THE EFFECTS OF RESIDENTIAL MOBILITY AND SCHOOL EXCLUSION HISTORY ON EDUCATIONAL ATTAINMENT

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ABSTRACT

Educational attainment in the U.S. continues to be marred by racial and socioeconomic (SES) disparities. Despite decades of research on the predictors of attainment and the decreases in dropout rates, minority-race and low-income youth continue to dropout at higher rates than their White and wealthy peers. Therefore, the question remains, why do many students persist while some drop out? To better understand attainment, an analysis of a nationally representative sample within which attainment is evaluated as part of a process of grade advancement and the nuanced nature that the timing, frequency, and severity of previous life events have on a child's educational path are addressed is needed. The study presented here is a first step to evaluate the effects of residential mobility and school exclusion history on the attainment of a cohort of the National Longitudinal Study of Adolescent Health (*Add Health*). First, patterns of school exclusion, residential mobility, and dropout over the study period were outlined. Next, the relationships between predictors of dropout and dropout examined. Finally, the effects of the frequency and timing of residential mobility, school exclusion, and other predictors on attainment were explored using discrete time survival analysis. Findings indicate the potential utility of these methods in future research to better understand the process of dropout so more informed interventions can be designed to serve students.

For My Family

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CHAPTER 1

INTRODUCTION

Why do students persist through school? Why do some drop out? These questions have been asked and answered by education researchers for decades. Through various forms of research, myriad factors have been identified as predictors of dropout, and conversely persistence and attainment. These factors range from the individual to the school and the familial to the community levels (Lessard, et al., 2008; Rumberger, 2011). Now with the U.S. status dropout rate for 16- to 24-year-olds (i.e., the percentage of youth who have not earned a high school diploma or equivalency, such as a GED certificate) at an all-time low of 6.1% in 2016, some may be inclined to believe this issue is no longer important (McFarland, Cui, Rathbun, & Holmes, 2018). However, when these numbers are examined more closely, clear disparities continue to exist.

Of youth in the lowest family income quartile, 9.7% dropped out in 2016 and in the middle low quartile, 7.3% dropped out, both far exceeding their peers in the middle high and highest quartiles 5.4% and 2.6%, respectively. Moreover, students of color, including Black (6.2%), Hispanic (8.6%), and Native American (18.2%) students, continue to dropout at higher rates, than their White peers (5.2%; McFarland, et al., 2018). In addition, these statistics mask the variability in reporting practices across districts and states and the practices many schools and districts employ to decrease reported dropout rates, such as not including those who transfer out of their schools to alternative programs or other schools, those who are over 17 and have parental permission to leave for work or to join the military, or those who turn 21 before the end of the school year, and do not return (Tuck, 2012). Therefore, the question remains, why do many students persist while some drop out?

Of the potential causes or predictors of dropout two factors emerge as unique: residential mobility and school exclusion history. Both have been disproportionately related to race and socioeconomic status (SES; American Psychological Association Zero Tolerance Task Force, 2008; Baker, Berning, Gowda, Zhang, & Hawn, 2020; Chu & Ready, 2018; Clark, 2010; Institute for Children and Poverty, 2009; Losen & Gillespie, 2012; Metzger, Fowler, Anderson, & Lindsay, 2015; Murphey, Bandy, & Moore, 2012; South, Haynie, & Bose, 2007; Sullivan, Klingbeil, & Van Norman, 2013) and both can occur at different times across a student's progression through school, including repeat occurrences in a single school year or over multiple school years (Anderson & Leventhal, 2017). Moreover, residential mobility and school exclusion on their surface are not necessarily harmful to students as mobility can be related to improvements in SES and greater access to resources (Hango, 2006; Murphey, et al., 2012), and the exclusion of some students is often utilized for increasing the safety of the school for all students (Casella, 2003; Levy, et al., 2014).

However, for marginalized youth, moving may be a result of economic necessity due to lack of affordable housing, which may result in increasingly frequent moves with only short periods of stability (Clark, 2010; Crowley, 2003; Institute for Children and Poverty, 2009; Murphey, et al., 2012). In addition, school exclusion in the form of out-of-school suspensions and expulsions has been shown over countless instances to disproportionately affect students of color, resulting in a disproportionate reduction in instruction time compared to their non-disciplined peers and greater disconnection from the learning environment (American Psychological Association Zero Tolerance Task Force, 2008; Chu & Ready, 2018; Losen &

Gillespie, 2012; Welsh & Little; 2018). Further, both residential mobility and school exclusion may be coupled with changes in schools as students move out of catchment areas or are expelled and forced to change educational institutions (American Psychological Association Zero Tolerance Task Force, 2008; Cordes, et al., 2019; South, et al., 2007; Welsh & Little, 2018). In the end, students who experience mobility and exclusion have been found to perform worse on measures of achievement (Arcia, 2006; Brown, 2007; Chu & Ready, 2018; Cutuli, et al., 2013; Tobin, 2014; Trout, Hagaman, Casey, Reid, & Epstein, 2008; Voight, Giraldo-Garcia, & Shinn, 2020; Voight, Shinn, & Nation, 2012), experience gaps in attendance/instruction time (Brown, 2007; Conger & Finkelstein, 2003; Chu & Ready, 2018; Crowley, 2003; Theriot, Craun, & Dupper, 2010) and demonstrate a lack of attachment to schools (Brown, 2007; Caton, 2012; Crowley, 2003; Green, DeFosset, & Kuo, 2019; Lessard, et al., 2008) when compared to their residentially stabled and non-excluded peers.

