobility, student and school characteristics within a district to third grade math achievement, and 2) what are the relationships among mobility, student, and school characteristics within a district to third grade reading achievement?

Through conducting a bivariate correlation analysis, relationships among individual variables were discovered. Only four predictor variables (SPED, NEP, FEP, and Better School) for the math sample, and six predictor variables (SPED, NEP, LEP, FEP, Gender, and Hispanic) for the reading sample, had significant correlations with the criterion, though many interesting correlations among predictor variables were discovered.

A factor analysis revealed a low Kaiser-Meyer-Olkin Measure of Sampling for both the math (.346) and reading (.361) samples, indicating that a low proportion of variance could be caused by underlying factors. Because of this, a factor analysis to determine underlying factors was not conducted.

The ordered block regression analysis determined that for the math and reading samples, the mobility block of variables did not account for a significant amount of variability in the scale scores, while the student characteristics block of variables accounted for a significant proportion of variance, even when controlling for mobility.
To determine how well mobility variable sets predict math and reading scores, single block regression analyses were conducted separately for the mobility sets: Academic Timing of Move, Time of Year Move, and School Quality. The mobility sets did not account for significant variance in scores in either the math or reading analysis.

The forward multiple regression analyses conducted for math and reading produced different results. In the math sample, four student characteristic variables (SPED, NEP, FEP, Hispanic) and two mobility binary variables (Between, Better) were accepted into the model and reached a low, but significant level of predictive ability (adjusted $R^2 = .21$). In the reading sample, four student characteristic variables (SPED, NEP, FEP, Hispanic) and zero mobility variables were accepted into the model, and also reached a low, but significant level of predictive ability (adjusted $R^2 = .26$).
CHAPTER 5
SUMMARY AND INTERPRETATION

Summary

Mobility is a present and growing characteristic of students in school districts in the U.S. (Schoen & Fusarelli, 2008). Both English Language Learners and Hispanic students are a growing population in schools as well (Tienda, 2001). As educators strive to meet the needs of these growing populations, a useful tool to meet their needs is the ability to identify students when they are at risk early in their academic careers. This study focused on Kindergarten through third grade, when early interventions can have the greatest effect (Sylva, 2012), and where students can begin their academic careers by building strong success.

Multiple challenges exist in the study of mobility, its dimensions, and the relationships that exist between them and academic achievement. For one, moving to a new school is commonplace, but there also can be extremely varied reasons behind doing so. General simplifications like reactive and proactive (Judy & Arthur, n.d.) moves can be useful at times, but don’t go in depth to explain the many reasons for the move. Students may move to a new district because the parents are interested in their child attending a better school. They may move because their parent lost their job and a family member lives in the district, or for any number of untold reasons. In studying mobility quantitatively,
the complexity of the move can be left out of consideration. For this reason this study used the aspects of mobility that have been shown to matter: the timing of the move in the school year (during or between), the timing of the move during academic career (Kindergarten, first grade, etc.), the number of moves, and the quality of the school moved to. However, each one of these aspects of mobility can have underlying and complex explanations. A child may have moved multiple times because the parents are constantly striving for a school or teacher that they think will help their child succeed. A child may have moved multiple times because the parents are avoiding law enforcement because of illegal activity, or may be unable to hold a job and afford rent. These more extreme explanations are only two of innumerable reasons a child may move many times. And yet, the statistical analysis only recognizes a three in the column for number of moves. That said, if the general scope of how mobility is affecting students is to be understood, quantitative studies are still useful tools to address the broader questions about mobility, especially when they attempt to account for the complexities and the vagaries of school mobility.

Other challenges exist for researchers as well. Among them is the challenge of generalizability. Every state, district, and school has a unique makeup. A school's racial make-up in one state may mirror that in another state, and yet the economic wealth of the region may be very different, with one school populated by low income families, and another populated by middle or higher income. In general, however, useful conclusions can be drawn when populations appear similar, and the district of study in the present research has a population
that reflects a growing trend in demographics in the U.S., namely Latino and Spanish speaking peoples.

