URBAN INTRADISTRICT SCHOOL MOBILITY AND ITS ASSOCIATION WITH ELEMENTARY SCHOOL ACADEMIC ACHIEVEMENT

by

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DEDICATION

This is dedicated to my partner, Dr. Caitlin Williams, for her support and understanding throughout the entire dissertation process, even while she was completing her own PhD. One of our favorite pastimes in between writing was walking on the beach, collecting rocks and shells, and talking about whatever thoughts and feelings came to mind. Many revelations related to my dissertation came about from these walks, and I am forever grateful to have had such an ideal context to identify otherwise easily overlooked elements of my research goals, not unlike reserving time to look closely at the rocks and shells that the waves deposited on the shore. This is also dedicated to my advisor, Dr. Adam Winsler. He was able to fluidly scaffold my growth throughout the PhD program, meeting me at whatever level of comprehension I was currently occupying. He was also true to the intentionality of applied research, always interested in making our lab's findings accessible to policymakers, educators, and researchers alike. I also have to mention that his mantra "if my grandmother couldn't understand this concept, then you can express it better" was instrumental in shaping my writing style -- precise yet approachable for a wide audience.

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ABSTRACT

URBAN INTRADISTRICT SCHOOL MOBILITY AND ITS ASSOCIATION WITH ELEMENTARY SCHOOL ACADEMIC ACHIEVEMENT

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The United States has one of the highest school mobility rates of any developed country and it is disproportionately experienced by ethnic minorities hailing from lower-income families, especially those attending schools in densely populated districts. Disentangling the effects of school mobility from other preexisting and concurrent factors has proven difficult, with considerable variability in effect size and even directionality in prior literature. Mixed findings reflect in part the choices that researchers make in defining school mobility for quantitative analysis. Prior research has been inconsistent with including child characteristics to reduce selection bias, modeling change in academic outcomes over time as a function of school mobility, and accounting for variance found within/between students and between higher clustering units, such as schools.

The main goal of this dissertation was to address some of these prior gaps with an applied developmental, ecological systems approach by controlling for preexisting and time-varying child characteristics, and then assessing the association of intradistrict school

mobility with academic outcomes over time during the first five years of elementary school. This was achieved by using a cohort-sequential longitudinal dataset of students attending schools in a densely populated school district between first and fifth grade (*N* = 20,806). Main analyses were conducted with cross-classified random effects growth models in HLM 6.4 software (Raudenbush & Bryk, 2002) to account for variance within students, between students, and between schools. Controls for student characteristics included time-varying annual status of free and reduced-price lunch, primary exceptionality, and English proficiency, and time-invariant controls included school readiness, gender, and ethnicity.

Students who ever moved schools had lower average GPA, reading and math test scores by the end of fifth grade compared to children who remained enrolled at the same school between kindergarten and fifth grades. Each additional move was increasingly negatively associated with fifth-grade academic outcomes. By extension, the most frequent (3+ moves) movers compared to nonmobile and less frequent (2 or fewer) movers had lower academic outcomes by the end of fifth grade. Students who moved earlier had lower fifth grade GPA compared to nonmobile students and those who moved later in elementary school, while later movers had lower test scores in reading and math than early and nonmobile students. The consistent negative association found in this study suggest that intradistrict school mobility should not be overlooked when forming education policy at local and national levels. As changes in school setting are not monolithically negative, increased standardization in reporting the reasons for and timing of school mobility would allow researchers greater precision in identifying the most problematic mobility patterns. Educators and policymakers need to remain vigilant in absorbing new students throughout elementary school, and future researchers should strive to track the academic growth trajectories of mobile students up through the end of secondary education.

INTRODUCTION

School mobility is found to be an important factor in explaining patterns of negative academic growth trajectories, and its spotlight in research and policy fields is steadily increasing. The United States has one of the highest rates of school mobility in the world (GAO, 2010; Mehana & Reynolds, 2004; Reynolds, Chen, & Herbers 2009; Welsh, 2017). While the national average for school mobility rate is high, low-income and ethnic minorities, especially Black students, disproportionately experience an even greater frequency of moves and have worse academic outcomes when they do move compared to Black students who are nonmobile as well as students from higher-income families that move less often (Hanushek, Kain, & Rivkin, 2004; Institute of Medicine and National Research Council, 2010; Reynolds et al., 2009; Schwartz, Stiefel, & Chalico, 2009; Xu, Hannaway, & D'Souza, 2009). A national report on school mobility found that 13% of students in K-8 moved four or more times (GAO, 2010). This 4+ mobility group was disproportionately Black and hailing from low-income households.

School mobility refers to the phenomenon of students switching from one school to another, however, several subcategorizations are helpful to consider in operationalizing school mobility. Some moves are planned (structural) while others are not planned (nonstructural). Structural mobility is most often in reference to grade promotion to higher levels of education but can also refer to school-initiated changes related to school closures, redrawing of district lines, and expulsion. In the case of grade promotion, the transition to middle or high school is often carefully orchestrated by school staff and faculty members working in tandem and is usually not thought to be negatively associated with academic performance, whereas school closures, redrawing of district lines, and expulsion, on the other hand may have a stronger negative association with achievement for some students (Welsh, 2017). Nonstructural, or nonpromotional, moves occur when a student changes school for a reason other than a school-initiated move, and is the focus of this dissertation. A student making a nonstructural move may do so for a variety of reasons (described below). While previous research has attempted to dichotomize reasons for nonstructural moves into “good” vs. “bad” mobility (Rumberger, Larson, Ream, & Palardy, 1999; Rumberger 2015), Welsh (2017) cautions that this conceptualization is too simplistic when considering the wide variability in the associations found between school mobility and academic performance observed in prior literature. The variety of possible patterns of school mobility suggest a need for finer-grained analysis of switching schools and academic performance.

The circumstances surrounding the reason for a school move likely account for much of the variability seen in academic outcomes for students who experience one or more nonstructural school moves. A nonstructural move may be motivated by, but not limited to, one or more of the following: a) residential mobility, b) family-based circumstances, negative or positive (e.g., divorce, eviction, unemployment, obtaining a better job), and c) reasons related to the school, such as seeking a higher quality school or one that better fits the needs of a student.

School mobility is closely related to residential mobility, but they do not always accompany one another. In a meta-analysis, Welsh (2017) found that for studies with both residential and school mobility measures, students moved schools between 30% to 40% of the time without an accompanying residential move. Local residential mobility within densely populated urban cities is more likely to include a school change (Temple & Reynolds, 1999) because attendance zones (the residential area used to assign students to a particular school within a district) are typically smaller there than suburban or rural areas. While it is ideal to have measures of both residential and school mobility, the fact that school mobility can happen without a change in residency and that there are likely unique consequences relating to disruptions of the school environment lends merit to studying school mobility independently. This is especially the case for exploring the association between academic outcomes and *intradistrict* moves.

Family-based circumstances surrounding school mobility, likely to account for a lot of the variation in student academic outcomes, are typically not accessible in research because of the heavy reliance on school administrative data for analysis. As a result, things like parent-based reports on *why* a school move took place are nearly nonexistent in school mobility research. It can be inferred that the desire of parents to find a better quality or better fitting school (with or without a residential move) accounts for some school moves, but prior research suggests that children attending lower quality schools seldom take advantage of open enrollment programs in their district (Kerbow, 1996). Whether school choice/open enrollment policies actually create more equal access to higher quality education, is still debated (Welsh, Duque, & McEachin, 2016). The multitude of possible reasons for school mobility makes it a problematic variable for modeling, especially in a quasi-experimental framework with known selection effects. The higher rates of school mobility for low-income, ethnically diverse students may partially account for what earlier research called the “achievement gap” (Welsh, 2017). It is also worth noting that the impact of school mobility is not limited to the mobile child. The effect of incoming and outgoing students potentially affects non-mobile students, teachers, administrators, as well as the academic performance of school districts more generally (Hanushek et al., 2004; Raudenbush, Jean, & Art, 2011; Rumberger, 1999). The GAO report (GAO, 2010) found that 12% of schools in their study had high student turnover rates, defined as 10% or more of a school’s student body leaving by the end of the year. Further, the schools in that 12% had greater proportions of low-income and ethnic diversity (i.e., non-White student bodies) compared to schools that had lower annual student turnover. Even if low-income, ethnic minorities manage to stay at the same elementary school until graduation, they are still at greater risk of being indirectly affected by the instability of (other) mobile students coming and going.

It is important to understand the variety of effects of intradistrict school mobility, in part, because of its potential positive impact on decision making for parents, teachers, administrators, and education policymakers that find themselves involved in some way with school mobility. Parents need information to weigh the pros and cons and decide what is most helpful if they are either forced to move or willingly move their child to another school (Hanushek et al., 2004). Teachers can better understand the impact mobility has on their students to help reduce the cost of moving for both the incoming student and the rest of their class (Reynolds et al., 2009). Schools vary greatly in terms of overall mobility rates (GAO, 2010) and in their policies for supporting incoming and outgoing students. At higher levels (i.e., district, state, and federal), policies related to school choice are actively shaping perceptions on who is entitled to attend different types of schools, and there is debate on whether school choice policies help or harm the most disadvantaged students (Welsh, 2017). Beyond education, housing policies for foster and homeless populations will also benefit from a greater understanding of the predictors and effects of school mobility (Fantuzzo, LeBoeuf, Chen, Rouse, & Culhane, 2012).

While there is widespread agreement among educators and policymakers that intradistrict school mobility is disruptive for academic outcomes, it has been a very difficult research topic to study. On the administrative end, mobile students are inherently hard to track, leading to lost or incomplete records during a school change. Researchers involved in district-wide studies who have strong relationships with administrators and other front-line data collectors have helped reduce the number of missing records for children switching schools in the same district. On the data analysis end, mobile students are, by nature, outside the realm of purely nested hierarchies. They are often the first subgroup to be omitted from longitudinal multilevel analysis because their school-level ID is not the same at every timepoint (Wolff-Smith & Beretvas, 2017), however, new methodological approaches allow for the inclusion of students who have membership to more than one school over time.

The current dissertation examines student outcomes associated with nonstructural school mobility in elementary school (i.e., students who moved schools for reasons other than grade promotion) for a sample consisting of ethnically diverse, low-income students. Below, I will first outline a socio-bioecological systems theory framework of school mobility. Then I will summarize three main methodological issues the reader should be aware of in school mobility research (e.g., selection effects, comparison groups, and nesting) before getting to the main literature review. A detailed account of procedures involved in the data analysis plan, research questions and hypotheses follows. Results are then presented followed by a discussion about the findings, limitations, and recommendations for future research.

Theoretical framework

Bronfenbrenner's bioecological theory of human development (Bronfenbrenner & Morris 2005), and Coleman's social capital theory (1988), have historically been the two most popular theories used by school mobility researchers. Recently, Welsh (2017) has consolidated aspects from both theories into a new conceptual framework. I provide a summary of Bronfenbrenner and Coleman's theories and then discuss the conceptual framework of Welsh below.

Bronfenbrenner made several revisions to what we now call the bioecological model of human development. I focus primarily on the "proximal processes" component of his theory as it relates to the Process-Person-Context-Time (PPCT) elements. Bronfenbrenner and Morris (2006) use the term proximal processes to describe the way that developmental trajectories and the ecology (the environment) reciprocally inform each other over time. The concept of proximal processes was first mentioned in two of the central propositions of the bioecological model (Bronfenbrenner & Morris, 1998) and is the underlying explanatory mechanism for how this reciprocity of influence between person and environment operates. Stability over time in an environment, especially early in development, is thought to be important for proximal processes to operate successfully because having a routine and predictable interactions with people, places, and symbols help manage increasing complexity and uncertainty throughout life. Repetition leads to proficiency, and proficiency leads to boredom, encouraging us to become proficient in something more challenging. This is true for any context the child interacts within on a regular basis, with school beginning to be included in the microsystem (i.e., an environment the child spends a good amount of time engaging in activities and interactions with others) around age 4-5, with the compulsory education requirements in place in the United States.

The microsystem is one of four ecological systems that Bronfenbrenner proposed. It is useful to think of the four systems as a series of four nested circles/spheres, with the individual at the center. Whereas the microsystem encompasses an individual's relations within their most immediate, or proximal, surroundings (e.g., family and school contexts), the next innermost layer, the mesosystem, represents the interaction of various microsystems (e.g., the relationship that parents have with their child's school). Zooming out to the third layer, the exosystem is broader and mainly indirect in its interaction compared to the micro and mesosystems in terms of the influence on the individual. For example, while parent unemployment may affect the child, the child is not directly involved in the parent's workplace change. The outermost layer, the macrosystem, had the broadest indirect influence and includes social and cultural ideologies. Laws and cultural expectations for individuals are included in the macrosystem. Finally, Bronfenbrenner realized that each level of ecological influence is not static over time, so the concept of the chronosystem was eventually added to reflect the changing features of each level over time. The chronosystem was primarily intended for accounting for the influence of historical context in which an individual's lifespan unfolds but has also been applied to examining how the expectations of the individual and environment change over an individual's lifespan.

Returning briefly to the Process–Person–Context–Time Model (PPCT; Bronfenbrenner & Morris, 2006), proximal processes fit in with the larger bioecological model of human development in several ways. As mentioned above, proximal processes, or the interactions that are most intimately experienced, are the driving force behind human development, and consequently, ecological development. An individual interacts over time not only with other people, but objects, spaces, and symbols in their immediate environment, creating a bi-directional relationship between person and environment. It is not simply a unidirectional influence of the environment shaping the individual's development (as some early behaviorists thought), but an active exchange between the two that explains developmental outcomes. The quality (form, power, content, and direction; Bronfenbrenner & Morris, 2006) of proximal processes is a combination of the person, environment, change and continuity of interactions over time, and the historical period of an individual's lifespan. Personal characteristics play an important role in interaction with the environment. Age, gender, and even physical appearance (demand characteristics) influence social interaction experiences as well as the perception of value placed on objects and symbols. Resource characteristics (mental, emotional, and material resource availability) of a person exert an influence on quality of interactions with people and access to objects and symbols. Motivation, persistence, and temperament (force characteristics) help explain the multifinality of developmental outcomes when resource characteristics are equal – some may be more motivated, persistent, and/or tolerant of discomfort in the face of adversity. Context refers to the nested ecological systems described above. Finally, the element of time plays out over three different levels. Micro-time refers to what is happening during a particular episode of a proximal process, for example, a transfer student interacting with a new teacher. Meso-time refers to the frequency of proximal processes over a longer period. Consider the contrast between a child who is often absent from school and a student who has perfect attendance – the frequency of proximal processes between teachers and classmates is quite different. Meso-time refers to the chronosystem and captures both the changing cultural expectations as well as changes in expectations of an individual at different points in their lifespan. Meso-cultural shifts are typically glacial as they change, and the reader is encouraged to reflect on the resistance and acceptance timeline of cultural norms they have noticed. Individual meso-time simply refers to the fact that people and the larger social structures expect different things from us depending on where we are in our lifespan (Bronfenbrenner & Morris, 2006).

Kindergarten is one of the first times that the microsystem structure expands beyond the family/caregiver environment. A successful transition to Kindergarten paves the way for later transitions to even larger, more complex, and demanding environments

(Bronfenbrenner & Morris, 2005). Even in a non-mobile student's school environment, there is a lot of change and uncertainty, however, the repetition of interactions over time in the same place with the same people can help children cope with uncertainty, anticipate peer and teacher expectations, and allow them to feel comfortable exploring and mastering new academic tasks as they learn. When children change schools, some of this repetition and familiarity is taken away, daily routines change, teacher expectations may be different, and adjusting to the new curriculum may come at a cost in academic performance that may persist beyond the initial adjustment period (Reynolds & Mehana, 2004). Students who frequently change schools may not even have time to adjust before moving again. For schools with high student turnover, non-mobile students' academic progress may be more likely to be impacted as new students enter and familiar faces exit than a non-mobile student at a school with lower turnover (Hanushek et al., 2004).

Of course, school is much more than meeting academic requirements. Peer relationships and the social resources that come along with friends and community involvement are often part of what is lost when children move schools. Coleman's (1988) social capital theory compliments the discussion of proximal processes outlined above by considering the specific benefits of social relationships and consequences when those social relationships are ruptured after a school move. Where Bronfenbrenner details the importance of the *process* of routine interaction with environments, symbols, and people, Coleman focuses on the *outcome*s of social interactions through a sociological lens.

When speaking of social capital, I refer to the interconnected network of people in a community and the resources (e.g., shared effort in helping care for each other's children, disseminating valuable information, or coming together to solve a common problem) made available to people in that community.

According to Coleman (1988), if there are strong ties among and between families and the larger local community, then school mobility will be discouraged because of the associated benefits and resources (capital) that are shared with them while staying put. Weak connections to nearby immediate/extended family and to the larger community, on the other hand, might encourage school mobility, either by choice or because the community decision to not share resources forces them to relocate to another school/residence. For those that do move schools, the ability of a mobile family to compel people in the new school community to share resources with them might help reduce social and academic costs associated with school mobility.

Researchers have since used Coleman's (1988) theory to develop self-reports that measure the amount and type of social capital shared with families. In the context of elementary school mobility, the decision to stay or move schools cannot take place without caregiver input, so parent-based self-reports are often used to measure social capital. There are several categories of items developed from social capital that are used in school mobility research, but a measure of intergenerational closure, or the number of parents of a child's friends the parent knows, may be a particularly important protective factor in reducing the negative effects of school mobility (Coleman, 1988; Fiel et al. 2013), especially for Black students, who are the most overrepresented group of highly mobile students (GAO, 2010). Essentially, Coleman (1988) thought that a network of parents that know each other well would benefit the child by enhancing social support, exchange of information, and shared responsibilities of raising their children.