Despite all these known effects of residential mobility and school exclusion, what has not been evaluated in previous research is how these predictors may impact educational attainment over time. Therefore, to better understand why there is a disparity across wealth and race in terms of educational attainment, this study reevaluated the findings of previous researchers with a specific focus on the timing of life events relative to one another and to attainment. By doing so, the research no longer solely focused on what relates to or potentially causes dropout, but also on how those factors relate to one another and whether some predictors are proximate while others are distal causes of dropout. As attainment is not simply an event, it is also a process (Lessard, et al., 2008; Rumberger, 2011), it is important to broaden the focus from questions of “who?” and “why?” to include questions of “how?” and “when?”

By better understanding how the timing and frequency of events, such as residential mobility and school exclusion, impact children as they advance from one grade to the next, better interventions can be developed in schools to ensure that all students persist through high school and graduate. This dissertation sought to address this need by functioning as a first step to evaluate the direct and indirect effects of residential mobility and school exclusion on educational attainment in relation to their event timing, frequency, and influence on and by other predictors in a large nationally representative dataset.

Theoretical Framework

Due to the extensive research on high school dropout, there have been myriad theories proposed to explain how the predictors of dropout explain its occurrence. These theories are based on theoretical models in various social scientific fields, including education, sociology, psychology, criminal justice, and anthropology, and empirical evidence from previous studies and all have informed the field in terms of how the process of dropout develops (Battin-Pearson, Newcomb, Abbott, Hill, Catalno, & Hawkins, 2000; Bradley & Renzulli, 2011; Jordan, Lara, & McPartland, 1994; Pesta, 2018; Rumberger, 2011). However, these theories are often limited by their focus on how only a few predictors in one or two domains relate to one another, instead of examining dropout from a more holistic perspective.

To that end, Russel W. Rumberger and Sun Ah Lim (2008) in a comprehensive literature review of student dropout combined predictors from all such domains into a conceptual model to explain how they likely interact as depicted in Figure 1.1. The model serves not only as one to describe the process of dropout, but also it also depicts the process of high school educational attainment and performance overall, which is especially fruitful as dropout is only one possible outcome on in those progressions.

As seen in Figure 1.1, predictors at the individual level, including background factors, attitudes, behaviors, and performance, and predictors at the institutional levels of families, schools, and communities are presented as interconnecting and influencing each other in the

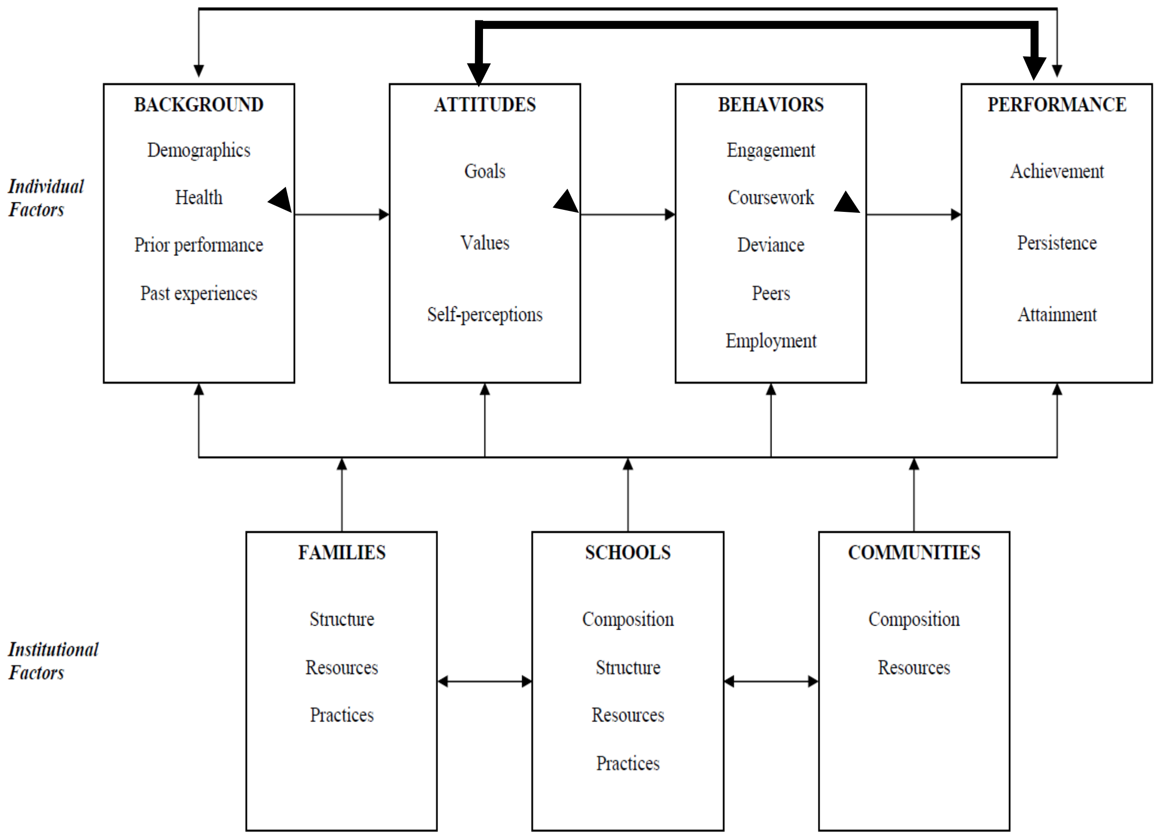


Figure 1.1. Adjusted Conceptual Model of High School Performance. Adapted from *Why students drop out of school: A review of 25 years of research,* by R. W. Rumberger and S. A. Lim, 2008, Santa Barbara: California Dropout Research Project. Retrieved from www.cdrpsb.org/download.php?file=researchreport15.pdf.

process of attainment. For example, one can see how demographic characteristics such as race and SES can influence attainment as can residential mobility as a family-level, structural factor. Also, though not clearly depicted in this model, school exclusion most closely relates to the relationship between individual deviant behavior and school institutional practices, which then directly relate to educational attainment (Rumberger & Lim, 2008).