Jackson district schools have a population of over 80% Latino, over 50% students who are learning English, and over 84% who qualify for free and reduced lunch. The district-mandated curriculum is an English immersion model, while at the same time, all TCAP assessments are conducted in English. The within-district transfer policies are of moderate stringency, so parents are able to move their child to a new school within the district when they present a good enough reason and by being insistent. In such a milieu, moves to better schools may take on new meaning, such as a positive 'strategic move' done on behalf of the child to improve academic performance. This study used multiple mobility characteristics in order to discover a useful district model. For districts with a similar general socio-economic status, this model might also prove useful.

By answering the research questions about relationships among student, mobility, school, and academic achievement variables, this study hoped to determine if there is a model of mobility and student characteristics that can identify students who may be at risk of academic failure, so that teachers, principals, and other education stakeholders may put interventions into place. With such a model, students struggling to achieve could be assisted in a timely manner to shore up any deficits they may have. Using multiple correlation and regression analyses, this study investigated to what extent mobility explains academic achievement, and whether a useful model exists for this population of students.
To address the research questions, existing student and assessment data was used. Though the data was mined from district applications, it did not exist in a readily useable form. Mobility data had to be interpreted from recorded start and end dates for each grade and each student. Moves within district for each student were recorded with sequential entries, but out of district moves were coded with only the name of the school and date of move. Coding for mobility characteristics, student characteristics, and school characteristics was a substantial and lengthy process that may be a major hindrance to districts that would want to use the model presented.

The correlation study among the predictor and criterion variables revealed a limited number of variables that significantly correlated to academic achievement, even when past academic achievement was not controlled for. The SPED ($r = -0.331$), NEP ($r = -0.312$), FEP ($r = 0.196$), and Better School ($r = -0.106$) variables were the only significant correlations in the math sample, while the significant correlations in the reading sample were SPED ($r = -0.411$), NEP ($r = -0.333$), FEP ($r = 0.174$), LEP ($r = 0.090$), Hispanic ($r = -0.104$), and Gender ($r = 0.102$). Only the Better School predictor variable emerged with a significant correlation coefficient out of all eleven mobility binary variables. This is discussed more in depth later in this chapter.

The ordered bloc regression determined that the mobility variables as a block did not account for a significant amount of variability for both math and reading TCAPSS, not when entered first, nor when controlling for student and school predictor variables by entering the student characteristics block first. In
addition, the mobility single block regression revealed that the three mobility variable sets did not account for significant variance in either math or reading TCAPSS.

The forward multiple regression analyses, with strict entry criteria based on the Bonferroni correction method, revealed a predictive math model of SPED, NEP, FEP, Hispanic, Between School move, and Better School variables, and a predictive reading model of SPED, NEP, FEP, and Hispanic variables.

**Organization**

This chapter is organized by presenting the interpretation and discussion of the outcome of each statistical test conducted, one by one. The individual analyses will be discussed in each section, and finally, the implications and recommendations for future research, based on all analyses, will be presented.

**Interpretation**

**Variable Correlations**

Four of 17 predictors were significantly correlated to the Math TCAPSS: SPED $r(521) = -0.331$, $p<.05$, NEP, $r(521) = -0.312$, $p<.05$, FEP, $r(521) = 0.196$, $p<.05$, and Better School, $r(521) = -0.106$, $p<.01$. In addition, some interesting significant correlations were revealed among predictor variables. For the purpose of
creating a model to predict the math scale scores, however, the most telling correlations are those with the criterion. Special education and English language learner status have clear mechanisms by which they can correlate with math scores. A learning disability, by definition, influences the ability to learn and prove that learning through assessment. Language ability, too, has clear mechanisms by which it influences academic achievement- if a child is not fluent in a language, assessments in that language will be more difficult for them than for a fluent speaker. The only mobility characteristic with significant correlation with math achievement was the Better School variable. At first glance, this seems perfectly reasonable since moving to a better school should lead to greater learning, and therefore, academic achievement on assessments. As a binary variable, however, all other characteristics of school quality are coded opposite Better School, including those students who moved to a Much Better School. This is discussed in greater detail in the forward regression section of this chapter.

The question of why only one mobility variable was correlated to math achievement must be raised. The literature has a wealth of studies that show the significance of mobility effects on achievement, including early moves (Voight et al, 2012), multiple moves (Judy & Arthur, n.d.), school quality moves (Xu et al, 2009) and time of year moves (Rumberger & Larson, 1998). It is possible that in the population of the present study, other hidden confounding variables are present. For instance, the district has a high rate of free and reduced lunch usage (84%). Since poverty and academic achievement have been shown to be
negatively correlated (Xu et al, 2009) the presence of this factor could crowd out any effects that mobility may have.