Fiel et al. (2013) conducted the only known experimental study that explored an intervention with the aim of reducing school mobility. Technically, the intervention was aimed at increasing the connection between family, community, and school – a mesosystem-level relationship to relate it back to Bioecological theory) – but the intervention, if successful, would ultimately discourage school mobility. Fiel et al. (2013) found that intergenerational closure played a significant role in reducing mobility for all participants, but it was especially the case for Black families involved in the experimental group. While there were quantitative shortcomings that prevented the authors from speculating why this was the case, it is perhaps fair to say that any marginalized population with above average school mobility would benefit from an intervention that gave them the opportunity to increase their social capital.

Drawing from Coleman's (1988) theory on social capital, and especially intergenerational closure, South, Haynie, and Bose (2007) offer four broad categories in an attempt to explain many of the mechanisms underlying the effects of school mobility in relation to the specific outcome of high school dropout: (1) parent–child relationship characteristics, (2) peer social networks, (3) academic performance and school engagement, and (4) psychological well-being. A close, healthy relationship between the parent and child may be a protective factor for the child during a school move – the parent can serve as an anchor to an otherwise changing sea of teachers and friends. Positive parent attachment may be an important moderator of school mobility and academic achievement (South et al., 2007). Who the mobile student's close friends become from the newly available peer group can also positively or negatively influence a student's academic performance (i.e., to what degree does the mobile student surround themselves with new friends who are engaged in lots of school activities?) (South et al., 2007). Academic performance and school engagement, when high, increase attachment to the school, yet incoming mobile students tend to be less engaged in extracurricular activities (Pribesh & Downey, 1999). Thus, the degree to which incoming mobile students get involved in the new school over time may also be an important moderator of academic outcomes (South et al. 2007). The goodness of fit between school and the incoming student may moderate levels of school engagement (i.e., does the mobile student identify with the student body and school climate?). Finally, moving schools can be stressful and threaten psychological well-being because a student may feel out of place (South et al., 2007). Some parents attempting to gain more intergenerational closure as their child enters a new school may find that it takes more time than anticipated to form new friendships with parents of their child's classmates and friends which, in turn, may hinder their ability to help their child adjust to a new school.

To unify the popular theoretical frameworks used in school mobility research, Welsh (2017) offers a model that is informed by the Bioecological Model (Bronfenbrenner & Morris, 2005) and Social Capital Theory (1988; see Figure 1). He argues that the costs and benefits associated with school mobility can be explained largely by the degree to which discontinuity in the learning environment and disruptions to social capital are present. Understanding both academic and socio-emotional factors can help detail the net effect of school mobility and help explain some of the mixed findings of previous research (Welsh, 2017). For example, a model predicting academic performance from school mobility is more complete if it also includes controls related to socio-emotional skills because those skills may help or hinder performance when there is a disruption in the school environment. More generally, his model serves as a shared platform to identify what selection effects previous studies may have left out and what future studies ought to strive to include whenever possible.

Welsh (2017) includes a conceptual figure that outlines the key relationships among school mobility and their academic outcomes (see Figure 1). At every step of the figure, concepts of proximal processes and social capital are thoroughly and meaningfully integrated. School mobility effects on academic outcomes are notoriously complex and prove to be problematic for statistical modeling. There are effects happening at the micro, macro, and mesosystem level, and the same effects are often happening concurrently and sometimes in competition with one another. To ease description of the figure, I have numbered all 10 pathways and will refer to numbered paths in parentheses when appropriate. It is recommended that the reader have the figure in front of them when reading this section. On the left, Bronfenbrenner's bioecological model is modified for the education setting: student nested withn school, nested within neighborhood, nested within district. The characteristics of the student, school, neighborhood, and district directly influence academic outcomes regardless of mobility status (path 1). Those same characteristics can influence the school and non-school circumstances leading to a school move (path 2). Academic outcomes can also be directly influenced by the school and non-school circumstances (the elusive "why") behind a school move (path 3). The student, school, neighborhood, and district characteristics can directly influence an actual school move (path 4). Obviously, the circumstances behind a school move influence the actual nature of the move (path 5). School mobility influences the cost of adjustment to a new neighborhood if a residential move accompanies a school change (path 6). School mobility likewise influences school adjustment costs (path 7). Note that adjustment costs pertain not only to the mobile student, but also the adjustments made by the neighborhood and school, which is in line with the proximal process of giving and receiving social capital. Moving to a higher or lower quality school (path 8) will also influence academic outcomes, possibly having a moderating effect on school adjustment costs. The amount and quality of social capital shared with a student in school and neighborhood affects academic outcomes (paths 9 and 10).

Methodological Challenges in School Mobility Research

There are several potentially confounding factors that need to be addressed to provide the least biased estimates of school mobility's association with academic outcomes. Establishing the true relationship between school mobility and academic outcomes is problematic because of the numerous and simultaneous sources of influence, outlined above, that accompany a move or series of moves (Welsh, 2017). Inadequately addressing any of the following is likely to contribute bias and/or limit generalization of results: selection effects, comparison group choices, and violations of pure nested data. I will first discuss the importance of controlling for selection effects in quasi-experimental designs. Related, deciding on appropriate comparison groups in the absence of a true control group is examined. Last, the advantages of cumulative and independent cross-classified random effects growth modeling as an appropriate way to include students who are not purely clustered in the same school at all timepoints are highlighted and compared to a simpler three-level HLM approach.

Selection Effects. Determining the effects of school mobility on academic achievement is confounded by the fact that not all children are equally likely to switch schools. There is selection bias observed in demographic characteristics (ethnicity, income, special education status, English language learner status), pre-Kindergarten environment, prior achievement, school readiness, and reasons for moving schools (Alexander et al., 1996; Conger, Gibbs, Uchikoshi, & Winsler, 2018; Kerbow, 1996; Hanushek et al., 2004; Welsh, 2017; Moffett & Winsler, 2020 in review). Not all studies adequately control for selection effects even though we know that those who make frequent nonstructural school moves are more likely to be Black or Latinx, come from low-SES families, and/or be English language learners (GAO, 2010; Alexander et al., 1996; Burkham, Lee, & Dwyer, 2009; Fong, Bae, & Huang, 2010; Hanushek et al., 2004; Kerbow, 1996; Mehana & Reynolds, 2004; Moffett & Winsler 2020 in review, Welsh, 2017). Welsh (2017) notes that most early studies on school mobility effects on academic achievement often did not include covariates for prior achievement and demographic characteristics. The negative effect of school mobility on achievement was almost always seen in these early studies (Rumberger, 2002; U.S. General Accounting Office, 1994). In later studies, when prior achievement and demographics were controlled for, researchers saw a decrease in significance and effect sizes for school mobility (Alexander et al., 1996; Reynolds et al., 2009), but it is notable that the association with academic outcomes usually persisted. There are countless ways that mobile students may differ from nonmobile students, many of which are likely to remain unobserved in even the best studies. While it is a good start, adequately controlling for prior achievement and demographic characteristics is not sufficient alone.

In my previous research on school mobility in Miami, I found most of the selection factors described above predicted a greater likelihood of ever experiencing school mobility, as well as the total number of moves, during elementary school. Using the same dataset used for the current study (Moffett & Winsler, 2020 in review), multivariate Poisson regressions examined predictors associated with ever moving schools between K-G5, and for those who moved, frequency of school moves in elementary school. Overall, 38% moved to a different elementary school at least once, with 66% moving once, 30% twice, and 4% moving schools 3 or more times. Controlling for all predictors (gender, disability status, ethnicity, poverty status, school readiness [cognitive, language, motor, social and behavioral] skills at school entry, and type of preschool program previously attended), students were more likely to move schools if they: a) attended center-based care or family childcare compared to public school pre-K programs at age 4, b) were Black compared to White, c) had a disability, and d) attended a lower-quality school the year before the move. Among students who moved at least once, those who scored lower on preschool teacher-reported social skills, students in poverty, and Black students switched schools more often. Other studies that have included measures of achievement prior to a school move, also find that pre-move academic skills explain a considerable amount of variance in later academic outcomes for mobile students (Alexander et al., 1996; Reynolds et al., 2009).

In a true experimental design, concerns about selection effects are handled by random assignment to different groups, and of course it would be unfeasible to randomly assign some students to move and others stay put. The next best thing in terms of inference is to conduct a long-term, prospective longitudinal study in which multiple important selection factors related to academic, social, and demographic characteristics are measured and controlled for statistically when examining outcomes for students associated with moving schools. This is what I did for this dissertation.

Comparison Groups. Most studies are interested in comparing outcomes of mobile students to nonmobile students, typically longitudinally. School mobility grouping has been defined in a variety of ways by previous research, with membership criteria ranging from simply ever moving during the study, to more detailed definitions based on frequency, whether a move was intradistrict, at what developmental stage a move occurred, or even what dates during the year a student exits one school and matriculates to a new school. When longitudinal data are available, it is possible to compare growth (typically academic achievement) over time.

Comparing the association of school mobility and academic outcomes between movers and nonmovers controlling for selection effects is a valid and meaningful approach, but it is possible that the lack of differentiating more common *once* movers from less common *multiple* movers in the same grouping may suppress any real negative associations with academic outcomes. Indeed, when studies do compare more (3+) and less (0-2) frequent movers to each other and nonmobile students, the effect size of school mobility is greater for frequent movers when this finer differentiation of frequency is implemented (Mehana & Reynolds, 2004). The majority of nonstructural school moves are local, occurring within the same school district, as opposed to a student entering a new school in a new district (Hanushek et al., 2004; Kerbow, 1996). When intradistrict moves occur, they tend to be made by students from low-SES families and ethnic minority students living in dense urban areas, while moves out of the district tend to be made by students from high-SES families, more often White, living in suburban areas (Alexander et al., 1996; Hanushek et al., 2004; Kerbow, 1996). The prior literature's findings lend credibility to studying intradistrict mobility as its own unique phenomenon (as I do in this dissertation) separate from inter-district mobility, as it may allow for a greater chance to isolate and identify key features specifically related to *negative* associations between school mobility and academic outcomes.

Early vs. late elementary school move comparisons are usually accomplished by comparing early movers to nonmobile students, and separately, late movers to nonmobile students (Lleras & McKillip, 2017; Mehana & Reynolds, 2004), but the same kind of issue of suppressing effect size seen in movers vs nonmovers by not distinguishing frequency of moves is present in this type of comparison. Herbers, Reynolds, and Chen (2013) did a comparison using K-12 data (described below), but allowed early (K-G4), and middle (G4-G8) mobility to vary as either 1 move or 2 or more moves (G8-G12 was coded y/n moved) in comparison to nonmobile students, a creative approach to reduce biases from comparison groups. A related but separate class of school mobility distinction involves classification by *when* during the year a school move takes place. Most studies compare between-school year moves (Welsh, 2017), when school moves are most likely to happen (Schwartz et al., 2009). Bias may be introduced in between-year comparisons by way of underestimating the number of school moves, as moves are often coded yes/no ever happening annually (as is done in this dissertation). This approach also results in an inability to determine whether school mobility is more disruptive, and thus more negatively associated with academic outcomes, if it happens at a particular time during the year (e.g., do growth trajectories vary if a move happens in the fall, spring, or summer?).

In my data analysis, I opted for a wide range of comparison groups. At its simplest, I compared movers to nonmovers to see whether ever moving was associated with academic outcomes. Once this was established, I included a continuous measure of total number of moves to determine whether, for each additional move, there was a significant amplified negative link to negative outcomes. I was also interested in whether the association with academic outcomes varied as a function of frequent (3+ moves) vs. infrequent moves (1-2 moves), as well as a function of earlier (G1-G3) vs. later (G3-G5) moves.

Nesting. Even when there is adequate control of selection effects and appropriate comparison groups in place, there is still the issue of violating the pure hierarchy assumption in traditional multilevel modeling. The threat to unbiased estimates comes from failing to model the effects attributable to a *set* of schools attended. For nonmobile students, a very straightforward three-level hierarchical model of repeated measures nested within child, nested within school could be used to account for school-level differences. Mobile students in the same model, however, would normally be omitted because their school-level ID changes at least once during elementary school. Previous research has worked around this limitation by including school-level data from the last school attended, simply ignoring earlier school-level data (Wolff Smith & Beretvas, 2017). Ignoring the unique set of schools attended for each student results in model misspecification because academic performance outcomes are explained in part by a student's entire school attendance history, not just the experience of the most recently attended school.

In this dissertation, I used cross-classified random effects growth models (CCREGM) to overcome the limitations of traditional hierarchical modeling. There are several advantages to cross-classifying annual academic outcomes and covariates (within-cell) between children (rows) and schools (columns). Most importantly, school IDs are free to vary within child, allowing for mobile children's data to be included in analysis. Accounting for this real cross-classification structure has been found to lead to less biased variance components and standard errors than ignoring school ID altogether, or misspecifying school-specific variance contribution by forcing it to fit into a pure hierarchical analysis (Luo & Kwok, 2012; Meyers & Beretvas, 2006).

Attrition, Off-Track Trajectories and Missing Data. Beyond random attrition expected in any longitudinal study, there are two major sources of nonrandom attrition likely to be present in school mobility research: grade retention and moves outside of the participating school district/region. Keeping track of retained students poses a challenge to researchers, especially if those that are retained are part of a longitudinal study with more than one cohort, where their grade performance data is found a year (or more) behind the rest of their on-time cohort. I only included on-time students in my dissertation in part to be like my thesis sample, but more importantly, so that I do not introduce temporally ambiguous error into my models. It is possible that retention may be caused by and/or the result of school mobility, and without having a variable that differentiates the two, I would be less certain about the association with academic outcomes and would not gain the ability to generalize results to a larger population. With a clear understanding of these methodological challenges, I now turn to my literature review on student outcomes from school mobility.

Outcomes Associated with School Mobility

School mobility is negatively associated with academic achievement even when controlling for pre-existing child characteristics (Grady & Beretvas, 2010; Gruman et al., 2008; Reynolds, Chen, & Herbers, 2009; Welsh, 2017) and school characteristics (Kerbow, 1996; LeBoeuf & Fantuzzo, 2018). While school mobility in some forms can have positive effects on children (e.g., military families moving, [Ruff & Keim, 2014]; the school move is made in part to be closer to stable family members, or so the student can attend a school that fits their needs [la Torre & Gwynne, 2009]), the majority of the research has found that unplanned school mobility is associated with negative academic outcomes and progress, including lower standardized test scores for reading and math and GPA, higher grade retention, and school dropout (Burkam, Lee, & Dwyer, 2009; Freidman-Krauss & Raver, 2015; Foorman, Petscher, Lefsky, & Toste, 2010; GAO, 2010; Kerbow, Azcoitia, & Bell, 2003; LeBoeuf & Fantuzzo, 2018; Mehana & Reynolds, 2004; Parke & Kanyango, 2012; Rumberger, Larson, Ream, & Palardy, 1999; Temple & Reynolds, 1999; Voight, Shinn, & Nation, 2012).

Across studies, children who change schools have demonstrated lower math and reading achievement during elementary and middle school compared to peers who did not experience school mobility (Gruman et al., 2008; Mehana & Reynolds, 2004; Temple & Reynolds, 1999). These outcome differences are still present when selection effects are included in the model, and although mobility effects are attenuated after bias from selection effects are removed, a sizable effect is still seen and warrants further exploration.

Reynolds (1992) examined the association between student mobility and grade retention with 4th grade students (N = 1,255, predominantly Black and low-income) in Chicago. Students who changed schools once between pre-K and 2nd grade were 7% more likely to be retained during Kindergarten through third grade compared to their stable counterparts (Reynolds, 1992). While child-level SES was not examined (due to little variance), school-level SES was positively correlated with retention which Reynolds (1992) speculated might mean that attending higher-SES schools does not negate the likelihood of retention. The goodness-of-fit dimension mentioned earlier may account for this discrepancy, in that low-SES students may not be as welcomed to a high-SES school as already high-SES mobile students. The discrimination that students and parents face may counter the advantages that a high-SES school carries.

In another large-scale study involving Chicago Public Schools, Kerbow (1996) reported on the cumulative effect of school transfers on reading and math outcomes over time. Controlling for child-level SES, linear growth was seen in reading performance for all mobility groups, however growth for highly mobile students (4 or more moves) was close to one standard deviation below non-mobile counterparts (Kerbow, 1996). While moving schools only once made little difference for reading outcomes, there were cumulative effects of school mobility for those who moved two or more times. Students who were relatively high in SES, but moved many times over five years, were more similar to economically disadvantaged peers in terms of academic achievement by the end of the study than to their high-SES peers who moved less often (Kerbow, 1996). Foorman, Petscher, Lefsky, and Toste (2010) found similar results in Florida showing that mobility to even a nearby school can disrupt the experience of special reading programs intended to span several years if the new school does not participate in the same program. Children who moved only once were quite similar to non-movers, while those that moved twice or more had lower reading scores in comparison to non-movers, controlling for SES (Foorman et al., 2010).

Some investigators distinguish between intradistrict and out-of-district mobility (Alexander et al., 1996; Hanushek et al., 2004). Hanushek et al. (2004) found that the more geographically distant a school change was, the association with academic performance was more positive compared than less distal moves. This is presumably because long-distance moves are usually made with the purpose to seek out better economic opportunity for the family and/or to have their child attend a higher-quality school (Hanushek et al., 2004). Indeed, there is little evidence to indicate that intradistrict moves are made from a lower to a higher quality school (Welsh, 2017). Kerbow (1996) found that less than half of moves within district accompanied an upward shift in school quality, even when parents reported the motivating reason for the move was for school quality, suggesting a mismatch of parent expectation and school quality. Related to academic outcomes, Xu et al. (2009) found that intradistrict moves often netted no change in reading and math scores after the move. Hanushek et al. (2004) found that moves across districts resulted in significant improvements to school quality for all demographic groups except for Black students. School moves within district, alternatively, did not result in a change in school quality, and the costs in later academic achievement, while small, were worse for low-SES, Black students.