Despite the benefits of this depiction of the factors, I elected to modify it further to better reflect the reality of the relationships between some factors that are not directly connected in the model. For example, making the connection between attitudes and background bidirectional can account for how a person's academic self-perceptions could influence their health status and connecting attitudes and performance bidirectionally and directly better reflects how a student's academic goals may impact their educational performance by making them work harder or relaxing or how their performance may conversely cause a student to reevaluate their goals (Rumberger & Lim, 2008). In this way, the conceptual model can better serve as a theoretical model for the process of educational attainment, while also providing a framework to understand how both residential mobility and school exclusion history may interact to influence attainment beyond their overlapping connections to race and SES.

Purpose of the Study

The purpose of this study was to better understand how both residential mobility and school exclusion histories relate to the process of educational attainment over time. Specifically, using data from ninth grade cohort of the National Longitudinal Study of Adolescent to Adult Health (*Add Health*), this study sought to understand the factors that contributed to a student's advancement through high school and how those factors relate to one another to better understand when and why some students prematurely end their educational progression. In addition, using discrete-time survival analysis (DTSA), event histories of attainment were analyzed to determine when students ended their high school education and how the timing and frequency of residential mobility and school exclusion events related to their advancement through school. Moreover, building on previous studies of educational attainment (Lessard, et al., 2008; Rumberger, 2011), the analysis also included numerous factors related to educational attainment at the student level to better depict and test the process of attainment outlined in the conceptual model.

Research Questions

From the purpose outlined above, three research questions guided this study:

1. What are the patterns of school exclusion, residential mobility, and educational attainment during the study period?
2. What are the relationships between the predictors of educational attainment and educational attainment?
3. What are the effects of the frequency and timing of residential mobility, school exclusion, and other predictors on attainment?

As attainment is a process, not an event (Lessard, et al., 2008; Rumberger, 2011), these questions seek to evaluate the relationships between the predictors, dropout, and time in three different ways: first by examining the data to see if patterns emerge across the variables, second by evaluating the relationship between the variables, and third by modeling the relationships between the variables over time. By evaluating the data in this way, the larger goal of serving as an initial foray into increasing analysis that addresses the frequency and timing of events in the process of attainment is met.

Significance of the Study

The significance of this study includes empirical and practical possibilities for the future. First, the research presented here can serve as a foundation for future studies on the impact of time on educational outcomes, particularly in terms of educational attainment. So much is already known about the predictors of attainment and the relationships between predictors, but what has been understudied is the relationship between those predictors over time (Battin-Pearson, Newcomb, Abbott, Hill, Catalno, & Hawkins, 2000; Jordan, Lara, & McPartland, 1994; Lessard, 2008; Pesta, 2018; Rumberger & Lim, 2008; Rumberger, 2011). In addition, previous research has not evaluated the relationship between school exclusion and residential mobility on educational attainment, despite the established overlaps between these factors in the literature (American Psychological Association Zero Tolerance Task Force, 2008; Baker, Berning, Gowda, Zhang, & Hawn, 2020; Chu & Ready, 2018; Clark, 2010; Institute for Children and Poverty, 2009; Losen & Gillespie, 2012; Metzger, et al., 2015; Murphey, Bandy, & Moore, 2012; South, et al., 2007; Sullivan, Klingbeil, & Van Norman, 2013). By expanding the literature in these domains and continuing to look at how multiple factors across individual and institutional domains interact to impact attainment, more can be learned about the process of attainment and how it manifests for different students following different paths.

By understanding those processes and paths, more informed interventions can be designed and implemented to address the needs of vulnerable students. For example, by identifying the critical grades when students are at most risk to dropout and as well as the combination and timing of predictors that likely contribute to that dropout, interventions can be designed to serve the most vulnerable students more effectively.

CHAPTER 2

REVIEW OF LITERATURE

The literature on residential mobility, school exclusion, and educational attainment is vast. Numerous studies have examined the predictors and outcomes related to these life events, separately and together, demonstrating both the potential positive and negative effects of each (Anderson & Leventhal, 2017; Anooshian, 2002; Arcia, 2006; Brown, 2007; Casella, 2003; Caton, 2012; Conger & Finkelstein, 2003; Crowley, 2003; Green, DeFosset, & Kuo, 2019 Hango, 2006; Lessard, et al., 2008; Levy, et al., 2014; Losen & Gillespie, 2012; Murphey, et al., 2012; Rumberger, 2011; Skiba, et al., 2014; Stearns & Glennie, 2006; Suh & Suh, 2007; Swanson & Schneider, 1999; Theriot, et al., 2010; Tobin, 2014; Trout, et al., 2008; Voight, et al., 2020; Voight, et al., 2012). However, no study has examined the unique influence of residential mobility and school exclusion events on the process of attainment as they relate over time. Therefore, building on previous research, this study seeks to address this gap.

What follows in this chapter is a discussion of the literature on residential mobility, school exclusion history and educational attainment, with a focus on dropout. In the sections on residential mobility and school exclusion, the literature on these phenomena and academic achievement as well as the work that has been done on their timing relative to outcomes will be discussed. The focus on academic achievement was selected as a representative overlapping outcome between the residential mobility and school exclusion to further demonstrate their connections beyond demographic characteristics and dropout. In the section on residential mobility, school mobility versus residential mobility will also be discussed. Next, in the discussion of educational attainment, research on residential mobility and dropout as well as school exclusion and dropout will be discussed along with the research on the timing of the predictors of dropout relative to the timing of the event to further establish the importance of approaching the research on educational attainment as a process versus a simple event. Finally, the chapter will end with a more extensive discussion of the theoretical framework for the research presented here.