Six of 17 predictors were significantly correlated to the Reading TCAPSS: SPED, \( r(521) = -0.411, p < 0.01 \), NEP, \( r(521) = -0.333, p < 0.01 \), Gender, \( r(521) = 0.102, p < 0.05 \), Hispanic, \( r(521) = -0.104, p < 0.05 \), FEP, \( r(521) = 0.174, p < 0.01 \), LEP, \( r(521) = 0.090, p < 0.05 \), with no mobility variables.

**Ordered Block Regression**

Before regression analyses could be conducted, a linear relationship had to be confirmed between each predictor variable and the criterion variable. All variables had acceptable linearity, save one. Contrary to the literature (Mantzicopoulous, 2000; Heinlin & Shinn, 2000), the number of moves did not have a linear relationship with academic success. The relationship between number of moves and academic success for the district studied seemed to be one in which, a child with no moves succeeds moderately, but those who move once or twice, lose their advantage slightly, then those who move three times have a distinct advantage over all others, but those who move four times are at a distinct disadvantage. Qualitative or mixed methods designs could study the exact reasons why there seems to be a benefit to three moves over one, two, four, and even none.
**Factor Analyses**

The initial phase of the factor analysis study revealed no useful underlying factors exist in either the math or reading sample. By conducting a Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO), it was discovered that the low threshold for pursuit of factor analysis, ranging from 0.5 to 0.7 (Hair et al., 2010), was reached by neither sample. With KMO values for math (.346) and reading (.361) far below the useful range, the factor analysis was not pursued.

**Ordered Set Block Entry Regression**

To determine the predictive power of the mobility variables, as well as the predictive power of the mobility variables when controlling for student and school variables, an ordered block regression analysis was conducted twice. Both the math sample and reading sample had the same regression equation, and similar results. The first analysis entered the mobility block first, then the student block. The mobility block did not explain significant variance in academic score, but the student block did achieve significance, even when controlling for the mobility block. The second analysis entered the student block first, then the mobility block. In this analysis, the first student and school variable block was significant in explaining academic score variance, while the mobility block did not explain significant variance when entered second, controlling for student and school variables.
To develop a model of predictive power, a variable block should at least have a significant predictive power, and even more desirable, predictive power even when controlling for the predictive power of easily recognizable student characteristics such as race, gender, special education status, and English Language Learner status. From these analyses, suspicions begin about the ability to produce a model for predicting academic scores using mobility characteristics, especially when salient student characteristics have significant and higher predictive power, even when controlling for mobility characteristics.

**Single Set Block Entry Regression with Mobility Variables**

To determine if the individual mobility variable sets had predictive power, single block regression analyses were conducted, one by one. For both math and reading, all mobility variables sets available (number of moves was excluded from all regressions because of non-linearity) had no significant predictive power. In light of these outcomes, suspicions continue about the lack of predictive power among the mobility variables, and thereby the unlikelihood of a useful mobility model to predict academic achievement.

**Forward Regression**

The forward regression analysis for the math sample revealed six non-mobility and two mobility variables as significant predictors of math score
variance (SPED, NEP, FEP, Hispanic, Between, Better). Most of these variables are evident to educators and stakeholders alike, in that the schools themselves determine them through assessment and observation (special education status and English language learner status). Race is a self-evident and reported characteristic as well, though it is not used, nor should be used, as an exclusive element for determining academic risk. In this math forward regression, two mobility variables were significant; between school moves, and moving to a better school. The predictive ability of the math model (adjusted $R^2 = .21$) was also low to moderate. The outcome echoes past research that mobility can have different effects on math and reading achievement (Mehana and Reynolds, 2004), as the reading predictors for reading vary from those of the math sample.