Gruman et al. (2008) examined the longitudinal effects of school mobility and four other time-varying covariates between second and fifth grade on three different outcomes: classroom participation, positive attitudes toward school, and academic performance. Their multivariate and multilevel approach highlight the advantages of including repeated measures from multiple sources (child, teacher, parent, and school) when gauging the relative impact that school changes have during and by the end of elementary school. Predominantly White children in a school district north of Seattle, Washington (*N* =1,003) and their families were followed from 2^{nd} - 5^{th} grade. They controlled for gender, total school moves, family stress, initial SES (free or reduced-price lunch), initial teacher-reported social skills (antisocial, shy) entering 2^{nd} grade. They also included four time-varying measures each year of the study: yearly school changes (school records, one or more school moves between June of a given school year and June of the next year, yearly family stress, self-reported teacher support, and self-reported peer acceptance. Outcome variables were annual measures of classroom participation (teacher survey), attitude toward school (child survey), and academic performance (teacher assessment on language, math, and reading).

Their results unfolded over four phases. The first phase consisted of correlations prior to any growth modeling of the outcome variables. Here, they found that student mobility was correlated positively with poverty (r = .22, p <.01) and stress (r = .17, p <.01), and negatively with peer acceptance (r = -.12, p <.01) and classroom participation (r = -.13, p <.01). Based on the concern that peer acceptance and classroom participation were measuring the same construct (r = .67), peer acceptance was omitted from subsequent models exploring classroom participation.

The remaining phases were required because Gruman et al. (2008) did not have enough power to test a model with all level 1 and 2 variables simultaneously, opting instead for a "step-up" HLM process where the final and most complex model tested in phase 4 was built by retaining any significant covariates found in phases 1, 2, and 3. The second phase involved testing the unconditional models for each of the three outcomes and then adding one-by-one the four time-varying covariates. The unconditional model for each of the three outcome models indicated significant negative linear change, meaning that the outcomes (classroom participation, positive attitude, and academic performance) decreased over time by grade 5. Linear change remained significant and negative for each outcome as each time-varying covariate was added. The third phase involved adding the level-2 predictors to the significant level-1 covariates for each outcome in a similar step-up approach. In the first step, total school changes were added and had a negative impact on fifth-grade classroom participation, and academic performance, but not on positive attitudes toward school. Linear change for total number of schools was found to be significant and negative for academic performance and would be retained for the final model of academic performance outcome.

In the second step, the remaining level-2 child characteristics (gender, income, antisocial, shy, and stress) were added for each of the outcomes. Total school changes still had a significant negative effect on classroom participation (G5 intercept), but no longer on academic performance. Total school changes did retain a significant negative impact on the slope of academic performance. Other noteworthy child-level predictors from phase 3 include initial antisocial behavior and low-SES remaining significant for all outcomes. Being male predicted declines in positive attitudes toward school and classroom participation. Shyness predicted declines in academic performance and classroom participation. Finally, total number of stressful events predicted declines in classroom participation. In phase 4, all significant level-1 covariates (related to each outcome) were entered in one-by-one for each outcome. The most relevant finding in phase 4 is that total number of school moves resulted in significantly greater declines in academic performance over time. Peer acceptance was positively related to academic outcomes, but the interaction between peer acceptance and initial antisocial behavior was significant and negative, in that being initially antisocial decreased the positive influence of peer acceptance on academic performance. School mobility proved to be a persistent negative predictor for academic performance outcomes across each phase of analysis, however the relationship among mobile students, positive attitudes toward school, and teacher support offer an optimistic framework for researchers to explore ways to reduce the impact school mobility has on academic outcomes in elementary school (Gruman et al., 2008). It is important to note that their multilevel models were inherently misspecified by ignoring the true cross-classification of mobile students attending different schools over time.

A meta-analysis of 26 studies published between 1975 to 1994 (*N's* = 62–15,000) examining school mobility during K and 6th grade found that mobile students were, on average, four months behind in reading and math performance, controlling for SES, time of move (K-G4 vs G4-G6), and civilian status (as opposed to military), compared to students who stayed at the same school (Mehana & Reynolds, 2004). A main criticism raised by the authors is the failure of most studies to adequately understand and control for selection effects like student achievement *before* school mobility took place.

Total number of school moves is the most commonly used metric in models of school mobility across studies. While there is not much difference between one-, and two-time movers regarding academic outcomes, the effect of school mobility is almost always noticeable when comparing highly mobile students (3+ moves) to nonmobile or less-mobile students (Alexander, et al., 1996; GAO, 2010; Gruman et al., 2008; Kerbow, 1996; Reynolds, Chen, & Herbers, 2009). A potential mechanism at play for frequent movers is that the accumulated cost of having to readjust to new peers, academic expectations, and teacher styles, in addition to adjustments beyond the school context at home and in the community. Once this passes some threshold that was not seen in once and twice movers, it interferes with their ability to maintain academic performance or catch back up to their prior academic achievement (Reynolds & Mehana, 2004).

Several studies support the idea that frequent moves are associated with worse academic outcomes (Alexander, Entwisle, & Dauber, 1996; GAO, 2010; Gruman Harachi, Abbott, Catalano, & Fleming, 2008; Kerbow, 1996; Reynolds, Chen, & Herbers, 2009). Alexander et al. (1996) found that students who move three or more times in elementary school had lower test scores and GPA, were assigned to special education more, and were retained more often by the end of fifth grade compared to once and twice movers. Alexander et al. (1996) noted that the effect of school mobility decreased as they entered selection effects into their multi-step OLS regression model, however, because they did not account for the nesting of students in different schools, their estimate may be biased due to unobserved variance in school characteristics. A nationally representative report on school mobility by the GAO (GAO, 2010) also found evidence that frequent moves are associated with worse academic outcomes. Specifically, students who moved four or more times had worse academic outcomes by 8th grade than those who moved two or fewer times. As mentioned above, Gruman et al. (2008), noticed that total school moves was related to a slowing down of academic outcomes from first to fifth grade.

In addition to considering the impact that the total number of school moves has on outcomes, it is important to also include measures that capture when a school move takes place. Students can move earlier, later, or possibly at several timepoints throughout their education. Overall, there is consensus that moving earlier is associated with poorer later academic outcomes (Burkham et al., 2009; Mehana & Reynolds, 2004; Welsh, 2017).

Lleras and McKillip (2016), utilizing data from the Early Childhood Longitudinal Study-Kindergarten (ECLS-K), for example, considered early moves as happening during Kindergarten through Spring of grade one and late moves as Spring of grade one through grade three. Children could be in early, late, or both mobility groups for analyses, and the comparison group for early and late movers was children who did not experience any moves during the same time (K-Grade 3). Herbers et al. (2013) employed a similar technique in a sample (*N*=1,539) of K-12 students using data from the Chicago Longitudinal Study (CLS). There were three mobility groupings (K-G4, G4-G8, and G8-G12) that mapped onto developmentally salient stages (middle childhood, early, and late adolescence). Herbers et al. (2013) timing-of-moves analysis utilized dummy coding to reflect whether a student moved either once or two or more times in K-G4 or G4-G8. The late adolescence group (G8-G12) was coded only to reflect that at least one move had taken place. The combination of frequency and timing of moves reflected in the five dummy codes allows for a more detailed picture of school mobility impact on outcomes than either can do separately. Lleras and McKillip (2016) found that students who moved both early and late had the worst impacts on reading growth than math by third grade compared to nonmobile students, controlling for prior achievement, behavior, and demographics, but mobile students who moved only early or late were not that different from nonmobile students in reading and math gains. Herbers et al. (2013) found that a threshold effect for multiple moves during G4-G8, but not during K-G4 or G8-G12, in that multiple moves in G4-G8 resulted in greater likelihood of not completing high school on time. More generally, each additional move during K-G12 resulted in significantly lower chances of on-time high school graduation.

Friedman-Krauss and Reaver (2015), using data from the Chicago School Readiness Project, followed children (*N* = 381) as they exited their Head Start program for the next six years, and explored math outcomes at the end of third grade for mobile students. Their methodology is one of the most comprehensive traditional HLM approaches to examining potential effects of school mobility on academic achievement to date. I only briefly describe their approach and results below. They used multi-level modeling where students were nested in their fourth-grade school. For school variables, they used measures of overall math score performance, and school-level SES. They controlled for a host of selection factors for students at level-1 including: SES, gender, ethnicity, age, grade when taking the standardized math test, caregiver education level, caregiver relationship status, cohort, prior math ability, and cognitive dysregulation measured in Head Start. Their mediation variable, cognitive dysregulation, was measured in two ways via teacher-report in third grade. Used as a predictor, cognitive dysregulation was measured via direct and assessor-rated measures in Head Start. Three multi-level mediation models (one for each measure of school mobility: total number of moves, ever moved, and frequent movers) were used to test whether cognitive dysregulation measured in third grade, controlling for all previously mentioned selection factors, had a mediating effect on math outcomes in fourth grade. They found that frequently changing schools was associated with greater teacher-reported cognitive dysregulation in third grade and with poorer performance on math scores in fourth grade, even after controlling for initial cognitive dysregulation in pre-K and child characteristics.

In a recently published article, LeBoeuf and Fantuzzo (2018) examined the association between intradistrict school mobility and reading achievement for a cohort of students between first and third grade in a large urban school district. It is the only school mobility study to implement cross-classified random effect growth modeling to a real-world sample. Student characteristics controlled for gender, ethnicity, annual free and reduced priced lunch status, annual special needs status, and annual English language learner status. They also included a school-level control for the annual rate of student turnover.

Prior to running the unconditional growth models, time was transformed into its square root to handle the observed nonlinear growth of reading achievement where growth was faster between first and second grade than second and third grade.

After the time transformation, results from the final unconditional model indicated that there was significant variation in reading growth rate and intercept within and between students and between schools, establishing their baseline for conditional models with two fixed effects (intercept and slope) and five random effects (three for student: residual error within student, and random variation between student rate of change and intercept, and two for schools: random variation between school's rate of change and intercept).

The conditional predictor models unfolded over a series 5 nested models, initially adding concurrent school mobility to intercept and slope, then testing the interaction of concurrent school mobility and rate of change (not significant and removed from future models). Total number of moves was added in the third model before adding in the school-classification control of student turnover rates in the fourth. Other than the interaction between school mobility and rate of change, all predictors were significant and retained for the final model with student characteristics added.

Several notable findings resulted from their analyses. Students who move had 10% of a standard deviation lower reading scores by third grade, even after controlling for student characteristics (LeBoeuf & Fantuzzo, 2018). There was also an increasingly negative association with reading scores for each additional move. High student turnover indicated a small but significant negative association with reading scores in first grade and by third grade, this ballooned into the equivalent of an entire year's loss in reading scores in third grade.

To summarize, school mobility effects on academic outcomes differ greatly depending on the frequency, timing, and nature (within- vs between-districts) of school moves, as well as the student's individual characteristics (GAO, 2010; Hanushek et al., 2004, Reynolds et al., 2009). Previous research has routinely found that frequent moves are negatively associated with academic outcomes compared to nonmobile and less frequent movers (Alexander et al., 1996; Gruman et al., 2008; Kerbow, 1996; Mehana & Reynolds, 2004; Welsh, 2017). There is also evidence that moves occurring during the school year (Schwarz et al., 2009) and mobility in early education (Mehana & Reynolds, 2004) are associated with the greatest cost in later academic performance. Transfers intradistrict have been shown to be associated with more negative academic outcomes than transfers between school districts (Hanushek et al.; Mehana & Reynolds, 2004). Students who are from low-income families and Black or Latinx are overrepresented in frequent, early, and intradistrict mobility groups.

Gaps in Research and Current Study

While the earliest school mobility research often failed to adequately control for selection effects or include comparison groups other than nonmobile students, there have been considerable advances in the quality of research over time (National Research Council and Institute of Medicine, 2010; Welsh, 2017). Several gaps remain, and this study aimed address the following: (a) accounting for differences in student characteristics between mobile and non-mobile students (b) differentiating types/timing of school mobility, (c) modeling change in academic achievement over time, and (d) accounting for variance attributable within students, between students, and between schools.

It is not enough to model the difference in average academic outcomes between mobile and nonmobile students when prior literature has demonstrated some attenuation of the relationship between school mobility and academic outcomes when student characteristics are included as covariates (Alexander et al., 1996). Since there is established expected variation in student characteristics between mobile and non-mobile students, attention must be paid to controlling for the variability in outcomes observed across these characteristics. When covariates are included, what remains is the additional variation, holding categorical covariates at their “0” group and all continuous covariates at their mean, in outcomes between mobile and nonmobile students.

Accounting for student characteristics is but one necessary step toward a model that better mimics the real association between school mobility and academic outcomes. The way that school mobility is quantitatively operationalized has also played a role in prior literature's reports of variability/effect size/direction accounted for by school mobility (LeBoeuf & Fantuzzo, 2018). This study addressed a limitation of prior between-year mobility studies by analyzing the between-year measures in four distinct ways: dichotomously, frequency (total number of moves and frequent vs infrequent vs non-mobile), and timing (early movers vs late movers vs non-mobile). This allowed for a rough comparison to previous studies and to discover any changes to model interpretation conditional upon the way that between-year school mobility was quantified.

The two remaining limitations relate to change over time. Coincidentally, cross-classified models were borne out of cross-sectional data that were not purely nested to reduce estimation bias (e.g., students crossed with neighborhoods and schools; Hill & Goldstein, 1998; Raudenbush, 1993). More recently, Luo and Kwok (2012) adapted cross-classified models to account for students who change schools over time and their simulation study demonstrated that estimation parameters were similarly less biased compared to approaches that ignore cross-classification.

In this study, I examined the association between school mobility (ever moving, total number of moves, frequent moves, and timing of move) and academic outcomes (GPA, Reading, and Math) of mostly low-income students across five sequential cohorts enrolled in public elementary school within a large and diverse urban school district, and the unique contribution of such mobility on the rate of change and fifth-grade academic achievement remaining after accounting for many student characteristics. The primary goal of this study was to address gaps in prior literature with the application of principles from bioecological and social capital frameworks on modeling occasions of academic achievement measurements cross-classified by students and school contexts.

Research Question

1.After controlling for time-invariant characteristics of gender, ethnicity, pre-K type, school readiness, and time-varying annual status of free and reduced price lunch, special needs, and English proficiency, to what degree is intradistrict school mobility ((a) ever move, (b) total number of moves, (c) frequent moves, and (d) early moves) associated with the rate of change over time and fifth grade academic achievement (GPA, standardized reading and math test scores) during elementary school.

METHOD

The research design and methodological approach is presented below, and includes a description of student characteristics, analytic constraints applied to the study sample, operational definitions for all variables, and procedural guidelines for how the unconditional models were built up for use as baselines in the conditional models.

Participants

Data used for analysis comes from the Miami School Readiness Project (MSRP; Winsler et al., 2008). In the MSRP, almost the entire local population of children receiving subsidies to attend childcare programs and children attending public school pre-K programs were assessed for school readiness throughout 2002-2007 and followed into school. This leads to a cohort-sequential structure, where a new cohort of incoming children is added each year from 2002-2007. Children from all five cohorts are included in the study sample (Cohort A = 6,457, Cohort B = 7,403 Cohort C = 8,940, Cohort D = 8,843, Cohort *E* = 6,988). On-time Kindergarteners, for example, can have data from the 03-04 school year through 08-09 school year depending on which cohort they are in. A subtle consequence of accommodating this sequential design is that “time” in this study strictly refers to grade level and not school year. I restricted the sample for this study to children from grades K through G5 continually enrolled in public elementary schools that had school ID data for all years, were never retained or skipped a grade (resulting in a

14.5% decrease from the larger K+ sample) and had outcome data from at least one timepoint (*N*=20,806). The continual enrollment requirement was made to assure that we were identifying intradistrict school mobility and not moves to or from another school district. These constraints yielded a study sample of 20,806, about 63% of the full MSRP sample (*N= 33,043*) of on-time students continuously enrolled for two or more consecutive years within the Miami-Dade school district.

As seen in Table 1, the analytic sample (*N* = 10,066) used for CCREGM in HLM was further reduced because of students having missing data on either type of pre-K attended and/or one or more of the school readiness measures. While HLM 6.04 software can handle missingness at level 1, cases are dropped if *any* missing data are detected within the student and school cross-classifications at level 2. The remaining cases strongly resembled the original study sample, with slightly more than half female, 59% Latinx, 32.6% Black, and 8.4% White/other. In first grade, almost 76% of students qualified for free or reduced priced lunch vouchers (FRL), 4.7% had a primary learning exceptionality (PREX), and 18.9% were classified as not yet English proficient (NEP). While FRL and PREX status were fairly stable over G1-G5, only 2.7% were considered NEP by the end of fifth grade.

MDCPS is one of the largest and most diverse school systems in the US, serving over 340,000 students from over 100 countries (Office of the Superintendent, M-DCPS, 2014). In 2013, nearly 66% of students were Latinx, 23% Black, and the remaining 11% were White/other (Assessment, Research, and Data Analysis, ARDA, M-DCPS, 2013). About

78.5% of elementary school students qualified for free/reduced lunch in 2013 across M-DCPS (ARDA, 2013), which our sample closely resembles.

Measures

School Mobility. I examined the association between school mobility and academic outcomes using four different mobility measures (ever moved, total number of moves, frequent moves, and early moves). Annual school mobility was first calculated by using concurrent pairs of yearly school IDs and determining whether the IDs match from grade to grade (i.e., K-G1, G1-G2, G2-G3, G3-G4, and G4-G5). For each of the five grade transitions, children who remained at the same school over two consecutive years received a 0 and those who changed schools received a 1. Note that all four mobility measures were derived from this process.