Residential Mobility

Residential mobility is a unique aspect of many students' lives because it is not a "one-size-fits-all" phenomenon. Residential mobility can vary in intensity from those who experience no mobility in their lives to those who only move once or twice over the course of their primary and secondary school years all the way to those who move frequently and consistently over short periods of time (from once every few weeks to once every few months; Ersing, Sutphen, & Loeffler, 2009; Kingsley, Jordan, & Traynor, 2012). Adding to the complexity of this issue is that residential mobility can be experienced alone or as part of a family, and can include experiences of changing residences between family homes, hotels/motels, friends' homes, shelter stays, child welfare out-of-home placements, and running away (Child Welfare Information Gateway, 2016; Institute for Children and Poverty, 2009). Moreover, a potential result of residential mobility is homelessness (Crowley, 2003; Institute for Children and Poverty, 2009).

Research analyzing residential mobility in school-age children and adolescents has noted the numerous effects residential mobility can have on a child's life, including strained relationships with peers and parents (Anooshian, 2002; Green, et al., 2019), lower academic achievement (Cutuli, et al., 2013; Ersing, et al., 2009; South, et al.; 2007; Voight, et al., 2020; Voight, et al., 2012), lower rates of attendance (Ersing, et al., 2009; Voight, et al., 2020), behavior issues (Anderson & Leventhal, 2017; Ersing, et al., 2009; Swanson & Schneider, 1999), dropout (Metzger, et al., 2015; South, et al., 2007; Swanson & Schneider, 1999), and the increased likelihood of frequent moving as an adult (Myers, 1999) compared to their residentially stable peers.

Residential Mobility and Academic Achievement

Focusing on academic achievement, Cutuli, et al. (2013) studied the achievement of homeless and highly mobile students from third to eighth grades in Minneapolis public schools. Their worked compared the academic experiences of four groups of students identified as homeless and highly mobile (HHM), federal free meal eligible (FM), federal reduced meal eligible (RM), and general; there was no overlap in students between the groups. Math and reading achievement were examined while controlling for different demographic variables over the span of the study.

The conclusion was that "homelessness and high residential mobility represented a substantial risk for lower achievement among students in this large, urban school district" (Cutuli, et al., 2013, p. 853). This followed the finding from the linear mixed models that homeless and highly residentially mobile students had lower math and reading achievement scores (compared to their housed peers). This finding persisted in the group of students who were ever identified as homeless or highly residentially mobile but were no longer classified as such. The researchers went on to report that these children also "showed a widening of the [achievement] gap over time compared to lower risk groups from third through eighth grades. There was no evidence of 'catch-up' or narrowing of achievement gaps over time" (p. 853). These results indicate that the effects of homelessness or high residential mobility are not limited to the periods of time that a student is experiencing these phenomena; rather, the residual effects can persist and impact future performance.

Extending the work of Cutuli, et al. (2013), Cordes, Schwartz, & Steifel (2019) examined the effects of residential mobility on academic achievement in New York City's (NYC) public schools. Data from the NYC Department of Education was used to measure residential mobility from one year to the next between the 2004-2005 school year, when the sample students were in third grade, and the 2011-2012 school year, when students should have been in eighth grade (assuming standard grade promotion). In addition, unlike in previous work, the distance between moves was also evaluated by distinguishing between those who moved less than one mile (short-distance moves) and those who moved one mile or more (long distance movers).

The results indicated that, consistent with previous research moving can have negative impacts on children's academic performance. The researchers found that "long-distance moves have a negative and persistent effect on students scores in both math and ELA [English/Language Arts]" (Cordes, et al., 2019, p. 1407). However, they also found that those students who made short-distance moves had the opposite effect on academic performance that was also sustained in subsequent years. The authors attribute these differences to the potential impact that the distance of move can have on students. In other words, short-distance moves did not accompany changes in school or neighborhood as compared to long-distance movers. Further, this conclusion was corroborated by their finding that academic performance was harmed for those who experienced short distance moves along with school changes.

Despite the contributions of these studies (Cordes, et al., 2019; Cutuli, et al., 2013) to demonstrate the impact of residential mobility on academic achievement, these studies only examined the experiences of youth through early adolescence and did not address high school students' experiences, though other research corroborates these findings in children and adolescents (Ersing, et al., 2009; South, et al., 2007; Voight, et al., 2020; Voight, et al., 2012). It should also be noted though that mobility is not only associated with negative outcomes but also improved opportunities beyond achievement as Cordes, et al. (2019) found, including access to better schools and neighborhoods (Cordes, et al., 2019; Crowley, 2003; Hango, 2006). Further, moving can be a life lesson that helps children learn how to deal with hardship (Hango, 2006). Even so, residential mobility has consistently been shown to disproportionately affect low-income students and their families and does not consistently demonstrate beneficial outcomes for these groups (Clark, 2010; Cordes, et al., 2019; Crowley, 2003; Cutuli, et al., 2013; Institute for Children and Poverty, 2009; Murphey, et al., 2012; South, et al., 2007).

Residential Mobility and School Mobility

One challenge in studying residential mobility is that researchers can conflate or jointly examine residential mobility with school or educational mobility, i.e. changing schools (Crowley, 2003; Rumberger, 2011; South, et al., 2007; Swanson & Schneider, 1999). For example, in South, et al.'s research (2007) of student mobility and dropout, the authors used a single measure of residential mobility that included school mobility (i.e., they did not examine the effects of these two phenomena). Their study, based on the first two waves of *Add Health*,, used data from "respondents who were attending school at the time of the initial in-home survey, who were age 14 or older at this time, who were subsequently interviewed in the second wave, and who were assigned valid sampling weights" (p. 74).