The forward regression analysis for the reading sample revealed four non-mobility variables as significant predictors of reading score variance (SPED, NEP, FEP, Hispanic). The same variables were found in the math analysis, with the exception that math also revealed the two mobility variables of Better and Between as also significant. The predictive ability of the reading model (adjusted $R^2 = .26$) was also low to moderate. Similar to the previous correlation and regression analyses, the forward regression to determine what predictor variables could significantly predict variance in reading achievement had no mobility variables in the model.
Discussion

By using varying correlation and regression analyses methods, mobility variables were given many chances to emerge as significant predictors of academic achievement in math and reading. Many student characteristics did emerge as significant predictors, but are not relevant to this study without mobility variables included in the model. The mobility variables were rejected as significant predictors as single blocks, as an entire block entry (first and controlled for student characteristics), and as individual binary variables in the forward reading regression. Only two binary mobility variables were accepted into the forward math regression: moving between school years, and moving to a better school. In other words, this study produced only one model that includes mobility variables. That is, a forward regression identified (in order of largest correlation) SPED, NEP, FEP, Hispanic, Between, and Better in a model to predict math achievement (adjusted $R^2 = .21$). Though they were accepted into the model, Between ($R^2$ change= .006) and Better ($R^2$ change= .008) added a very small increase in predictive value to the model. Of these two mobility characteristics, one is quickly and readily identifiable by district stakeholders (moving between school years) while the other (moving to a better school) takes a large amount of time and effort to identify and code.

Between School Years Move

For the between school years binary variable, one population moved between school years, and the other either didn’t move at all, or moved during
the school year. This suggests that a child who has moved between school year has a mild advantage over those who didn’t move or those who moved during a school year. What quality of between school year moves gives children an advantage? Perhaps parents who are organized enough to wait for a child to finish school before moving them, might also be better parents, or who are less likely to have a financial emergency (and so they won’t move during the school year).

Better School Move

This section discusses the possible interpretation of the binary mobility variable Better School Move reaching the threshold of significance for entry into the math forward regression. This binary variable has students divided into those who moved to a better school (4-14 percentage points higher of proficient and advanced) and those who had moves of other quality. Interestingly, those other moves range from moving to a much better school, moving to a similar school or staying at the same school, moving to a worse school, or moving to a much worse school. What do these ‘other’ assignments have in common? At first glance, it doesn’t seem like they have much in common at all. However, there may be characteristics of a child who moved to a better school that they other characteristics do not have. For example, if the school they moved to was only 4 to 14 percentage points better, it means that it is possible that the first school where they moved from, was not that bad. In other words, in order to move to a school that is ‘much better’, or above 14 percentage points, it is more likely that the first school was quite bad, in order for the second school to be over 14
percentage points better. A lot can be speculated on here, and there are many caveats even when coming up with any sort of solid understanding. For one, the coding for quality of school was put into the data no matter when the child moved. A child could have moved in Kindergarten from a terrible school to a good one, or in third grade from a terrible to a good one, and the code would have still been 'better school'.

One must also include in the discussion that the quality of school coding used simplified comparisons between schools to a large degree. At the state level, it compared the percentage of students who scored proficient or advanced on the TCAP test for year that this study is focused on, and not necessarily the largest amount of time the child spent at a given school. A move could have been earlier in their academic careers when the school was great, but the quality could have faltered by the time the child reached the third grade, when the test was taken, and the coding does not account for the quality of school change over the years.

In addition, the school comparison coding for schools out of state to schools in state was also extremely simplified in order not to lose a substantial number of students out of the data set. General state quality of education studies were used (NCES, 2013), without regard for specific, individual school quality in the state where the child was coming from. Moves from international locations (mainly Mexico) were coded in a similar simplified way.

That said, the idea that somehow moving to a slightly better school has more positive predictive power over moving to any other rank of school raises
interesting questions for further research. For example, future studies could account for the number of years at the first school and second school, and use an algorithm to code the quantity and quality of the education they had at each school, through school ratings and/or teacher ratings. In that manner, a clearer picture of how moving to a different quality school truly does affect a child's academic skills could emerge.