For the school ID matching process, a dichotomous mobility variable was calculated by assigning a 0 to students who made no moves and a 1 to students who made one or more moves (i.e., had a "1" for any grade transition) between kindergarten and fifth grade. Total number of school moves was calculated by summing the number of moves made between kindergarten and fifth grade, with a possible range of 0-5. Nonmovers (=0) were included in the total number of moves so that the slope and intercept were interpretable as the overall starting point and change over time for nonmobile students, and so that the total moves coefficient would be the intercept and slope difference for each additional move.

Total number of moves was then used to create a frequent move variable where a value of "2" represents 3 or 4 moves and a value of "1" represents 1 or 2 moves (nonmobile students received a “0”). This three-level categorical variable was dummy coded. For the main analyses, the nonmobile group was left out, meaning that the coefficients for frequent and infrequent movers represent the mean difference in GPA or test scores compared to nonmobile students. Secondary models swapped out the infrequent dummy for the nonmobile dummy and the intercept and slope coefficients for frequent vs. infrequent were reported.

Timing of first move was calculated by determining the first transition that school IDs did not match and then assigning early movers (K-G3) a “2”, late movers (G3-G5) a “1”, and nonmobile students a “0.” Just like the frequent mobility variable, after comparing early and late movers to nonmobile students, dummy codes were swapped out to allow differences in intercept and slope between early and late movers to be reported.

I could not determine if a student made multiple moves in a school year, so the method of using annual school ID matching likely underestimated the total number of school moves made by some students. Because the reason for a school move is unknown, there is no differentiation made relating to the type of move made, however, all elementary schools in this sample follow either a K-G5 or K-G8 structure, effectively eliminating grade promotion (a positive structural form of mobility) as an explanation of school mobility.

The condition of remaining within the district for all of elementary school requires that a student have no missing school ID data between kindergarten and fifth grade, regardless of mobility status, for both GPA and test scores. The decision to have complete school ID data between G1-G5 for all analyses was made in part so that GPA and test score samples were as similar as possible, and as a way to avoid the introduction of inter-district school mobility, as the primary interest was in isolating the unique association that *intradistrict* moves has with academic outcomes over time.

Student characteristics.

Demographics. Data were collected, often annually, for each student in the MSRP. Time-invariant characteristics, gender (coded as 1=male, 0=female) and ethnicity (Latinx, Black, White/other, dummy coded) were collected from school records and were included as time-invariant controls at level 2 in the student classification. In the primary analysis, White/other was the reference group for Black and Latinx students, and a second analysis was used to get the contrast between Black/Latinx students. Free/reduced price lunch status (FRL; Free lunch, reduced price lunch, did not apply/qualify, dummy coded) is measured at every time point and was added as a level-1 time-varying covariate in each model, with the primary comparison to students who didn't apply or qualify for FRL, and a secondary analysis comparing free priced lunch to reduced price lunch.

Not English Proficient. Children whose parents reported a home language other than English were given the Miami-Dade County Oral Language Proficiency Scale—Revised (M-DCOLPS-R; Dade County Board of Public Instruction, 1978). The 25-item test is a grade-normed English oral proficiency test that places children into five ordinal levels according to their raw scores, with level one for beginners (raw score of 4 or less) and level five (raw score 20 or more) for those deemed "proficient" in English. If a child does not achieve Level 5, he or she is placed in an English for Speakers of Other Languages (ESOL) program with more hours/services received for those with lower levels. Children are assessed every year until they reach Level 5, and native English speakers are given a

6 in our dataset. English proficiency will be used as a dichotomous time-varying covariate at level-1 in analyses, where in any given year G1-G5, a 1= those with an ESOL code between 1 and 4, and a 0= those with an ESOL code of 5 *or* those that have been given a 6 to indicate native English speaker (parents who reported English as their home language). For example, an ESOL student who became proficient in third grade would be coded G1=1, G2=1 G3=0, G4=0, G5=0, where a native speaker would have 0's for every grade.

Special Educational Needs. There are 22 broad categories of primary exceptionality that a child could be assigned to in the MSRP dataset as determined by the school district for each grade/year. The categories range from physical, emotional, cognitive, and developmental impairments to gifted status, although gifted students were not considered as having a primary exceptionality in this study. Students that had a primary exceptionality were assigned a "1" and those that did not have a primary exceptionality or were gifted received a "0". Primary exceptionality is measured at every time point and was used as a time-varying covariate at level-1 in each model.

Preschool Cognitive, Language, and Motor Skills. Children's school readiness skills were assessed directly ay age four through the Learning Accomplishment Profile–Diagnostic (LAP-D; Nehring, Nehring, Bruni, & Randolph, 1992), which was chosen by the community because it lined up with the states' Early Learning Performance Standards, was available in Spanish and English, and was for large-scale use. The LAP-D is a national, norm-referenced instrument with strong internal consistency reliabilities both nationally (α = .76–.92; Nehring et al., 1992) and within the larger MSRP sample

(.93–.95; Winsler et al., 2008). The LAP-D is a standardized direct assessment from which I used three subscales: cognitive (matching and counting), language (comprehension and naming), and fine motor (writing and manipulation). The LAP-D is intended for children between 30 and 72 months of age and was administered by children's pre-K teacher at the beginning (Time 1—September/October) and end (Time 2—April/May) of the children's 4-year-old academic year. Teachers administered the LAP-D at public school pre-K programs while outside trained assessors were responsible for administering the LAP-D at center-based care and family childcare programs. Spanish and English versions of the LAP-D were available, both of which have demonstrated strong test–retest reliability (α = .93–.97; Hardin, Peisner-Feinberg, & Weeks, 2005). I used the latest time point of LAP-D measurement when available as it is temporally the closer to school entry, however, the first time point was used if the second time point was unavailable. If neither of those two were available, there was an age three time point that was used for some.

Socio-emotional skills. Parents and teachers reported on children's socio-emotional and behavioral strengths with the Devereux Early Childhood Assessment (DECA; Lebuffe & Naglieri, 1999) at the beginning (Time 1—September/October) and end (Time 2—April/May) of the children's 4-year-old academic year, which consists of four subscales: initiative, self-control, attachment, and behavior concerns. The DECA was available in both English and Spanish, with parents and teachers choosing the language in which they were most comfortable. Parents and teachers were asked to rate children's social skills and behavior from the prior 4 weeks on a 5-point scale (0 = *never*, 1 = *rarely*, 2 =

occasionally, 3 = *frequently*, and 4 = *very frequently*). The first three subscales (initiative, self- control, and attachment) combine to make a total protective factors score (TPF), in which bigger numbers signal greater socio-emotional strengths. The behavior problems subscale stands alone, and bigger numbers are indicative of greater behavior problems. Sample questions from the initiative subscale include “starts or organizes play with other children,” whereas an example item for self-control includes “listens to/respects others.” For the attachment subscale, an example includes “responds positively to adult comfort when upset,” and an example of the behavior scale items includes “fights with other children.” It should be noted that the internal consistency within this community sample is strong—teacher TPF = .94, teacher behavior concerns = .80; parent TPF = .91, parent behavior concerns = .71 (Crane, Mincic, & Winsler, 2011). Further, there are no differences in the reliability of these scales as a function of the language in which the DECA was completed or between Latinx and Black children (Crane et al., 2011), thus, the DECA has strong reliability for ethnically and linguistically diverse children. I used the latest time point of measurement when available.

Child Outcomes

GPA. Annual academic performance is available each year. The end-of-year grades were created by averaging the children’s scores across 11 different academic domains (15 for fifth-graders). First-grade through fifth-grade grades were measured on a five-point scale (1 = F, 2 = D, 3 = C, 4 = B, 5 = A).

Reading and Math Scores. Beginning in third grade, students take the Florida Comprehensive Assessment Test (FCAT; Human Resources Research Organization &

Harcourt Assessment, 2007). The FCAT is a standardized achievement test used by the state of Florida to assess children ’s reading and math skills (in English; range of 100–500). The Florida Comprehensive Assessment Test has strong internal consistency across all populations (alpha = .98; Harcourt Assessment, 2007). However, starting in the 2011-2012 school year, the school system changed to a significantly updated version of the exam with a different scale range, and one cohort of on-time fifth graders and another of on-time fourth and fifth graders in my sample took the updated exam. To deal with the two different scales, we standardized each exam version’s standard scores by converting them to a z-score (using the entire sample mean of the larger MSRP involving about 40,000 students). Once the two variables were standardized within themselves, we combined them to form one aggregated and standardized variable. As a result of centering about the mean, the intercept and slope are interpreted as the standardized average FCAT score and the standardized average rate of change. Because standardization was performed with the full MSRP sample, my sub-sample has ZFCAT means and standard deviations that are not equal to 0 and 1, respectively. As seen in Table 3, means were greater than 0, and this is likely driven by the exclusion of retained students, who have lower average FCAT scores than on-time students. The highest mean was for ZFCAT reading in third grade (mean= .2773) and the lowest was for ZFCAT reading in fifth grade (mean= .1179). Table 3 also illustrates that standard deviations were, in general, lower than 1, with a range of .80822 for ZFCAT reading in G3 and .94424 for ZFCAT reading in G5. Intercept and slope are still readily interpretable as standardized average scores in fifth grade and rate of change, with the caveat that the study sample performed slightly above the FCAT mean of the full sample.

Analytic Framework and Rationale

The first step toward modeling academic achievement over time was to determine the prevalence rate of school mobility. The proportion of school mobility within each student characteristic was calculated and compared to overall school mobility rates s. The categorical student characteristic prevalence rates allowed us to determine whether school mobility was experienced differently based on gender, ethnicity, pre-K type, and first grade status of FRL, special needs, and English proficiency. The second step was to report the mean and standard deviation of annual outcome scores. The standard deviations for fifth grade GPA and FCAT scores were useful benchmarks for determining the magnitude of effect school mobility has on academic outcomes in the conditional models. Effect sizes of school mobility and covariates are reported as the percent of a standard deviation an estimated value is from the fifth grade (intercept) mean (e.g., mobile students fifth grade GPA, controlling for student characteristics, is 50% of a standard deviation below the overall mean).

Main analyses were conducted using cross-classified random effects growth models (CCREGMs), or HCM2, as it is known in HLM 6.4.1 software (Raudenbush & Bryk, 2002). HCM2 is geared to account for multilevel data structures that are not purely clustered in hierarchies. For this study, individual change is represented through the cross-classification of repeated measures within two classifications: students (as rows, and each row ID represents one of between three to five timepoints for each student) and schools (as columns, and each column ID represents one of up to 293 schools). By allowing level 1 cells (repeated outcome measures and time-varying covariates within-student) to be *cross*-classified among students and schools, the requirement of pure hierarchies found in traditional HLM approaches is relaxed and data from mobile children can be included in the growth model parameter estimates.

What follows is a brief description of two possible HCM2 approaches to modeling school-specific random effects and how they differ from a three-level HLM design. Where a traditional three-level HLM design matrix for random school effects (the school-specific intercept, c_{00k}, illustrated below; Cafri, Hedeker, and Aarons, 2015) only activates the random intercept effects associated with one school across timepoints,

$$\boldsymbol{Z_j} = \begin{bmatrix} 1 & 0 & 0 \dots & 0 \\ 1 & 0 & 0 \dots & 0 \\ 1 & 0 & 0 \dots & 0 \end{bmatrix} \boldsymbol{c_j} = \begin{bmatrix} c_{001} \\ c_{002} \\ c_{003} \\ \vdots \\ c_{00k} \end{bmatrix}$$

a two-level acute-effects cross-classified design matrix will activate school-specific random intercept effects associated with *any number* of varying school IDs at different timepoints,

$$\boldsymbol{Z_j} = \begin{bmatrix} 1 & 0 & 0 \dots & 0 \\ 0 & 1 & 0 \dots & 0 \\ 0 & 0 & 1 \dots & 0 \end{bmatrix} \boldsymbol{c_j} = \begin{bmatrix} c_{001} \\ c_{002} \\ c_{003} \\ \vdots \\ c_{00k} \end{bmatrix}$$

or in the case of a cumulative-effects cross-classified matrix, school-specific random intercept effects from any number of school IDs *carry over* into each subsequent timepoint from the intercept,

$$\boldsymbol{Z}_j = \begin{bmatrix} \\ 1 & 0 & 0 \dots & 0 \\ 1 & 1 & 0 \dots & 0 \\ 1 & 1 & 1 \dots & 0 \\ \\ \end{bmatrix} \boldsymbol{c}_j = \begin{bmatrix} c_{001} \\ c_{002} \\ c_{003} \\ \vdots \\ c_{00k} \end{bmatrix}.$$

There are several things to note about what each style of matrix implies as well as the commonalities between each type. In the traditional three-level HLM approach, the design matrix assumes that school ID is time invariant, and consequently, cases with varying school IDs would be dropped from analyses or must be misspecified as associated with one school ID (typically the first or last timepoint's school ID, but conceptually could be any timepoint). At time 0, there is *no difference* in the estimation parameters between a traditional hierarchical growth model and a cross-classified growth model for an individual student. When the equations for the second, third, and later timepoints are compared, however, it becomes clear that where a traditional HLM approach includes only one time-invariant school-specific random effect, equations for cross-classified models differ in their calculation of individual change. Acute-effects cross-classified estimation parameters after time 0 will substitute the time-invariant school-specific random effects seen in traditional HLM with the school-specific random effect at that timepoint. It should be noted that acute-effects equations will simplify to a traditional HLM equation for non-mobile students (as they are purely clustered in the same hierarchy over time), but the school-specific random effect for mobile students' equations are capable of being assigned a new school's random effect after a move. Instead of time-variant substitution, cumulative-effects equations retain and sum all previous school-specific random effects at each subsequent timepoint from the intercept. Where we saw a simplification to traditional HLM equations in the acute-effects equations for nonmobile students, every student's school-specific random effects regardless of mobility status is summed (carried over) for each additional timepoint. The decision to cumulate school random effects was driven in part by bioecological theory, where the consequences of disruptions to the reciprocal relationship between student (individual) and school (ecology) *over time* are of interest. Another rationale for cumulative school random effects stems from a practical/methodological consideration that school experiences are not mutually exclusive from one another. A positive, neutral, or negative change in school context may be reasonably hypothesized to have lasting effects on academic achievement. With the aforementioned acute-effects models, the school-specific deflection of variance on average outcome measure/growth rate attributable to previous years of school membership would *disappear* at each subsequent timepoint from the intercept (Raudenbush & Bryk, 2002). The school-specific deflections of variance in the acute-effects model ignore the contribution from prior school contexts, when in reality, those prior contexts may be critical in understanding the variation in student's growth trajectories and final fifth grade outcomes. Conceptually, the intercept (fifth grade) is equivalent to both the acute-effects cross-classified model and a three-level nested (repeated measures within child within school) model, but for each additional timepoint from the intercept, the school random effects carry over. While it is not obvious from the cross-classified HLM6 output, the residual files can be used to visualize the impact of either acute or cumulative school-specific random variation on *individual* students' growth trajectories. What becomes clear is that a cumulative-effects model offers a better glimpse as to how a student's entire first through fifth grade school context history shapes their trajectory compared to an acute-effects model only factoring in the most recent schoolyear's context influence on a student's trajectory.

Within the HLM software, CCREGMs have a couple of advantages beyond the ability to include students who do not retain the same school membership across all timepoints (Raudenbush & Bryk, 2002). Level-1 outcome data need not be complete for every student, and full maximum likelihood estimation was utilized to reduce bias that may otherwise be introduced by listwise deleting cases with incomplete time-varying data (Grady & Beretvas, 2011; Raudenbush & Bryk, 2002). Maximum likelihood also allows for the comparison of fitness among nested models. The chi-squared difference between the deviance statistic provided by HLM (essentially a "badness-of-fit" [Raudenbush & Bryk, 2002] measure) was calculated for each nested model, with the change in degrees of freedom representing the change in number of parameter estimates for each nested model. A significant reduction in deviance reflects a better model fit and served as a guide to determine whether a more complex model was appropriate.

Unconditional Growth Models

In this study, the unconditional CCREGMs were first estimated and included no predictor variables. These models identified whether there was significant variation over time in residual GPA, FCAT reading, and FCAT math achievement scores within student, across students, and across schools to determine if a multilevel approach is even necessary. For ease of equation interpretability, the adjusted cumulative-effects HCM2 format used by Raudenbush and Bryk (2002) is applied below for both level-1 and level-2 equations. The structure for the level-one unconditional equation used for each outcome is

$Y_{jt} = \pi_{0jt} + \pi_{1jt}t + e_{jt},\ e_{jt} \sim N(0, \sigma^2)$

Where Y_{jt} is GPA, reading, or math achievement for student *j* at time *t;*

π_{0jt} is the expected GPA, reading, or math achievement for student *j* at time *t;*

π_{1jt} is the GPA, reading, or math achievement growth rate for student *j* at time *t;*

t is the time variable denoting the number of years before student *j* was in grade 5; and

e_{jt} is the residual variance in GPA, reading, or math scores at time *t* for student *j*, which is assumed to be normally distributed with a mean of zero and variance of σ^2.

Choosing the zero point for *t* is an important decision in multilevel modeling, because it determines how the intercept coefficients are interpreted. When *t* is equal to zero, the product created with π_{1jk} is equal to zero, and as a result of this zero product, predicted GPA, reading, or math achievement at level one is equal to the average reading achievement across students plus the residual variance for student *j* at time zero. In this study, *t* was coded as either (-4, -3, -2, -1, 0) for GPA or (-2, -1, 0) for both reading and math achievement so that the intercept represented the final achievement status at the end of fifth grade. This decision was made to primarily because of the interest in examining how school mobility was associated with academic achievement by the end of fifth grade. A secondary reason for specifying the zero point at fifth grade was so that the discussion of GPA and FCAT intercepts would revolve around the same grade level, as GPA starts in first grade, while FCAT scores only begin in third grade.