They then focused their analysis on how residential and school mobility before the Wave I interview and the aggregated rate of mobility at the school level before Wave 1 affected the likelihood of dropping out between Waves I and II. This more specific definition of mobility was justified by the authors to ensure that long-distance moves and changes between schools that are not normative (for example, from junior high to high school within the same district) were captured. However, by restricting mobility in this way and not examining multiple groups of mobile students, such as non-movers, residential movers, and school and residential movers, the results are do not allow for generalization beyond those who recently experienced mobility at both levels. Examining each event separately, as has been done in other research (e.g., Cordes, et al., 2019), is important to better understand the unique contribution of residential mobility on educational outcomes.

Timing of Residential Mobility

Though not always examined, some studies have explored the effects of timing, frequency, and social mobility (i.e., moving to economically stronger or weaker neighborhoods) of residential mobility on educational attainment (Anderson & Leventhal, 2017; Cordes, et al., 2019; Metzger, et al., 2015; Swanson & Schneider, 1999). Results are not always consistent as some analysis is limited by sample size, making them not generalizable to a national context, but the findings generally show that residential mobility is a developmentally disruptive event (Anderson & Leventhal, 2017; Cordes, et al., 2019; Ersing, et al., 2009; Murphey, et al., 2012; Swanson & Schneider, 1999).

For instance, Anderson & Leventhal (2017) examined the effects of residential mobility on adolescent (at age fifteen) academic achievement and socioemotional development. Using propensity score models, the authors examined the effects of the timing and frequency of residential mobility by defining six categories children in their sample. First, there were low childhood movers; those who moved only once in childhood (birth to eleven years old), not adolescence (twelve to fifteen years old). Those who moved two or more times only during childhood were categorized high childhood movers. Similarly, those who experienced a move once in childhood and adolescence (two times total) was a low child-adolescent mover, while those who moved two or more times in both periods (four or more times total) was a high child-adolescent mover. Adolescent mobility alone was a rare occurrence in this sample, but it was also examined in the analysis, though not by separating participants into high and low categories. The remaining category was for stable youth who did not move in either childhood or adolescence.

Their findings indicate that those who experienced low or high childhood mobility demonstrated no significant differences with their residentially stable peers on any of the outcomes. When comparing those who experienced low or high child-adolescent mobility, significant differences between high child-adolescent movers and stable peers were found on internalizing problems and marginally on externalizing problems. In both cases, movers demonstrated more problems. However, no significant differences were found on the academic measures. Finally, for adolescent movers, no significant differences were found when compared to the residentially stable youth. The authors attributed this to the limited sample size of this group (3% of the 1056 participants). However, they also compared adolescent movers to all other youth (regardless of mobility status) after dividing the adolescent movers into high and low categories and found that high adolescent movers compared to adolescent non-movers displayed significantly more externalizing and internalizing behaviors (Anderson & Leventhal, 2017).

Anderson & Leventhal (2017) attribute the lack of significant findings surrounding academic achievement compared to previous research to the focus only on residential mobility in this study. They posit that significant differences between movers and non-movers in the past may have been due to the examination of school and residential movers as a single group in previous research and the possibility that since the authors did not examine late adolescent movers (i.e., those sixteen and older), they could be missing the academic achievement deficits found in other works (e.g., Swanson & Schneider, 1999). However, an additional possibility is that academic achievement was examined using the Woodcock-Johnson Psycho-Educational Battery Revised instead of using more traditional measures of academic performance such as grades in courses or performance on state or federal standardized tests of achievement. In addition, I would argue that by grouping movers into multi-aged categories instead of analyzing their moves at each age or grade, may also be masking some of the variability in the effects of residential mobility on student achievement. Thus, though these findings demonstrate the impact that moving can have on youth, beyond the classroom, there are still opportunities to better understand the effects that residential mobility can have on students across their entire academic careers. More specific, yet comprehensive, analysis of residential mobility and its relation to educational attainment is needed to better appreciate how residential mobility functions as a predictor of attainment. By examining residential mobility over of a student's life through the alignment of episodes of mobility to a student's advancement through school year to year, the influence of residential mobility can be better understood.

School Exclusion History

School exclusion is comprised of out-of-school suspension and expulsion, which are the most serious forms of school disciplinary action, short of police involvement and formal arrests with prison sentences (American Psychological Association Zero Tolerance Task Force, 2008). School exclusion involves a loss of instruction time and the removal of students from the school, either temporarily while remaining on the school rolls (suspension) or permanently while being removed from the school rolls (expulsion; Losen & Gillespie, 2012; Skiba, et al., 2014; Theriot, et al., 2010). Utilization of these practices vary across schools, as schools that employ exclusionary practices often favor suspension over expulsion, resulting in higher suspension rates overall (Skiba, et al., 2014; Theriot, et al. 2010). However, exact definitions of the criterions for suspension or expulsion can vary by school or district (Petras, Masyn, Buckley, Ialongo, & Kellam, 2011; Skiba, et al., 2014; Theriot, et al, 2010). For instance, some schools employ zero tolerance policies, which "mandate the application of predetermined consequences, most often severe and punitive in nature, that are intended to be applied regardless of the gravity of behavior, mitigating circumstances, or situational context" (American Psychological Association Zero Tolerance Task Force, 2008, p. 852), while others have shifted to alternative discipline policies to reduce exclusion (Ersing, et al., 2009; Losen & Gillespie, 2012; Skiba, et al., 2014) or to reduce the probability of disruptive or dangerous events by preemptively removing students who are deemed "dangerous" (Casella, 2003).