**Implications and Recommendations**

This study set out to define relationships among variables in order to create a viable predictive model for academic achievement using student, school and mobility predictor variables. The understanding that emerges from this study is that many student characteristics have strong predictive power, and nearly all mobility characteristics do not, especially when controlling for student characteristics. In casting a wider quantitative net, this study shows that mobility characteristics can be difficult to quantify for quantitative study when many in-depth aspects of each mobility variable can have very different effects. Within the district of study, with its large Latino population, majority of English Language Learners, and large percentage of people living at or near the poverty level, mobility has very little predictive power in the face of such difficulties. Districts with similar populations apply as this study can take the results and apply the understanding with such demographics, mobility has minimal outstanding effects on academic achievement.
Recommendations for Future Research

Future studies could look into the interaction effect of mobility and demographics using a multivariate analysis of variance (MANOVA), furthering the study of how the relationships among variables predict achievement. Two-district comparative studies could look at how the level of predictive power changes in districts with different populations. For example, mobility within a wealthy district of mostly English-speakers may have different effects on achievement than a poorer district with a majority of Spanish-speakers.

The uniqueness of the high level of mobility in international Department of Defense Schools, which have protocols for welcoming new students and families (Smrekar & Owens, 2003), also provides fertile ground for mobility studies that look at school-based programs for helping highly mobile children achieve academically. Such a study could include student characteristics to see if they correlate with achievement in a school situation where students are all generally highly mobile, and all are receiving the same intervention and support for it.

The present study is an example of how some behaviors or not easily quantifiable. A future qualitative or mixed method study could attempt to understand the complexity of mobility by focusing on understanding the reasons behind individual cases, and how they affect the individual student.

The present data set also pointed to another possible future study. In the present study, it was discovered that some students moved to a new school
during or after January in their third grade year, and subsequently took the TCAP assessments in the middle of March. Their TCAP scores officially reflect on their new teacher and new school, even when they were only present for two and a half months of instruction. It is arguable that the 'credit' or 'blame' for that child's achievement should be laid at the feet of the school where they attended the longest, and not the most recent school attended. Future studies might look at the differences in school reporting when such cases are left out of the equation. Would TCAP scores go up or down? Would some schools move from turnaround status to priority improvement? In a climate of high stakes testing and accountability for schools and teachers, could there be a way to account for late mobility in testing years?

Conclusion

The purpose of this research was to find out if mobility can be a useful predictor in a model, so that a child with certain mobility and other characteristics might be identified for intervention. The various statistical analyses in this study showed that mobility is not a good predictor of math or reading achievement, and that student characteristics are, by far, a much better way to predict children who may need some extra help. Special education, Non English Speaking, Fluent English Speaking, and Hispanic/Latino status all have much greater predictive power than any mobility characteristics. There was one instance of two mobility variables fitting in the forward math regression, where movements between
school years and movement to a better school have significant predictive power. With such small predictive power between the two, and because other student variables are more readily identifiable and hold much greater predictive power, the conclusion of this study must be that, in a predominantly Latino district with high poverty and high numbers of English language learners, mobility characteristics are not useful for inclusion in a model to predict academic achievement.
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doi:10.1016/j.ssresearch.2005.10.001


## APPENDICES

### Appendix A

Comparing Colorado Schools TCAP Math Percentage of Proficient and Advanced Students with Jackson District Schools, Abridged (16 of 125 Schools)

<table>
<thead>
<tr>
<th>Schools</th>
<th>%</th>
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<th>Jackson School 2</th>
<th>Jackson School 3</th>
<th>Jackson School 4</th>
<th>Jackson School 5</th>
<th>Jackson School 6</th>
<th>Jackson School 7</th>
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Appendix B

Comparing Colorado Schools TCAP Reading Percentage of Proficient and Advanced Students with Jackson District Schools, Abridged (16 of 125 Schools)

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*Full table continues in original file*
VITA

John C. Hicks
Old Dominion University
Child Study Center
Norfolk, VA 23529-0136
Author Email: haifajohn@yahoo.com

EDUCATION

Doctor of Philosophy in Education, Aug. 2014
Early Childhood Education
Old Dominion University, Norfolk, Virginia

Early Childhood Special Education
University of Colorado, Denver

Master of Science in Education, Dec. 2005
Early Childhood Education, PreK-3
Old Dominion University, Norfolk, Virginia

Bachelor of Arts in Fine Arts, May 1995
Music/Music Theater
Colorado Mesa University, Grand Jct., Colorado

EXPERIENCE

Child Find Coordinator, 2014- present

NEA Teacher Leadership Institute Participant, 2013-2014

CTA Bargaining Representative, 2012-2014

Early Childhood Special Educator, 2009-2014

Adjunct Professor, 2008-2009

Graduate Assistant, 2005-2008