The level two unconditional growth models estimated the amount of variance attributable to students and schools. The structure of the level two equations are

$\pi_{0jt} = \theta_0 + b_{00j} + \sum_{k=1}^{K} \sum_{h=0}^{t} D_{hjk}\, c_{00k}$

$\pi_{1jk} = \theta_1 + b_{10j} + \sum_{k=1}^{K} \sum_{h=0}^{t} D_{hjk}\, c_{10k}$

where θ_0 is the overall average fifth-grade GPA, reading, or math score;

θ_1 is the overall average rate of change;

b_{00j} is the random variance in fifth-grade GPA, reading, or math score for student *j*;

b_{10j} is the random variance in rate of change for student *j*;

c_{00k} is the random variance in fifth-grade GPA, reading, or math score for students attending school *k*;

c_{10k} is the random variance in rate of change over all timepoints for students consecutively enrolled (for at least two years) in school *k*;

D_{hjk} is a dummy indicator, where 1 if student *j* is in school *k* at time *h*, 0 otherwise (see cumulative z-structure design matrix above);

The double summations in the intercept and slope equations allow for school random intercept and rate of change effects to carry over time.

The choice to treat school-specific random intercept and slope effects as cumulative rather than acute was motivated by gaps in previous research and the readily available annual school ID information in the current data structure. A limitation encountered in prior literature was ignoring of or misapplication of school-specific random effects from earlier timepoints for later timepoints. In this study, the repeated measures structure and large sample size put us in a good position to include these additional power-sapping sources of variation, which often overextend the iterative procedure's potential to improve model fit (Cafri et al., 2015). While several notable simulation studies relating to school mobility have modeled cumulative-effects of the school context for the intercept (Cafri et al., 2015; Grady & Beretvas, 2010; Meyers & Beretvas, 2006; Raudenbush & Bryk, 2002), no other school mobility paper that I am aware of has implemented cumulative-effects of the school context for the rate of change over time in outcome measures. The addition of school-specific random slope effects allows me to examine whether a student's historical and current school context contributes to variation observed in the rate of change over time. This is especially valuable if the unconditional models suggest better fit with the inclusion of school-specific random slope effects, even if a small contributor of variance explained, as it may deflect variance away from level 1 residual error. A final consideration, at least within HLM 6.04, is that if both school-specific intercept and slope effects are specified as random, there is no way to declare one as acute and the other as cumulative, they either both accumulate over timepoints, or one must be considered a fixed effect, potentially at the expense of model fit.

The best way to illustrate the implications of a cumulative-effects approach is by seeing how the predicted values for an individual student are calculated. Consider the calculation of a student's expected FCAT math score in third grade. The cumulative-effects equation could be written as

$$\hat{Y}_{-2/3} = \theta_{00} + b_{00j} + 2(\theta_{10} + b_{10j}) + c_{001} + c_{002} + c_{003} + c_{101} + c_{102} + c_{103}$$

The predicted FCAT math score at time -2 is equal to the average FCAT math score in fifth grade plus individual intercept variance plus average rate of change and individual slope variance multiplied by two plus the school-specific variation in intercept and slope of the three schools attended (regardless of mobility) between third and fifth grade. Compared to an acute-effects model, the difference is $c_{001} + c_{002}$ and $c_{101}+c_{102}$, or in comparison to traditional three-level HLM, the difference is $c_{002} + c_{003}$ and $c_{102} + c_{103}$. Note that in the case of an acute-effects model, the school-specific random effects are swapped out over time, and in the case of traditional HLM, the same school-specific random effects are time invariant. The accumulation of multiple and potentially varying school contexts is what distinguishes cumulative-effects models from others. Another important distinction related to cumulative and acute HCM2 school-specific random *slope* effects is that they will never include students who attended different schools for any pair of consecutive school years, because it would be computationally unclear which school (leaving vs. entering) should get the rate of change score (Luo & Kwok, 2012). Taken all together, the cumulative-effects approach allows for the intercept and slope to vary linearly over time for individuals.

The mixed model equation for each unconditional model is

$$Y_{jt} = \theta_0 + \theta_1 t + b_{00j} + c_{00k} + b_{10j} t + c_{10k} t + e_{jt}$$

This indicates that there are two fixed effects, θ_0 and θ_1, and five random effects (b_{00j}, c_{00k}, b_{10j}, c_{10k}, and e_{jt}). A series of nested unconditional growth models was carried out to determine if the addition of random effects improved model fit of the estimation of GPA, FCAT math/reading scores over time. The total sum of random effects is equal to the total residual variance in GPA, FCAT math or reading achievement over time. The proportion of variance explained by each random effect was calculated by dividing each by the total residual variance. Next, I describe the models used for each research question.

Research Question 1: After controlling for time-invariant characteristics of gender, ethnicity, pre-K type, school readiness, and time-varying annual status of free and reduced price lunch, special needs, and English proficiency, to what degree is intradistrict school mobility ((a) ever move, (b) total number of moves, (c) frequent moves, and (d) early moves) associated with the rate of change over time and fifth grade academic achievement (GPA, standardized reading and math test scores) during elementary school?

In order to determine the degree of association between intradistrict school mobility and academic achievement controlling for all covariates, school mobility was operationalized in four separate models. As a first step, a dichotomous yes/no school mobility was introduced as a level-2 row (student) predictor along with all covariates in both the intercept and slope equations. Next, a total number of moves variable was used as a level-2 row predictor to determine, for every additional move, how the association changed. A dummy coded nonmobile/frequent/ infrequent variable and a dummy coded nonmobile/early/late variable were also introduced in separate models to gain further insight as to how the association changed for the most frequent and earliest movers compared to nonmobile and their less frequent/later school move counterparts. All variants of the school mobility variable remained uncentered, as their zero point was meaningfully interpretable as the estimated value of nonmobile students, or in the case of frequent/early alternative dummy contrasts, as less frequent/later mover's expected values. Time-varying student characteristics were added to the level-1 equation simultaneously along with time-invariant student characteristics among the intercept and slope equations at level 2. Time-varying controls included annual status of free, reduced, and did not qualify/apply for free/reduced price lunch (dummy coded), primary exceptionality, and English proficiency. Time-invariant controls consisted of gender, ethnicity (Black, Latinx, White/other; dummy coded), pre-K center type, LAP-D scores, and measures of total protective factors and behavior concerns from the DECA. LAP-D and DECA scores were grand centered around their means. Grand-mean centering allows for their respective parameter estimates to be interpreted as the expected deviation in intercept and rate of change over time for a student with average LAP-D and DECA percentile scores, holding all other predictors constant at their specified zero value. An added benefit of grand-mean centering percentile scores was the ease of calculating magnitude of effect for individual students and the average effect size +/- 1 standard deviation of the average LAP-D and DECA scores (i.e., the coefficient can be multiplied by the number of units above or below the average to determine the impact on intercept and slope for individuals). Refer to Table 2 for means and standard deviations of each LAP-D and DECA subscores.

The primary mixed model for EVERMOVE with all student characteristics added is

$$Y_{jt} = \theta_0 + \theta_1 t + \theta_2 * FREE_{jt} + \theta_3 * RED_{jt} + \theta_4 * PREX_{jt} + \theta_5 * NEP_{jt} +$$

$$\gamma_{01} EVERMOVE_j + \gamma_{02} MALE_j + \gamma_{03} HISPANIC_j + \gamma_{04} BLACK_j + \gamma_{05} CHILCARE_j +$$

$$\gamma_{06}(FM_j - \overline{FM}_{...}) + \gamma_{07}(COG_j - \overline{COG}_{...}) + \gamma_{08}(LANG_j - \overline{LANG}_{...}) + \gamma_{09}(GM_j - \overline{GM}_{...}) + \gamma_{010}(TPF_j - \overline{TPF}_{...}) + \gamma_{011}(BC_j - \overline{BC}_{...}) + \gamma_{11}EVERMOVE_j * t + \gamma_{12}MALE_j * t + \gamma_{13}HISPANIC_j * t + \gamma_{14}BLACK_j * t + \gamma_{15}CHILCARE_j * t + \gamma_{16}(FM_j - \overline{FM}_{...}) * t + \gamma_{17}(COG_j - \overline{COG}_{...}) * t + \gamma_{18}(LANG_j - \overline{LANG}_{...}) * t + \gamma_{19}(GM_j - \overline{GM}_{...}) * t + \gamma_{110}(TPF_j - \overline{TPF}_{...}) * t + \gamma_{111}(BC_j - \overline{BC}_{...}) * t + b_{00j} + +b_{10j}t + c_{00k} + c_{10k}t + e_{jt}$$

where θ_2, θ_3, θ_4, and θ_5 are the fixed intercept effects of the time-varying student characteristics, holding all other predictors constant. The FREE and RED effects are in comparison to those who did not apply/did not qualify for FRL, while the fixed effects for PREX and NEP are in comparison to those without a primary exceptionality and those who are English proficient. The intercept coefficients γ_{02} - γ_{011} are the main effects of the time-invariant student characteristics, holding all other predictors constant. The coefficient for MALE represents the degree to which there are gender differences in fifth-grade outcomes. The coefficients for HISPANIC and BLACK represent the difference in fifth-grade outcomes compared with White/other. The coefficient for CHILCARE indicates whether there are differences in fifth-grade outcomes between students who attended a public-school pre-K vs. a child or family-based center. All coefficients relating to LAP-D and DECA can be interpreted as the difference in fifth grade outcomes for one unit increase or decrease away from each LAP-D or DECA average score. The same pattern for slope coefficients $\gamma_{12} – \gamma_{111}$ holds, but instead of fifth-grade outcomes, they refer to the rate of change each year/grade between groups (MALE, HISPANIC, BLACK, CHILCARE) or for every single point increase or decrease from the average (FM, COG, LANG, GM, TPF, BC).

For brevity, the mixed equations for TOTMOVE, FREQ, and EARLY mobility models, as well as the accompanying alternative contrast models are not displayed. The results will feature the outcomes discovered from comparing frequent vs. infrequent movers, early vs. late movers, as well as free vs. reduced price lunch, and Latinx vs Black students. The primary analyses intercept and slope with all control variables can be conceived of as the average fifth grade academic outcome and average rate of change for nonmobile, female, White/other, public school pre-K attending students with average LAP-D and DECA performance who did not apply/qualify for FRL, had no primary exceptionality, and were English proficient.

RESULTS

What follows is a detailed description of the outcomes from the procedures outlined in the analytic method above. A bivariate description of the prevalence rate and variation of school mobility among student characteristics is offered first (Table 4). Next, the process of building up the unconditional growth models by adding in sources of variance is provided to justify the level of model complexity decided upon for the baseline models (Table 5). Finally, results from the conditional growth models are presented (Tables 6-8). The means and standard deviations of LAP-D and DECA found in Table 2 are also utilized throughout the conditional results to give an idea of effect size. The format of the tables for conditional results is organized by school mobility type.

Descriptive Statistics for Intradistrict School Mobility

Overall, almost 4 out of every 10 students changed schools at some point between kindergarten and fifth grade (see Table 4). However, not all groups of students were equally likely to experience school mobility. Chi-squared statistics are reported for categorical student characteristics. In the case of race/ethnicity and lunch price, the only categorical predictors with more than two groups, the chi-squared statistic is reported for the reference group to all other groups (e.g., free-priced lunch vs reduced- *and* full-priced lunch). Table 4 indicates nearly half (47.7%, $\chi^2 = 203.345$, $p < .001$) of all Black students experienced at least one move, a significantly higher prevalence compared to Latinx

(34.8%, $\chi^2 = 57.061$, $p < .001$), and White/other students (20.7%, $\chi^2 = 114.593$, $p < .001$). Table 4 also shows the proportion of Latinx students ever moving (34.8%, $\chi^2 = 57.061$, $p < .001$) was less than that of Black students but more than White/other students. Examining the total number of moves (not listed in Table 4) indicated a disproportionately higher representation of Black students making between one and five moves compared to Latinx and White/other students. The 47.7% of Black students in the sample who moved is broken down into 28.4% moving once, 13.2% moving twice, and the remaining 6.1% moving three or more times. For every one White/other student who made one move there were two Black students. For two and three+ moves, the ratio was even greater, with nearly 3 Black students to every one White/other student moving twice, and a doubling of that for three or more moves. About 25% of mobile Latinx students changed schools once, 7.7% moved twice, and another 2.09% moved three or more times, closer but still notably less representation than Black students, especially as the total number of moves increases. Those who attended center and family-based childcare at age 4 had significantly higher average mobility rates (46.0%, $\chi^2 = 123.775$, $p < .001$) compared to students attending a pre-K program at a public school (34.3%, $\chi^2 = 123.775$, $p < .001$; see Table 4). Prevalence rates for total number of moves were consistently lower for public pre-K attendees, although both groups had similar prevalence rates for three or more moves. Those qualifying for free-priced lunch in first grade had a significantly higher mobility prevalence (42.9%, $\chi^2 = 180.545$, $p < .001$) than their reduced-price and full-price-lunch counterparts (29.6%, $\chi^2 = 180.545$, $p < .001$; see Table 4). Total number of moves for free-priced lunch was also higher than either reduced- or full-price lunch. Worth noting, all 16 students who would go on to change schools at every timepoint had a free-priced lunch status in first grade.

The second column in Table 4 shows that about 3.3% of students were categorized as frequently mobile (three or more moves). Significant differences were found among ethnicity groups, with 6.1% of Black students ($\chi^2 = 159.686$, $p < .001$), 2.1% of Latinx students ($\chi^2 = 64.873$, $p < .001$), and 0.7% of White/other students ($\chi^2 = 19.189$, $p < .001$) moving three or more times. Students attending pre-K programs at public schools had a significantly lower prevalence of frequent mobility slightly below the overall rate at 2.7% ($\chi^2 = 22.854$, $p < .001$), while center- and family-based pre-K programs had a significantly higher rate at 4.6% of frequent mobility ($\chi^2 = 22.854$, $p < .001$). Similarly, full-priced status in G1 yielded the lowest frequently mobile rate at about 1% ($\chi^2 = 53.94$, $p < .001$), 2.4% of students qualifying for reduced-price in G1($\chi^2 = 3.722$, $p < .10$) were considered frequent movers, and 4.4% of free-price lunch status qualifiers in G1 ($\chi^2 = 61.782$, $p < .001$) represented the highest frequent mobility rate. Information about early moves can also be gleaned from the last column in Table 4.
The third and final column in Table 4 shows that 28.1% of students moved schools before the beginning of third grade. Among ethnicities, Black students had the highest prevalence of changing schools before third grade (36.3%, $\chi^2 = 53.94$, $p < .001$), while 25.5% ($\chi^2 = 53.94$, $p < .001$) of Latinx students experienced an early move, which was comparable to the overall rate, and White/other students moved early the least at 14.8% ($\chi^2 = 53.94$, $p < .001$). About a quarter of public school pre-K attendees made early moves ($\chi^2 = 53.94$, $p < .001$) compared to 34.3% of students attending center- or family-

based care ($\chi^2 = 53.94$, $p < .001$). One in every four students qualifying for free-priced lunch in G1 made at least one move before the beginning of third grade ($\chi^2 = 53.94$, $p < .001$), while only 20.4% of students paying full price for lunch experienced school mobility before third grade ($\chi^2 = 53.94$, $p < .001$). No significant differences were found between genders, special needs, or English proficiency for ever, frequent, or early school mobility.

Building the Unconditional Growth Models

It was assumed that change in academic outcomes over time was linear. After visually examining the Q-Q plots for residual variation in annual GPA and test scores, this seems fairly reasonable, however, there was a presence of slight tailing across academic outcomes. The highest GPA and test scores were higher than what a normal distribution would predict, while the lowest GPA and test scores were lower than what would be expected on a normal distribution. This discrepancy between expected and observed high/low values suggests that a non-transformed linear model would underestimate high performers and overestimate low performers in terms of final status and growth rate to some degree. Since the purpose of this study was not concerned with modeling differences in growth rate year-to-year, and given the large sample size, the potential inflation of standard error estimates resulting from greater residual variation among the highest and lowest achievers compared to those closer to the average achievement was perceived as a tolerable source of error. I decided that no linear transformation of time needed to be applied, and proceeded with analysis taking this assumption into account.

Table 5 shows the process of building up the unconditional growth models for GPA, FCAT reading, and FCAT math by adding in sources of variance that exist within students, between students, and between schools. The variance components are displayed in terms of total percentage of variance explained (sum of all sources of variance divided by their total x 100). Also included are the main intercept, slope effects, and Deviance statistics provided by HLM output used to determine if more complex models were warranted. In the first unconditional growth model (UG1), random intercept effects were included for within-students (e), between students (b_{00}) and between schools (c_{00}). Across all outcomes, the random effects were significant. For GPA, 65.74% of the variance in fifth grade outcome existed between students, 33.62% within students over time, and the remaining .65% between schools. For FCAT reading, 65.11% of the variance in fifth grade outcome existed between students, 33.42% within students, and the remaining 1.47% between schools. For FCAT math, 68.01% of the variance in fifth grade outcome existed between students, 31.01% within students, and the remaining .98% between schools.

Next, a random effect for between-student variation (b_{10}) in rate of change was added to the second unconditional growth model (UG2) to determine whether there was significant variation in student's GPA, FCAT reading, and math scores over time. This model fit was significantly better than UG1 (GPA ΔDeviance = 1133.57, Δdf = 1, FCAT reading ΔDeviance = 272.56, Δdf = 1, FCAT math ΔDeviance = 95.47, Δdf = 1) and the amount of new variance explained was 1.82% for GPA, 2.11% for FCAT reading, and 3.01% for FCAT math, suggesting that, while significant, students did not vary too much in their rate of change over time. Finally, a random effect for the rate of change between schools was added (c_{10}) to a third unconditional growth model (UG3) which improved model fit (GPA ΔDeviance = 1596.18, Δdf = 1, FCAT reading ΔDeviance = 318.42, Δdf = 1, FCAT math ΔDeviance = 367.15, Δdf = 1; $p < .001$) but underwhelmingly accounted for 1.01% of additional variance for GPA, .51% for FCAT reading, and .02% for FCAT math. Across all outcomes, UG3 was retained for use as the baseline in the conditional growth models.