No matter the specific definition, school exclusion, like residential mobility and educational attainment, has been studied for decades and there have been consistent findings that exclusion is disproportionately used as a disciplinary practice with boys, students of color, low-income students, and disabled students as early as kindergarten (American Psychological Association Zero Tolerance Task Force, 2008; Losen & Gillespie, 2012; Skiba, et al., 2014; Sullivan, et al., 2013). Furthermore, exclusion has been associated with many of the same negative effects as residential mobility, including lower academic achievement (Arcia, 2006; Brown, 2007; Chu & Ready, 2018; Noltemeyer, Ward, & Mcloughlin, 2015; Welsh & Little, 2018), feeling unwanted in the school (Brown, 2007; Caton, 2012; Lessard, et al., 2008), and dropout (Arcia, 2006; Caton, 2012; Stearns & Glennie, 2006; Suh & Suh, 2007).

School Exclusion and Academic Achievement

Regarding academic achievement, numerous studies have demonstrated the effects of school exclusion on academic achievement. There is a consistent general consensus that school exclusion is associated with lower academic achievement on either standardized tests and academic courses (Arcia, 2006; Chu & Ready, 2018; Noltemeyer, Ward, & Mcloughlin, 2015; Welsh & Little, 2018)

For example, expanding on previous works, Arcia (2006) conducted a three-year, retrospective, longitudinal study using a matched pair comparison of suspended and unsuspended students in an urban Southeast school district to analyze the educational outcomes of these students based on "standardized reading achievement scores" and dropout. The results indicated that as students advanced in school, the number of suspensions increased, and that increases in suspensions correlated with high school dropout. Further, reading achievement declined with increasing suspensions, and there was a correlation between low achieving students and increased suspensions.

More recently, Chu and Ready (2018) explored the effects of "principal's suspensions" (one to five days) and "superintendent's suspensions" (more than five days) in the early high school semesters on student outcomes in using "longitudinal administrative data on [first-time ninth grade] public school students in New York City" (p. 485). Utilizing multiple analytic techniques, including propensity score matching and fixed-effects regression modeling, the results indicated that suspended students were more less likely to pass their Regents exams (New York's state-mandated standardized tests), less likely to pass earn their course credits, and less likely to graduate in four, five, or six years. These findings are consistent with the findings of Arcia (2006) and others (Noltemeyer, et al., 2015; Welsh & Little, 2018) indicating the overall negative effects that suspension has on academic achievement as well as its relation to delayed completion of high school and/or high school dropout.

Timing of School Exclusion

Turning to the impact of timing, few studies have examined the longitudinal effects of school exclusion by examining suspension over several time periods (Arcia, 2006; Chu & Ready, 2018). What more often is done, when the longitudinal effects are examined is that school exclusion at one or two early time points are used as predictors in future outcomes. For example, in the Arcia (2006) study, any suspension during the three-year time span of the study was used as a criterion for inclusion into the suspended cohort. Similarly, only early high school suspensions were evaluated in the Chu & Ready (2018) study, ignoring the potential impact of school exclusion in later high school years. Another example, using the *Add Health* data set by Rosenbaum (2020), only examined the effects of suspension during Wave II on outcomes twelve years later. This dearth of research on the longitudinal effects of exclusion (beyond just suspension) further supports the need for analysis that examines how the timing and frequency of exclusion events relate to attainment over time.

Educational Attainment

Residential Mobility and Educational Attainment

As discussed above with the literature on residential mobility, residential mobility has been found to be a predictor of dropout (Metzger, et al., 2015, Rumberger, 2011; South, et al., 2007; Swanson & Schneider, 1999). For example, in a study of residential mobility in adolescence and its relation to high school educational attainment thirteen years later, Metzger, et al. (2015) used data from Waves I, II, and IV of the *Add Health* dataset. Though the authors only focused on residential mobility between Waves I and II for the seventh to twelfth grade sample, they did include a measure that asked about the frequency of moves within that year. Using logistic regression modeling and by evaluating the effects of different mediating variables on attainment, the authors found that “after accounting for individual and family risk for housing instability and poorer educational outcomes” (p. 12), residential mobility in one year in adolescence predicted a reduced probability of dropout by Wave IV. Though it was a unique contribution to the field to look at the frequency of moves in a year in this piece, this work was still limited by the lack of examination of moves before the single move in adolescence.

School Exclusion and Educational Attainment

Studies on school exclusion and attainment have largely focused on the implications of exclusion at the high school level on dropout (Caton, 2012; Stearns & Glennie, 2006; Suh & Suh, 2007), as was the case in the Arcia (2006) and the Chu & Ready (2018) pieces discussed above. This limited focus on exclusion in these grades does not allow for the longitudinal effects of exclusion at earlier grades to be evaluated on the likelihood of attainment. Thus, it is largely unknown how exclusion before high school, particularly before adolescence, impacts attainment.

Timing of Educational Attainment

Though dropout rates are not at the crisis levels they once were, they remain at concerning levels and disproportionately affect low-income and minority-race (McFarland, et al., 2018). Through examination into questions of why students drop out or what affects student attainment, researchers have learned that dropout is a complicated process without a single path that students follow (Bowers & Sprott, 2012; Lessard, et al., 2008; Rumberger, 2011). However, despite this knowledge, dropout and attainment largely continue to be modeled as event outcomes in analyses of predictors affecting them, largely neglecting these nuances (Rumberger, 2011; South, et al., 2007; Suh & Suh, 2007; Swanson & Schneider, 1999). The research using longitudinal data at the national level is no exception.