Conditional Predictor Growth Models

Results are organized by outcome measure in both the text and Tables 6-9. Student characteristics and the association with the intercept and slope are reported first, followed by findings from alternate contrasts of Black/Latinx and Free/Reduced-price lunch, and then the association of ever moving with end-of-fifth grade performance and linear annual rate of change for each outcome is detailed. Results relating to the association of total moves (1b), early school mobility (1c), and frequent mobility (1d) will focus on reporting the expected differences school mobility has with the intercept at fifth grade and the rate of change over time. All four variants of school mobility (ever, total, early, frequent) are created from the same source of dichotomous year-to-year school ID matching, and is the only variable changed in between models. As a result, the only coefficients that are given the flexibility to noticeably vary during the iterative process of cross-classified modeling are related to the values assigned to school mobility. Across all models, the coefficients corresponding to predictors other than school mobility were equivalent among school mobility type within each outcome (GPA, reading scores, math scores).

Research Question 1a: Association Between Ever Moving and GPA, FCAT Reading and Math After Accounting For Student Characteristics.

As a starting point, the simplest conceptualization of school mobility was tested in a conditional model setting. The dichotomous school mobility variable (yes/no ever experienced a school change K-G5), along with all time-invariant student characteristics, were simultaneously added to the level-2 intercept and slope equations of the baseline model. All time-varying covariates were added at to the level-1 equation at the same time as the predictors at level-2. This simultaneous addition of predictors in the intercept, slope, and level-1 equations was repeated for all variants of school mobility across the three outcome models for questions 1b, 1c, and 1d. Results for ever moving are presented in Table 6 and show that the addition of school mobility alongside all other predictors significantly improved model fit relative to the final unconditional models (see Table 5) across the three outcomes (GPA ΔDev = 4017.82371, FCAT Reading ΔDev = 2517.118909, FCAT Math ΔDev = 2738.861247; $p < .001$).

GPA. The intercept now reflects the average fifth grade GPA (4.46, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. With every other predictor held at its constant, male students had significantly lower fifth grade GPA (-0.14, $p < .001$) than female students. Latinx students had only slightly lower final GPA compared to White/other students by -0.05 ($p < .001$), while Black students were found to perform almost a half of a standard deviation (-0.26, $p < .001$) worse compared to White/other students.

For the continuous measures of school readiness, the largest effect size among LAP-D and DECA measures on fifth-grade GPA after controlling for other predictors was cognition (0.003 for every point above or below the average cognition score of 59.8; see first column in Table 6). For a student who scores one standard deviation below the average for cognition (-27.3*0.007; see Table 2 for school readiness standard deviations), they are estimated to have a GPA that is .08 lower than the intercept of 4.46, holding other predictors constant. Gross motor skills (0.001, $p < .001$) and behavior concerns (0.002, $p < .001$) were the only school readiness measures that had a negative association with GPA, meaning that students who teachers rated lower on gross motor skills and lower on behavior concerns were expected to have higher GPA's relative to the intercept. For students scoring one SD below the average (see Table 2) on either one, they were expected to have a GPA 0.03 higher (gross motor) or 0.06 (behavior concerns), than the intercept. The remaining school readiness measures were all positively associated with GPA and all carried a 0.001 coefficient for every point away from their average. A student scoring one standard deviation below any one of the remaining readiness measures (TPF, fine motor, or language) would be expected to have a GPA that is about 0.03 lower than the intercept, holding all others constant. A hypothetical student that scored exactly one standard deviation below the average on TPF, fine motor and language skills would have a GPA that is 0.09 lower than the intercept, all else held constant.

The time-varying covariates indicated several negative associations with fifth grade GPA, all of which were minor in magnitude relative to the mean and standard deviation of GPA (see Table 3). Free-priced lunch was associated with an average GPA -0.05 ($p < .001$) below the intercept, holding other predictors constant. Reduced-price lunch students had a GPA -0.02 ($p < .001$) below the intercept, which is about 4% of a standard deviation decrease relative to the mean fifth grade GPA. Students with a special needs designation had an average -0.05 ($p < .001$) lower GPA than the intercept, equivalent to free-priced lunch, and about 1/10 of a standard deviation decrease relative to the mean GPA in fifth grade, all other predictors held constant. A lack of English proficiency had the greatest magnitude of association at -0.07 below the intercept, or about 13% of a standard deviation decrease.

The slope reflects the average annual change in GPA between first and fifth grade for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL students without a special needs designation and who are English proficient. Overall, the trend in GPA rate of change was negative regardless of mobility status. Male students declined in GPA scores more steeply than females at an average rate of -.02 ($p < .001$), taking into account the intercept, males not only didn't narrow the gap, but expanded it slightly over time on average. Latinx students declined in GPA by a rate that was steeper, by -.03 ($p < .01$), than White/other students while Black students declined more steeply by -.01 ($p < .05$). Those attending family- and center-based pre-K programs declined at a slightly less steep rate than public school pre-K attendees at .007 ($p < .05$). The only significant LAP-D and DECA measure associated with GPA slope was cognition, which indicated that for every point above the average cognition score, students were expected to decline at a faster rate of .0002. For a child scoring one SD above the average cognition score of 59.81 (see Table 2), this results in a significant, but mildly steeper negative change rate of .006 ($p < .001$).

The results from secondary group contrasts are also provided in Table 6. Next to the coefficients for Latinx/Black and Reduced/Free rows are the intercepts reflecting the reference groups as Latinx students and Reduced-price lunch students. The new slopes reflecting swapping of White/other with Latinx as the indicator group are also included; FRL being a time-varying level-1 predictor, does not have a slope coefficient to modify. Latinx students ended with a GPA in fifth grade that was .21 ($p < .001$) higher compared to Black students. The rate of change for Latinx student's GPA was slightly less steep by .02 (p < .001) compared to Black students. Those qualifying for free-priced lunch had a lower average fifth grade GPA by .02 ($p < .001$) compared to reduced-price lunch qualifying students.

Ever-Move. Accounting for all student characteristics and time-varying covariates, ever moving between kindergarten and fifth grade was still found to have a negative association with fifth grade GPA (See Table 6). On average, ever-movers had a fifth grade GPA of 4.29 ($p < .001$), or 0.17 points lower than the intercept holding all others constant, which is equal to about 32% of a standard deviation decrease relative to the mean GPA (see Table 3 for fifth grade GPA SD). The rate of change for ever-movers was also significantly steeper than the overall slope by -0.006 ($p < .05$).

Reading Scores. Similar to GPA, the intercept (middle column of Table 6) now reflects the average fifth grade FCAT reading score (0.44, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. Males did not differ significantly than females when all other predictors were held at their constant. Latinx students performed significantly worse (-0.06, $p < .05$) than White/other students while Black students' performance was significant and more pronounced (-.41, $p < .001$) than White/other, equal to nearly half a standard deviation (49%) decrease from the fifth grade FCAT Reading average (see Table 3 for FCAT Reading SD). Family- and center-based child care attendees performed marginally better than students attending public school pre-K programs (0.06, $p < .01$).

A similar pattern found in the GPA conditional model emerged for continuous measures of school readiness association with FCAT reading scores in fifth grade. Again, gross motor skills (-0.002, $p < .01$) and behavior concerns (-0.002, p < .001) were negatively associated with the FCAT reading intercept. One SD decrease in either gross motor skills or behavior concerns was equal to an increase of about .06 in expected fifth grade FCAT reading performance, or about 7% of a standard deviation increase from the average FCAT reading score in fifth grade. The remaining LAP-D scores were all significantly and positively associated with FCAT reading scores, with Language (0.005, $p < .001$) having the strongest relation, followed by Cognition (0.004, $p < .001$) and Fine Motor Skills (0.0008, $p < .01$). Total Protective Factors from the DECA was also positively related to reading scores (0.0008, $p < .05$). Using Language as an example, scoring one

SD below the average was equal to about .15 points below the intercept, or a little over 17% of a SD from the average fifth grade reading score (see Tables 2 and 3 for reading/school readiness means and SDs).

For time-varying covariates, the pattern seen in GPA held for reading in terms of the negative direction of association with the intercept, but with greater magnitude relative to the overall fifth grade mean scores. Compared to students who paid full price for lunch, free-priced lunch qualifying students scored -.12 ($p < .001$) points lower on FCAT reading in fifth grade, about a 14% of a SD difference (see Table 3), holding other predictors constant. Reduced-price lunch students also scored lower on average than full-price lunch students (-0.06, $p < .001$) but were only 7% of a SD below the overall fifth grade reading average. Students with special needs scored an average of -0.27 ($p < .001$) below the intercept, or 31% of a SD decrease from the average reading score. Not being proficient in English was found to have the greatest magnitude of association with reading scores in fifth grade among the time-varying covariates at -0.40 ($p < .001$), nearly 46% of a SD difference compared to the average reading score in fifth grade.

The slope represents the average annual change in reading scores between third and fifth grade for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL students without a special needs designation and who are English proficient. Overall, the trend in reading score rate of change was negative regardless of mobility status, just like the GPA model, with the slope declining at -0.07 ($p < .001$) on average year-to-year. Males declined in reading performance at a rate of -0.04 steeper compared to females. Latinx students did not significantly differ from

White/other students while Black students displayed a difference of -0.03 ($p < .05$) compared to White/other students' rate of change. Latinx rate of change in reading was less steep compared to Black students (0.03, $p < .001$). Family and center-based child-care attendees declined at a slightly less steep rate than their public school pre-K counterparts (0.02, $p < .05$). No school readiness measures were found to be significantly associated to the rate of change in reading scores over time.

The results from secondary group contrasts are also provided in the second column in Table 6. Latinx students ended with a reading score in fifth grade that was .28 ($p < .001$) higher compared to Black students. The rate of change for Latinx student's GPA was slightly less steep by .02 ($p < .001$) compared to Black students. Those qualifying for free-priced lunch had a lower average fifth grade reading by .02 (p < .001) compared to reduced-price lunch qualifying students.

Ever-Move. With all of the covariates controlled for, ever experiencing school mobility was found to have a significant negative association with fifth grade reading scores (-0.16, $p < .001$) and no significant with the rate of change over time (-0.009, ns), as seen in the second column in Table 6. Ever movers had an average reading score of .28, or 18% of a SD decrease from the overall sample's FCAT reading score (see Table 3).

Math Scores. Just like reading scores, the intercept now reflects the average fifth grade FCAT math score (0.36, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students (see the third column in Table 6). With all other predictors held constant, males outperformed females by 0.019 ($p < .001$) points in average fifth grade math scores, 21% of a standard deviation difference in terms of the sample's average math score (see Table 3). Latinx students had a slightly lower fifth grade math score average compared to White/other students by -0.09 ($p < .01$) while Black students scored almost 45% of a SD lower (-0.40, $p < .001$) compared to their White/other counterparts. Family- and center-based child care attendees had a 0.11 ($p < .001$) higher math score average than public school pre-K students in fifth grade.

The slope represents the average annual change in math scores between third and fifth grade for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL students without a special needs designation and who are English proficient. As with the other two outcome models, the trend in math score rate of change was negative regardless of mobility status, with the slope declining at -0.04 ($p < .01$) on average year-to-year. Males increased rather than decreased on average math scores at a nearly unobservable rate of 0.1 ($p < .05$) compared to females. Neither Latinx nor Black students significantly differed from White/other students in rate of change. Family and center-based child-care attendees did not decline like their public school pre-K counterparts (0.02, $p < .05$). No school readiness measures were found to be significantly associated to the rate of change in reading scores over time.

Turning to the continuous school readiness measures, cognition was found to have the greatest association with math scores in fifth grade. For every point above or below the average cognition score of 59.81, fifth grade math scores were expected to change by 0.007 ($p < .001$). This means that a cognition score one SD away from the mean (SD = 29.35), would be equivalent to a .21 point difference in predicted 5th grade FCAT math performance. This is almost a quarter of a SD difference relative to the average FCAT math score in fifth grade. Consistent with GPA and reading outcomes, Gross Motor Skills (-0.002, $p < .001$) and Behavior Concerns (-0.002, $p < .001$) were both negatively associated with reading performance in fifth grade, with nearly identical magnitudes of association as reading scores. Similarly, LAP-D measures of Fine Motor Skills (0.004, $p < .001$) and Language (0.002, $p < .001$), along with TPF (0.001, $p < .01$) from the DECA were all positively related to reading scores.

Ever-move. Accounting for all other predictors, ever-movers were expected to score on average -0.14 ($p < .001$) points below the intercept. This equates to about a 16% of a standard deviation decrease relative to the mean math score in fifth grade. There was no significant difference between the overall slope of nonmovers and ever-movers, both were expected to decrease at the same linear rate of -0.04 ($p < .01$) between third and fifth grade, holding all other predictors constant.

Research Question 1b: Association between total number of moves and academic achievement after adding student characteristics.

The next step involved expanding the range of the yes/no mobility variable to count the total number (0-5) of school moves made between kindergarten and fifth grade for the whole sample. This finer-grained measure will allow us to see if the association with the academic outcomes is significantly different as the number of moves increases from 0 to 5. As a reminder, in the case of the MSRP dataset, year-to-year school ID matching was the best option for counting the highest number of moves. Total number of moves essentially represents the number of times a student ended the academic year at a different school than the previous year. This approach almost certainly underestimates the actual number of moves made by students in the sample, but it also allows us to be reasonably confident that overvaluation was not a source of error for our primary mobility predictors.

GPA. The intercept now reflects the average fifth grade GPA (4.46, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The intercept, slope and time-varying coefficients were identical, along with the corresponding standard errors and p-values, to the EVERMOVE GPA model (compare the GPA columns in Tables 6 and 7). The same applies to the alternate contrast intercept and slope values for ethnicity and lunch status. This pattern will hold throughout the subsections below, and the focus will now be on interpreting the school mobility predictor's association (here total moves) with the slope and intercept controlling for all predictors.

Total Number of Moves. Each additional move between kindergarten and fifth grade was found to be significantly negatively associated with GPA at the end of fifth grade with all predictors held constant. For each additional move, GPA was expected to be -0.11 ($p < .001$) lower on average in 5th grade than the intercept. For the most mobile (five-time movers), this is equal to a .55 reduction in GPA, or a little over an entire standard deviation away from the overall GPA in fifth grade (see Table 3). The rate of change for each additional move was -0.005 ($p < .01$) steeper than the overall slope of -0.06 ($p <$

.001) meaning that five-time movers were expected to decline at an even faster rate compared to nonmovers (by 0.03, .06*5) and single-time movers (by 0.02, .06*4).

Reading Scores. With all of the predictors in the model, the intercept is the average fifth grade FCAT reading score (0.44, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The intercept, slope and time-varying coefficients were again identical, along with the corresponding standard errors and p-values, to the EVERMOVE FCAT Reading model (compare the Reading columns in Tables 6 and 7). The same applies to the alternate contrast intercept and slope values for ethnicity and lunch status.

Total Number of Moves. Accounting for all other predictors, each additional move between kindergarten and fifth grade was found to be significantly associated with reading performance at the end of fifth grade. For each additional move, reading performance was expected to be -0.11 ($p < .001$) lower on average than the intercept. For the most mobile (five times), this is equal to a .55 reduction in reading performance, or about 62% of a standard deviation away from the overall reading score in fifth grade (see Table 3). No significant slope difference was found for each additional move.

Math Scores. When the predictors are added to the math model (final column in Table 7), the intercept is the average fifth grade FCAT math score (0.36, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. Again, the intercept, slope and time-varying coefficients were identical, along with the corresponding standard errors and p-values, to the EVERMOVE FCAT Math model (compare the Math columns in Tables 6 and 7). The same applies to the alternate contrast intercept and slope values for ethnicity and lunch status.

Total Number of Moves. With predictors held constant, each additional move between kindergarten and fifth grade was found to be significantly associated with lower math performance at the end of fifth grade. A single unit increase in number of moves was estimated to be -0.10 ($p < .001$) lower on average than the intercept. For the most mobile (five times), this is equal to a 0.50 reduction in GPA, or over one half (56%) of a SD away from the overall math score in fifth grade (see Table 3). The total number of moves was not significantly associated with the rate of change in math performance over time, all students declined at similar rates, holding all predictors constant.

Research Question 1c: Association between initially early moves vs. Late Moves and academic achievement Accounting for student characteristics.

The next model was set up to determine if, after accounting for all student characteristics, initially early movers (students with mismatching school IDs between K-G1, G1-G2, or G2-G3) and late movers (students with first observed mismatch of school IDs between G3-G4 or G4-G5) differed in average fifth grade academic performance and the rate of change over time compared to nonmobile students as well as each other. As a reminder, the dummy coded variable was created from the same matching procedure that allowed us to count total number of moves. Nonmovers were assigned a zero if school ID matched all years, 1 if they had their first school ID mismatch was between G3 and G4 or later, and 2 if their mismatch occurred between G2 and G3 or earlier.

GPA. With all of the predictors in the model, the intercept is the average fifth-grade GPA score (4.46., $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The coefficients corresponding to student characteristics and time-varying covariates were identical in value standard error and significance level to the ever-move model. Table 8 excludes student characteristics just like the table corresponding to the models for total moves.

Early School Mobility. Accounting for all other predictors, both initially early and late school mobility were estimated to have significantly lower 5th grade GPA scores compared to nonmobile students. For early movers, GPA was expected to be -0.16 ($p < .001$) lower on average than the intercept, and late movers were predicted to be -0.20 ($p < .001$) below the intercept. These equate to 30% and 38%, respectively, of a SD decrease relative to the overall mean GPA in fifth grade (see Table 3). The rate of change for early movers was not significantly different from nonmovers, but the late mover's slope was slightly significantly steeper (-0.01, ($p < .01$) than the nonmobile intercept, holding all else constant. Compared to each other, early movers had a slightly higher expected 5th grade GPA than late movers (0.04, $p < .05$), with no significant differences in rate of change between the two groups.

Reading. With all of the predictors in the model, the intercept is the average 5th grade FCAT reading score (0.44, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The middle column in Table 8 includes the intercept and slope coefficients for early and late school mobility compared to nonmovers and each other.

Early School Mobility. Accounting for all other predictors, early and late school mobility were both found to have a negative association with 5th grade FCAT scores compared to nonmovers. Early mover's average reading scores were -0.15 ($p < .001$) lower than nonmovers while late moves had an additional .06 points lower at -0.21 ($p < .001$). No significant differences were observed for the rate of change in reading scores.

Math. With all of the predictors in the model, the intercept is the average 5th grade FCAT reading score (0.36, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. See Table 8 for coefficients related to early and late mobility on intercept and slope.

Early School Mobility. Similar to the relationship to reading, early and late school mobility were both found to have a negative association with 5th grade FCAT scores compared to nonmovers. Early mover's average reading scores were -0.14 ($p < .001$) lower than nonmovers while late moves had an additional .06 points lower at -0.17 ($p < .001$). No significant differences were observed for the rate of change in reading scores.

Research Question 1d: Association Between Frequently vs. Infrequent Moving and Academic Achievement After Adding Student Characteristics.

Frequent movers (3+ school mismatches K-G5) and infrequent movers (1 or 2 mismatches K-G5) were compared to nonmovers in the same fashion as the early- and late-move models. See Table 9 for the frequent/infrequent intercept and slope coefficients.

GPA. With all of the predictors in the model, the intercept is the average 5th grade GPA (4.46., *p* < .001) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The coefficients corresponding to student characteristics and time-varying covariates were identical in value standard error and significance level to the ever-move model. Table 9 excludes student characteristics because of their fixed nature across models.

Frequent Moves. Accounting for all other predictors, both frequent and infrequent mobility were estimated to have significantly lower 5th grade GPA scores compared to nonmobile students. For frequent movers, GPA was expected to be -0.33 (*p* < .001) lower on average than the intercept, and infrequent movers were predicted to be -0.15 (*p* < .001) below the intercept. The rate of change for frequent movers was significantly but only slightly different than nonmovers (-0.02, p < .01), as was infrequent movers (-0.006, p < .05) in relation to the nonmobile intercept with predictors at their constant. Compared to each other, frequent movers had a lower expected 5th grade GPA than infrequent movers (0.17, *p* < .001), with no significant differences in rate of change between high and low frequency groups.

Reading. With all of the predictors in the model, the intercept is the average 5th grade FCAT reading score (0.44, *p* < .001) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. The middle column in Table 9 includes the intercept and slope coefficients for frequent vs. infrequent school mobility compared to nonmovers and each other.

Frequent Moves. Accounting for all other predictors, frequent and infrequent school mobility were both found to have a negative association with 5th grade reading scores compared to nonmovers. Frequent mover's average reading scores were -0.33 ($p < .001$) lower than nonmovers while infrequent movers were closer to the average at -0.15 ($p < .001$). below the intercept. Frequent school moves differed slightly but significantly in rate of change (-0.07, $p < .05$) but there were otherwise no significant differences in reading scores over time between groups. Frequent movers were expected to score -0.18 (p < .001) lower on 5th grade reading than infrequent movers in fifth grade.

Math. With all of the predictors in the model, the intercept is the average 5th grade FCAT reading score (0.36, $p < .001$) for nonmobile, female, White/other, public school pre-K attending, average LAP-D and DECA performing, non-FRL, non-special needs, English proficient students. See Table 9 for coefficients related to frequent and infrequent mobility on intercept and slope.

Frequent Moves. Similar to the reading association with frequency, frequent and frequent school mobility were both found to have a negative association with 5th grade FCAT scores compared to nonmovers. Frequent mover's average reading scores were -0.26 (p < .001) lower than nonmovers while infrequent movers were -0.14 (p < .001) below the nonmobile intercept controlling for all predictors. No significant differences were observed for the rate of change in reading scores between any of the groups. Math scores did significantly differ between frequent and infrequent movers, with the higher frequency group scoring -0.12 ($p < .01$) on average in 5^{th} grade.

DISCUSSION

School mobility, particularly the type that happens within densely populated districts serving a high proportion of students from low-income households, is certainly a national problem (GAO, 2010; Fantuzzo et al., 2012). Prior research on school mobility has not been consistent with the strength of association between school mobility and academic outcomes. This inconsistency has been attributed, among other things, to a lack of precision in quantifying the timing and frequency of school mobility by Fantuzzo et al. (2018), Mehana and Reynolds (2004), and Rumberger (2015).

The primary goal of this study was to address limitations related to unaccounted random variance by examining the association between academic outcomes and school mobility from a longitudinal study design informed by bioecological development theory (Bronfenbrenner & Morris, 2005). This was achieved by examining the association between GPA, reading, and math scores by fifth grade and four measures of school mobility related to timing and frequency, all while controlling for key student characteristics and time-varying covariates. Fixed and time-varying student characteristics' contribution to variation in academic performance is vital to model, and this study acknowledges that without the inclusion of these predictors, it would be problematic to attribute the observed variation in later outcomes solely to school mobility. The four unique specifiers of school mobility were essentially the only thing changing from model-to-model within outcome. While not nested (i.e., cannot determine goodness of fit between school mobility model types), all four mobility measures together allow the reader to see how the timing and frequency of school moves relates to academic achievement.

While other longitudinal studies on school mobility exist, this is only the second after Fantuzzo et al. (2008) to utilize cross-classified models with real-world data to study the association of school mobility with academic outcomes. Several publications utilizing simulated data have also highlighted the advantages that cross-classification has over hierarchical ordering specifically in the context of school mobility (Grady & Beretvas 2005; Cafri, Hedeker, and Aarons, 2015; Luo & Kwok, 2012). The cross-classification of student- and school-level data, along with time-varying covariates allowed me to account for variance from five different sources: (1) within-student variation from year-to-year, (2) between-student variation in final status or the fifth grade intercept, (3) between-student rate of change, (4) between-school variation in fifth grade intercept and (5) between-school rate of change. Note that the variation related to schools on the intercept and slope were specified as cumulative to capture any carry-over effects from year-to-year in all models. Those random effects(c_{00k} and c_{10k}), while in the current study were indicative of very little variation in academic performance between school's fifth grade intercept and the rate of change in academic performance over time, are more inclusive of mobile students and their academic performance over time in their cumulative form because the equation to calculate a student's predicted score reflects their entire history of education through fifth grade, not just the most recent school's performance in fifth grade and change from fourth grade. Acute effects in the context of school mobility would simply forget the contribution of school context from prior years during the iterative procedure of running the models. The results are discussed below in the context of prior literature to determine how the findings fit in and contribute to the field of school mobility research. Limitations of the current study and recommendations for future research follow, as well as potential implications for policy makers involved in, or adjacent to, education.

Ever moving and academic outcomes. The association between ever moving and the three academic outcomes over time and at the end of fifth grade was initially examined. The ever-move coefficient serves as a decent proxy for comparison to a variety of previous research designs related to school mobility. Also, a significant difference between mover's and non-mover's fifth grade academic performance and/or change over time, after accounting for the variance among student characteristics, would merit additional models exploring the timing and frequency of school mobility. Within the ever-move models, the magnitude of effect for subcategories of students were reported. The corresponding coefficients for student characteristics in the ever-move analysis did not change for total, early, and frequent school mobility models because the nonmobile group remained the same. While the models are not nested (i.e., no fit statistics can be computed between mobility models), they could be considered parallel: the only interchanging element is the school mobility variable, which themselves are derivatives of the same school ID matching procedure. The variance attributable to student characteristics functions with indifference as to how the school mobility variable is coded. The weights attributable to student characteristics in the ever-move models can readily be used to calculate SD from the intercept in total, early, and frequent models as well as for calculating individual student's expected score.

The findings indicate that students who ever moved schools were anywhere from 32% (GPA) to 16% (math) of a standard deviation below non-mobile students with all predictors set at their zero point. There was also an almost negligible but significant difference in rate of change over time in GPA (-0.006, $p < .001$) compared to non-mobile students, however, reading and math scores of mobile and non-mobile students were not significantly different year-to-year. The absence of a significant slope difference in reading and math and the relatively small slope change in GPA indicates that ever moving has a similar association with academic performance across timepoints.

Even without differentiating the frequency and timing of school mobility, this outcome demonstrated that disruptions in an otherwise reliably routine school context between kindergarten and 5th grade can have a negative impact on academic achievement. This rupture in predictability of reciprocal relations within the school environment is in line with what bioecological theory would consider a threat to student's ability to reach their highest possible academic performance (Bronfenbrenner & Morris, 2005).

The final models included six covariates related to student characteristics, three of which were time-invariant (sex, ethnicity/race, and pre-K type, and three that were annually-varying (lunch price status, special needs status, and English proficiency). In previous research, these student-based controls typically explained a significant amount of variation in academic outcomes (Fiel et al., 2012; Gruman et al., 2008; LeBoeuf &

Fantuzzo, 2018). The only other cross-classified study on school mobility (LeBoeuf & Fantuzzo, 2018) used a similar covariate setup and concluded, not unlike the current research, there remains significant variance in academic outcomes attributable to school mobility even after considering the variance explained by other covariates. Their treatment of the school mobility variable as annually-varying and inclusion of student turnover rate as a school-based classification (i.e., a school's mobility rate) fit the models well for the testing of interactions between school mobility and student characteristics to be calculated, while our treatment of school mobility as more of a student-based fixed frequency/timing index did not lend itself to model convergence (set at 10,000 iterations) when we tested similar mobility by student characteristic interactions. Like LeBoeuf and Fantuzzo (2018), the current study specified school-specific variance components for intercept (C_{00}) and slope (C_{01}) to accumulate over timepoints. Raudenbush and Bryk (2002), in describing the cumulative-effects setting in HLM 6, point out that this is simply a way to add up the school-based variance in intercept and slope, a departure from the default setting (acute-effects) which has no sum function for school-based variance. From a bioecological perspective, summing the annual variance was the more natural fit, and was an in improvement from previous research that either ignored school context altogether or fixed the school-based variance for all students regardless of mobility ignoring any positive or negative variation for schools year-to-year.

Frequency of school mobility and academic outcomes. Both models relating to the frequency of school mobility (total number of and frequent school moves) illustrated a negative association with academic outcomes: each additional move was associated with lower academic performance by the end of fifth grade compared to non-mobile students, and the most frequent students performed lower than less frequent and nonmobile students. This is comparable with findings from previous research that included some measure of total number of school moves (Alexander, et al., 1996; GAO, 2010; Gruman et al., 2008; Kerbow, 1996; Reynolds, Chen, & Herbers, 2009). Fantuzzo and LeBoeuf (2018) found that after adjusting for student characteristics, students who moved every school year declined more steeply in reading scores between first and third grade and had a final third grade reading score lower than non-mobile students. The findings from their research and the current study are in line with what the bioecological model would predict from repeated significant disruptions to the interaction between the student and their school context (Bronfenbrenner & Morris, 2005).

Timing of school mobility and academic outcomes. The last models tested were related to determining whether moving earlier in elementary school was associated with the rate of change in academic performance over time and through the end of fifth grade. Findings indicated that both early and late movers performed worse than non-mobile students, with virtually no difference between early and late movers other than early movers expecting to have a small but significantly higher fifth grade GPA than late movers. These outcomes are different than what was hypothesized from the bioecological model, and although I thought that there may be some recency effect of late mobility disrupting reading and math scores happening on the same (3rd to 5th grade) timeline, the association with first through fifth grade GPA was surprising. The results suggest that mobility at any time through fifth grade is comparably harmful, not just something that is unique to the earliest school moves. Another related implication is that finer granularity in the measurement of timing of a school move may be critical for discovering more nuanced associations with academic performance. In this study, we only know if school ID's do not match year-to-year, and since software like HLM 6 can handle longitudinal data with very specific timepoints quite easily, it is possible to imagine that specifying down to the day of the year that a school transition occurred would yield more compelling results than a dichotomous annual value can deliver.

In comparison to previous research, the impact of school mobility on academic achievement found in this study is generally comparable, especially for other cross-classified approaches (LeBoeuf & Fantuzzo, 2018) as well as studies implementing standard HLM (Gruman et al., 2008) and linear/logistic regression (Alexander et al., 1996; Hanushek et al., 2004; GAO, 2010). After controlling for student characteristics, LeBoeuf and Fantuzzo (2018) discovered that there was a persistent, negative association between cumulative and concurrent school mobility and reading achievement by third grade, and this study found similar results examining reading, math, and GPA outcomes by fifth grade controlling for very similar student characteristics. Alexander et al. (1996) found a larger decrease in the effect size of total number of school moves as student characteristics were added in their logistic regression analysis of academic performance between first and fifth grade, but even without hierarchical modeling, the impact of school moves remained significant, and is consistent across other linear/logistic regression-based studies as they add controls for student and school characteristics. Hanushek et al. (2004) studied school mobility with a public economics approach and found that within-district moves come at a greater cost in academic achievement than moves outside of the district after controlling for ethnicity and SES, and while this study only looked at within-district moves, the sample was restricted to students who stayed in the same district for all years and supports the within-district cost.

Limitations. The current study adds to the existing research by examining the association between intradistrict school mobility and reading, math, and GPA through fifth grade. Through the cross-classification of students and schools, this study was able to address a major gap seen in prior research related to isolating the association that school mobility has with outcomes from student characteristics and the school environment. There are several limitations that were identified during the current study that may help future researcher's methodology and collaboration with schools/districts of interest. The greatest limitations include a lack of temporal precision in school mobility measurement, no information on the motivation for a school move, and no moderation testing to determine whether the relationship between school mobility and academic performance varies as a function of student or school characteristics.

The current study was limited to an operational definition of school mobility that relied on annual school ID matching. This is by far the most common definition of school mobility used in previous research (Fantuzzo, et al., 2018, Reynolds et al., 2009), but the very nature of annually-based school ID matching does not allow for finer-grained testing related to the timing of school mobility and fails to capture multiple moves made in the same school year. Since the bioecological model indicates that disruptions of student-school interactions are potentially risky, it is useful to know when those disruptions happened relative to the start and end of school sessions, and if there were multiple disruptions within one school year. Hanushek et al. (2004) is the only study thus far to include measures of within-school-year moves, finding that for math performance, transitioning to a new school during the school year had a stronger negative association than summertime moves. Additionally, they had information on number of moves within-year and tracked students across multiple school districts and found that multiple moves were most strongly negatively associated with math performance when staying within the same school district (Hanushek et al., 2004). It should be noted that Hanushek et al. (2004) is rooted in economic-focused methodology, and future developmentally focused research ought to strive to include greater depth in the timing and geographical (inter- vs intradistrict) nature of school moves.

Another limitation is the lack of qualitative information surrounding the motivation for and the context of a school move. Forging meaningful and lasting relationships with those responsible for collecting and maintaining school records is a necessary but insufficient step toward obtaining more detailed information about a student changing schools. There was no standardized form or exit interview protocol for mobile students in the current study that signaled why a move took place, so future researchers should collaborate with schools and school districts to develop user-friendly forms for their incoming and outgoing student body. Adding at least the primary reason for a school move to the models in the current study would allow researchers to test whether the strength of association with academic performance differs between sub-groups of mobile students (e.g., expulsion vs residential eviction vs parental job change), whereas currently there is no differentiation between any motivations for a school change.

In this study, only the direct association between school mobility and the three academic outcomes was tested. Since the bioecological model is primarily concerned with the interaction between the individual and their environment (Bronfenbrenner & Morris, 2005), future research should aim to quantitatively test whether there are key student and/or school characteristics that strengthen or weaken the negative association with academic outcomes found in this study. For example, testing whether the association varies as a function of classroom behavior would allow for researchers to examine if mobile students with preexisting and persistent exceptional classroom skills fared better academically than less skilled mobile students who have the same frequency/timing of school moves. Similarly, within the school classification, including a covariate meant to reflect the capacity of a school to adequately accommodate a transferring student would be helpful, like annual turnover rate, and then one could test whether there is an interaction such that the higher the turnover rate the more negative the association between moving and academic performance becomes. In both instances, it allows the researcher to get away from blanket statements about the overall effect school mobility on academic performance and speak more specifically about how it varies as a function of student and school characteristics. From an applied developmental psychology perspective, this is useful insofar as diverting resources toward students and schools that are at the greatest risk for disruptions surrounding a school move. Including potential moderating effects of the quality of the child's post-move school is an particularly important recommendation for future research, since it is possible that moving to a better school might buffer the negative effects of school mobility.

Implications. Given that the findings in the current study establish a negative association between student intradistrict school changes and academic performance through the first five years of elementary school, it is surprising that school mobility is not a higher priority agenda item at the national level. The No Child Left Behind Act, which ramped up standardized testing accountability, despite its name, actually left out the testing performance of students who were not continuously enrolled in the same school for the year. While not all mobile students move mid-year, test results for those that do transfer schools during the academic year, are unfortunately ignored in the calculation of a school's performance. This results in a scenario where there is little incentive for schools to assure that incoming transfer students receive attention that they need to fully readjust to their new school setting since their funding/accreditation is not tethered to how they perform. Worse, because many mobile student's scores are not counted each year, determining where to divert resources is obfuscated merely so a school can appear as high-performing as possible. Setting a national education policy that rewards transparency in reporting all enrolled student's test scores would be a step toward being able to recognize patterns within the school mobility population of differing growth trajectories and final outcomes of academic performance.