Much of the work using datasets such as the National Educational Longitudinal Study of 1988 (NELS:88), the National Longitudinal Study of Adolescent to Adult Health, the National Longitudinal Survey of Youth 1997, and the Educational Longitudinal Study: 2002-2004 continues to be limited by the examination of predictors at one time point with dropout at another time point as the outcome (Suh & Suh, 2007; Swanson & Schneider, 1999). For instance, in an analysis of dropping out early in high school (by tenth grade) or late in high school (between tenth and twelfth grade), Swanson & Schneider (1999) performed logistic regression analysis to evaluate dropout using the NELS:88. Independent variables for early dropouts came from the eighth grade wave of the survey, with the outcome drawn from the tenth grade data, and independent variables for late dropouts came from tenth grade wave, with the outcome from twelfth grade.

This practice of modeling dropout as an event outcome in relation to predictors at other time points is widely seen in studies using longitudinal data, but it is limited by the lack of appreciation for the independent effects of time. When time is accounted for in the analysis, it is treated as part of a predictor (for example, change in achievement from eighth grade to tenth grade; Swanson & Schneider, 1999). Even when different analytic methods are used, such as latent class analysis to determine subgroups of dropouts, how predictors relate over time within subgroups is not addressed (Bowers & Sprott, 2012). More recent research has begun to address this shortcoming by using various forms of survival or event history analysis, which account for time as a covariate (Kim, Chang, Singh, Allen, 2015; Lee-St. John, et al., 2018), but these studies are still the minority in the field and, of the ones that I have seen, they do not address either school exclusion or residential mobility.

Qualitative research more often appreciates attainment as a process that takes time, but studies that evaluate dropout as an outcome are not usually designed to model the relationship for larger populations (Bowers & Sprott, 2012; Lessard, et al., 2008; Rumberger, 2011; South, et al., 2007; Suh & Suh, 2007; Swanson & Schneider, 1999).

What is needed to better understand attainment is an analysis of a nationally representative sample within which attainment is evaluated as part of a process of grade advancement and the nuanced nature that the timing, frequency, and relative impact of previous life events may have on a child's educational path are addressed.

Theoretical Framework

From previous research on high school dropout, and inversely high school completion, there are numerous predictors that contribute to a student's advancement through school and its eventual completion. Myriad theories have been proposed to explain the relationship between several combinations of factors across individual and institutional domains, but not many have examined factors from nearly all such domains at once. Russel W. Rumberger and Sun Ah Lim (2008) in a comprehensive literature review of student dropout combined predictors from all such domains into a conceptual model to explain how they likely interact (Figure 2.1).

From the model, one can see that Rumberger and Lim (2008) posit that individual background factors both influence an individual's attitudes and performance, while also being influenced by performance, in turn, and by the institutional factors within the family, school, and community. Similarly, an individual's attitudes influence a person's behaviors and are

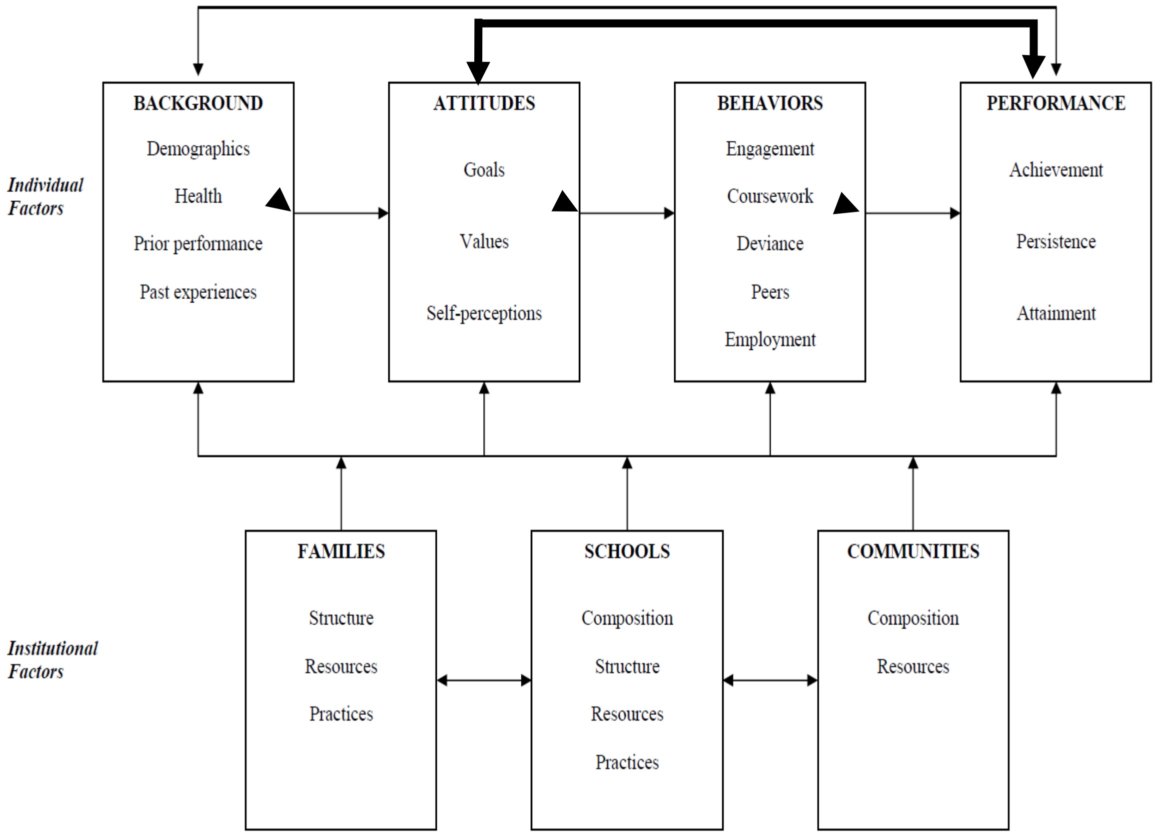


Figure 2.1. Adjusted Conceptual Model of High School Performance. Adapted from *Why students drop out of school: A review of 25 years of research,* by R. W. Rumberger and S. A. Lim, 2008, Santa Barbara: California Dropout Research Project. Retrieved from www.cdrpsb.org/download.php?file=researchreport15.pdf.