Related to transparency in reporting standardized testing for mobile students, there is a greater need for schools to exchange information about incoming and outgoing students. A secure national database that tracks the timing and reason for a school move would allow schools to prepare for an incoming student as early as possible and would give researchers and policymakers valuable information on the most disruptive school mobility scenarios. There is already an established database for reporting other disruptive threats (e.g., school absences) to academic achievement from the No Child Left Behind Act (2001), and as Fantuzzo et al. (2018) mentioned, the financial cost for adding a mandate for reporting school mobility data would be minimal if the same system is used. Finally, this study found that later movers have comparable variation in academic outcomes to early movers, which implies that there is no safe developmental stage (through fifth grade) where educators and policymakers can ignore the disruptions associated with school mobility. Any interventions developed to help mobile students transition to a new school context ought to keep the focus broad rather than targeted at students who move before third grade. Future longitudinal research should follow mobile students throughout high school to examine the growth trajectories for even later movers, and to see how K-G5 movers fare by the end of high school

Table 1. Student Characteristics

	% in Full Sample (N = 20,806)	% in Analytic Sample (N = 10,066)
Male	49.4	47.6
Ethnicity		
Black	31.4	32.6
Latinx	60	59
White/other	8.6	8.4
Family- and Center-Based Care	26.2	30
Free or reduced price lunch G1	74.9	75.7
Primary Exceptionality G1	10.1	4.7
Not English Proficient G1	77	81.1

Table 2. Descriptive Statistics School Readiness Measures (N = 10,066)

Variable	*M*	*SD*	Minimum	Maximum
LAP-D				
Fine Motor	62.08	27.261	1	99
Gross Motor	68.99	28.159	1	99
Language	51.87	30.792	1	99
Cognition	59.81	29.348	1	99
DECA				
TPF	63.97	26.529	1	99
Behavior Concerns	41.48	28.711	1	99

Table 3. Descriptive Statistics of Academic Achievement

Grade Level	GPA			
	Student (Row)		School Avg (Column)	
	M	*SD*	*M*	*SD*
First (*n = 9,971)*	4.43	0.49	4.43	0.22
Second (*n* = 9,963)	4.30	0.51	4.29	0.24
Third (*n =9,951*)	4.12	0.54	4.17	0.25
Fourth (*n = 9,828*)	4.20	0.52	4.17	0.26
Fifth (*n = 9,683*)	4.21	0.53	4.19	0.29
	FCAT Math			
	Student (Row)		School Avg (Column)	
	M	*SD*	*M*	*SD*
Third (*n =10,003*)	0.16	0.93	0.12	0.40
Fourth (*n = 9,888*)	0.20	0.85	0.07	0.46
Fifth (*n = 9,716*)	0.17	0.90	0.12	0.43
	FCAT Reading			
	Student (Row)		School Avg (Column)	
	M	*SD*	*M*	*SD*
Third (*n =10,002*)	0.31	0.81	0.23	0.36
Fourth (*n = 9,893*)	0.17	0.87	0.08	0.44
Fifth (*n = 9,726*)	0.17	0.87	0.09	0.45

Table 4. Prevalence of School Mobility by Student Characteristic

	Mobility Type		
Student Characteristic	Ever Move %	Frequent Moves %	Early Moves %
Overall	37.80	3.28	28.13
Gender			
Male	37.30	3.34	27.20
Female	38.30	3.22	29.00
Race/Ethnicity			
Black	47.71***	6.10***	36.28***
Latinx	34.76***	2.09***	25.53***
White and Other	20.71***	0.71***	14.79***
Pre-K Type			
Public School	34.28***	2.72***	25.51***
Center- or Family-Based	46.02***	4.58***	34.30***
Lunch Price Status G1			
Free	42.91***	4.38***	31.42***
Reduced	35.83	2.43*	27.05
Did Not Apply/Qualify	25.96***	0.98***	20.41***
Special Needs Status G1			
Has Primary Exceptionality	39.83	2.94	28.93
No Primary Exceptionality	37.60	3.20	27.90
English Proficiency Status G1			
Not English Proficient	38.11	2.42	26.89
English Proficient	37.72	3.48	28.42

Note. Chi-squared p values reported for ever, frequent, and early mobility

*p < .05 ** p < .10 *** p < .001

Table 5. Unconditional Growth Models of GPA, Reading Scores, and Math Scores

Unconditional Models	GPA			FCAT Reading			FCAT Math		
	UG1	UG2	UG3	UG1	UG2	UG3	UG1	UG2	UG3
Main Effect (G5 intercept), θ_0	4.13***	4.13***	4.15***	0.056***	0.07***	0.08***	0.12***	0.12***	0.11***
Rate of Change, θ_1	-0.06***	-0.06***	-0.08***	-0.10***	-0.10***	-0.09***	-0.02***	-0.02***	-0.02***
Variance Component (%)									
Within-student, e	33.62	25.58	22.67	33.42	27.01	26.9	31.01	27.24	26.67
Between-student final status, b_{00}	65.74	72.01	70.63	65.11	69.67	69.2	68.01	68.76	67.18
Between-student rate of change b_{10}		1.82	1.78		2.11	2		3.01	2.73
Between-school final status, c_{00}	0.65	0.59	3.91	1.47	1.21	0.7	0.98	1	1.12
Between-school rate of change, c_{10}			1.01			1.3			0.02
Fit Statistics									
Deviance	42644.78***	41511.21***	39915.03***	60596.03***	60323.50***	60085.48***	59144.23***	59048.76***	58681.61***
ΔDeviance		1133.56***	1596.18***		272.56***	237.99***		95.47***	367.15***
Δdf		1	1		1	1		1	1
Comparison model		UG1	UG2		UG1	UG2		UG1	UG2

*p<.05, **p<.01, ***p<.001.

Table 6. Conditional Model 1a for Movers vs Non-Movers Academic Achievement

Table 6. Conditional Model 1a: for Movers vs Non-Movers and Academic Achievement

Final Conditional Models	GPA	FCAT Reading	FCAT Math
Fixed Effects			
Intercept (fifth grade)	4.46 *** (0.02)	0.44*** (0.03)	0.36*** (0.03)
Ever moved	-0.17 *** (0.01)	-0.16*** (0.02)	-0.14** (.02)
Male	-0.14 ***	-0.01 (0.02)	0.19*** (0.02)
Latinx/White and other	-0.05* (0.02)	-0.06* (0.03)	-0.09** (.03)
Black/White and other	-0.26*** (0.02)	-0.41*** (0.03)	-0.40*** (.03)
Latinx/Black	0.21*** (0.1) (4.20***)	0.35*** (0.02) (0.25***)	0.309*** (.02) (-.05***)
Family and center-based child care	-0.0001 (0.01)	0.06** (0.02)	0.11*** (.02)
Fine motor skills ($\bar{x}$ = 62.08)	0.001***	0.0008**	0.004***
Cognition ($\bar{x}$ = 59.81)	0.003***	0.004***	0.007***
Language ($\bar{x}$ = 51.87)	0.001***	0.005***	0.002***
Gross motor skills ($\bar{x}$ = 68.99)	-0.001***	-0.002***	-0.002***
Total protective factors (Teacher Rated; $\bar{x}$ = 63.97)	0.001***	0.0008*	0.001**
Behavior concerns (Teacher Rated; $\bar{x}$ = 41.48)	-0.002***	-0.002***	-0.002***
Free priced lunch/Non-FRL	-0.05***	-0.12*** (0.01)	-0.09*** (.01)
Reduced price lunch/Non-FRL	-0.02***	-0.06*** (0.02)	-0.05*** (.01)
Reduced price lunch/Free priced lunch	-0.02*** (4.43***)	-0.06*** (.01) (0.32***)	-0.03** (0.01) (0.30***)
Special needs	-0.05 (.01)***	-0.27*** 0.02)	-0.21*** (.02)
Not English proficient	-0.07***	-0.40*** (.03)	-0.32*** (.03)
Rate of Change			
Slope (grade level)	-0.06***	-0.07*** (0.01)	-0.04** (.01)
Ever Moved	-.006*	-0.009	-0.004
Male	-0.02***	-0.04***	0.01*
Latinx/White and other	-0.03 (0.02)***	0.005 (.01)	0.006 (.01)
Black/White and other	-0.01*	-0.03* (.01)	-0.0007 (.12)
Latinx/Black	0.02*** (-0.09***)	0.03*** (-0.10***)	0.008 (-0.03***)
Family and center-based child care	0.007*	0.02*	0.05***
Fine motor skills ($\bar{x}$ = 62.08)	0.00005	-0.000009	0.0007***
Cognition ($\bar{x}$ = 59.81)	-0.0002***	0.000040	0.0004**
Language ($\bar{x}$ = 51.87)	0.000004	0.0002	-0.0005**
Gross motor skills ($\bar{x}$ = 68.99)	0.00007	-0.0001	0.0006***
Total Protective factors (Teacher Rated; $\bar{x}$ = 63.97)	-0.00006	0.000088	-0.0002
Behavior concerns (Teacher Rated; $\bar{x}$ = 41.48)	-0.00004	0.00004	-0.0003*
Proportion of Variance (%)			
Within-student (e)	27.82***	42.69***	33.65***
Between-student final status (b00)	63.60***	51.38***	60.63***
Between-student rate of change (b10)	2.08***	2.80***	3.18***
Between-school final status (c00)	5.17***	2.18***	1.24***
Between-school rate of change (c10)	1.33***	0.96***	1.30***
Model Fit			
Deviance	35897.21	57330.40	55720.312
Δ Deviance from baseline model	4017.82***	2517.12***	2738.86***
Δ df	26	26	26
Nested Comparison Model	UG3 GPA	UG3 FCAT-R	UG3 FCAT-M

Note: Unstandardized parameter estimate SE's in parentheses, SE < .01 suppressed. GPA n = 10,065, FCAT-M n = 10,038, FCAT-R n = 10,037
*p < .05, **p < .01, ***p < .001.

Table 7. Conditional Mofel 1b for Total Number of Moves and Academic Achievement

Table 7. Conditional Model 1b: for Total Number of School Moves and Academic Achievement

Final Conditional Models	GPA	FCAT Reading	FCAT Math
Fixed Effects			
Intercept (fifth grade)	4.46 *** (0.02)	0.44***	0.36***
Ever moved	-0.11 *** (0.01)	-0.11***	-0.10***
Rate of Change			
Slope (grade level)	-0.06***	-0.07***	-0.04**
Total School Mobility (0-5)	-0.005*	-0.009	-0.004
Proportion of Variance (%)			
Within-student (e)	27.91***	32.48***	33.65***
Between-student final status (b00)	63.47***	63.62***	60.63***
Between-student rate of change (b10)	2.09***	2.14***	3.18***
Between-school final status (c00)	5.18***	1.01***	1.24***
Between-school rate of change (c10)	1.35***	0.74***	1.30***
Model Fit			
Deviance	35841.29	57303.28	55709.00
Δ Deviance from baseline model	4073.74***	2782.20***	2972.61***
Δ df	26	26	26
Nested Comparison Model	UG3 GPA	UG3 FCAT-R	UG3 FCAT-M

Note: Predictor coefficients not displayed in Table 7, see Table 6. Unstandardized parameter estimate SE's in parentheses, SE < .01 suppressed. GPA *n* = 10,065, FCAT-M *n* = 10,038, FCAT-R *n* = 10,037 *p < .05, **p < .01, ***p < .001.

Table 8. Conditional Model 1c for Initially Early vs Late School Mobility

Table 8. Conditional Model 1c: Early and Late School Mobility

Final Conditional Models	GPA	FCAT Reading	FCAT Math
Fixed Effects			
Intercept (fifth grade)	4.46 *** (0.02)	0.44***	0.36***
Early Moves/Nonmobile	-0.16***	-0.15***	-0.14***
Late Moves/Nonmobile	-0.20***	-0.21***	-0.17***
Early Moves/Late Moves	0.04*	0.07	0.03
Rate of Change			
Slope (grade level)	-0.06***	-0.07***	-0.04**
Early Moves/Nonmobile	-0.004	-0.004	-0.003
Late Moves/Nonmobile	-0.01**	-0.02	-0.008
Early Moves/Late Moves	0.01	0.01	0.005
Proportion of Variance (%)			
Within-student (e)	27.83***	32.45***	33.65***
Between-student final status (b00)	63.58***	63.68***	60.63***
Between-student rate of change (b10)	2.01***	2.13***	3.18***
Between-school final status (c00)	5.18***	1.01***	1.24***
Between-school rate of change (c10)	1.34***	0.73***	1.30***
Model Fit			
Deviance	35891.51	57325.42	55718.70
Δ Deviance from baseline model	4023.52***	2760.05***	2962.91***
Δ df	28	28	28
Nested Comparison Model	UG3 GPA	UG3 FCAT-R	UG3 FCAT-M

Note: Predictor coefficients not displayed in Table 8, see Table 6. Unstandardized parameter estimate SE's in parentheses, SE < .01 suppressed. GPA *n* = 10,065, FCAT-M *n* = 10,038, FCAT-R *n* = 10,037 *p < .05, **p < .01, ***p < .001.

Table 9. Conditional Model 1d for Frequent and Infrequent School Mobility

Table 9. Conditional Model 1d: Frequent and Infrequent School Mobility

Final Conditional Models	**GPA**	**FCAT Reading**	**FCAT Math**
Fixed Effects			
Intercept (fifth grade)	4.46 *** (0.02)	0.44***	0.36***
Frequent Moves/Nonmobile	-0.33***	-0.33***	-0.26***
Infrequent Moves/Nonmobile	-0.15***	-0.15***	-0.14***
Frequent Moves/Infrequent Moves	-0.17***	-0.18***	-0.12**
Rate of Change			
Slope (grade level)	-0.06***	-0.07***	-0.04**
Frequent Moves/Nonmobile	-0.02**	-0.05*	-0.02
Infrequent Moves/Nonmobile	-0.006*	-0.006	-0.003
Frequent Moves/Infrequent Moves	-0.01	-0.04	-0.02
Proportion of Variance (%)			
Within-student (e)	27.89***	32.45***	33.66***
Between-student final status (b00)	63.46***	63.68***	60.615***
Between-student rate of change (b10)	2.08***	2.13***	3.17***
Between-school final status (c00)	5.22***	1.01***	1.24***
Between-school rate of change (c10)	1.35***	0.73***	1.31***
Model Fit			
Deviance	35846.90	57315.67	55712.60
Δ Deviance from baseline model	4068.13***	2769.81***	2969.00***
Δ df	28	28	28
Nested Comparison Model	UG3 GPA	UG3 FCAT-R	UG3 FCAT-M

Note: Predictor coefficients not displayed in Table 9, see Table 6. Unstandardized parameter estimate SE's in parentheses, SE < .01 suppressed. GPA *n* = 10,065, FCAT-M *n* = 10,038, FCAT-R *n* = 10,037 *p < .05, **p < .01, ***p < .001.

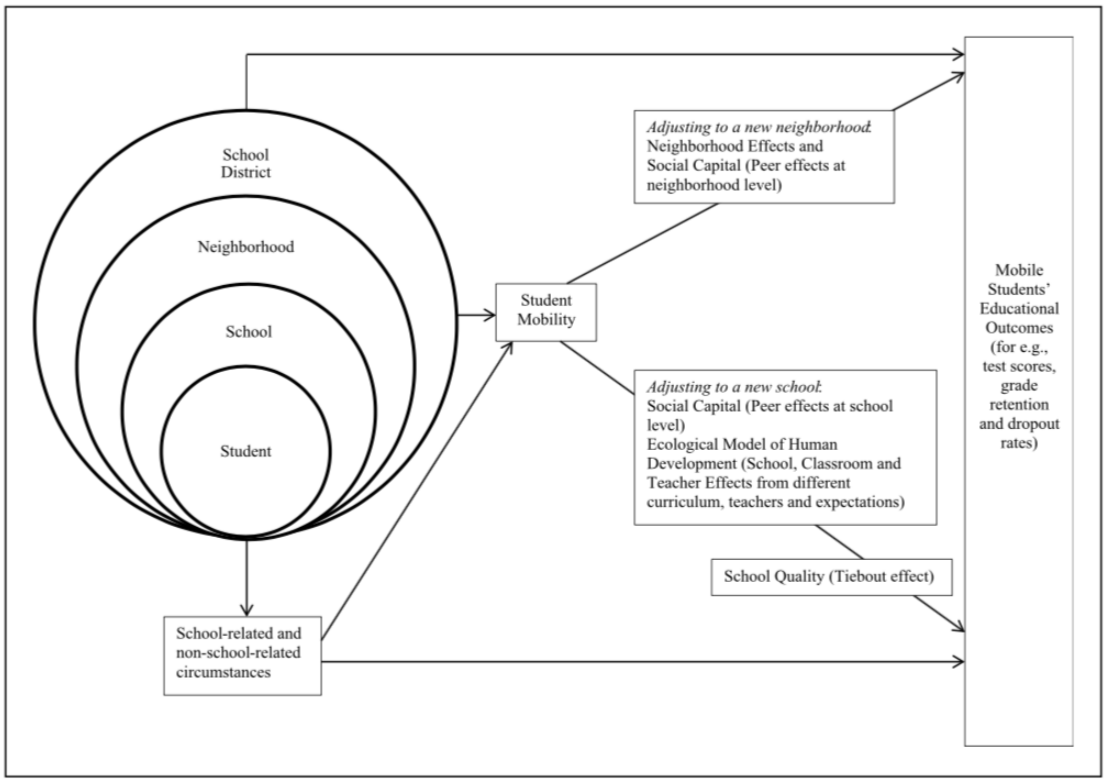

FIGURE 1. *A model of the key relationships among student mobility and mobile students' educational outcomes.*

Figure 1. Visual Adaptation of Theoretical Perspective for School Mobility Research

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