influenced by all three institutional categories' factors; just as a person's behaviors impact their performance and both are impacted by the institutions to which they belong. Examples of background factors include race, gender, health and ability status, prior academic performance, and prior life experiences, such as emigrating from another country, participation in preschool, and after-school activities. Attitudes include a students' academic and life goals, their values of academics, and their self-perception. An individual's behaviors refer to their engagement with the school community, the number of courses they take in a year, their engagement with drugs, violence, and pregnancy, their friend group, and the number of hours a week they work. Performance refers to a student's academic achievement in terms of grades and standardized test scores, their persistence in a single school, school mobility, and dropout, and attainment refers to progression through school, advancing from one grade to the next and the completion of school by earning degrees and diplomas.

Rumberger and Lim's (2008) model also describes institutional factors that include the family, which is comprised of family structure: "the number and types of individuals in a child's household" (p. 44); family resources: financial, human (parent education), and social (relationships in and out of the family), together comprising SES; family practices: generally referred to as parental involvement or parenting style, including parental expectations for students. A second institutional domain is the school, which is comprised of factors related to its student composition (example: aggregate demographic profile of students in the school), structure (ex.: location – urban, suburban, rural, student population size, type – i.e., public or private), resources (ex.: expenditure per student or percentage of teachers with advanced degrees), and practices (ex.: discipline policies and practices, attendance rates, engagement in school activities and programs). The final institutional domain is communities, which are analyzed via their composition (ex.: aggregate demographic characteristics and crime statistics) and resources (ex.: access to healthy food, parks, libraries, employment, and positive role models). Following Rumberger and Lim's (2008) analysis, residential mobility constitutes an institutional factor within the family structure, while school exclusion most closely relates to the relationship between individual deviant behavior and school institutional practices. Thus, this framework allows for the examination of a student's progression through school and attainment of a degree as a process influenced by factors across multiple domains and does not limit analysis to a few domains, potentially ignoring or minimizing the influence of other important areas.

Rumberger and Lim (2008) contend that the model is not intended to depict particular theory or process of dropout. However, I believe that if the model is adjusted to include a more complete depiction of how the individual factor domains interact with one another, it can be utilized as a framework for educational persistence and attainment. For instance, it does not demonstrate the potential influence that attitudes may have on a person's health, for example, a person's negative self-perception may exasperate symptoms of depression and the severity of their condition. Nor does it demonstrate the influence that behaviors have on attitudes, and performance on behavior, and finally that attitude and performance have on one another (Rumberger & Lim, 2008). For instance, if a student does poorly in a math course, they may no longer believe they can become an engineer, and that may result in their disengagement in further math and science courses. The combination of the altered goal and reduced engagement may then lead to a further decline in their achievement. Taking these modifications of the model into account, the adjustments are presented in red in Figure 2.1. These modifications reflect interactions between factor domains that previous researchers and theorists have proposed (Rumberger & Lim, 2008).

CHAPTER 3

METHODS

Data

Add Health

The data for this study were drawn from the first three waves of the National Longitudinal Study of Adolescent to Adult Health (*Add Health*). *Add Health* is a multi-year, multi-site, longitudinal panel study of U.S. students from adolescence through adulthood. It is also a uniquely robust dataset in that, though it is a public health dataset, it was the only nationally representative one that I could find that included data on attainment, residential mobility history, and school exclusion history. In addition, Add Health includes measures that address educational performance, deviant/risky behavior, educational goals, employment history, self-esteem, among many others.

Since the start of the project, there have been five waves of data collected for *Add Health*. Data from the first four are currently fully available (Wave I: 1994-1995, Wave II: 1996, Wave III: 2001-2002; Wave IV: 2008); only partial data for Wave V are currently available (Wave V: 2016-2018). In the initial two waves of the study, school administrators (Wave I, Wave II), and parents (Wave I) were also interviewed. In Wave I, 90,118 students in grades 7-12 from 80 high schools and 52 of their "feeder" middle schools or junior high schools completed an in-school questionnaire. From those participants, a sub-sample of students was interviewed at home (20,745 adolescents in Wave I), and those individuals were interviewed again in the subsequent waves of the study (Wave II = 14,738 adolescents in grades 8-12, Wave III = 15,197 young adults aged 18-26, and Wave IV= 15,701 adults aged 24-32; Harris, 2009; The National Longitudinal Study of Adolescent to Adult Health, n.d.).

For the purpose of this study, only students in ninth grade at Wave I were included in the analysis. The benefit of focusing on this cohort is that data were available on these students for more of their academic careers, including the ability to examine factors that may contribute to their educational attainment as they began high school.

Weighting and Analysis Files

The sampling design for *Add Health* included the oversampling of some subgroups of students, such as students from high-SES, Black families and those of Cuban, Puerto Rican and/or Chinese descent, so the analysis included sampling weights to adjust for the sampling procedures. Based on the recommended procedures by the *Add Health* research team, data analysis for this study included the entire sample in the analysis file, while statistical adjustments were made to ensure that the main findings only represented the subpopulation of ninth graders analyzed. Standard errors were subsequently adjusted by the sampling weights to increase their accuracy and representativeness. This process was designed reduce the risk of inaccurate calculations from incorrectly adjusting the sampling weights if only the ninth-grade cohort was examined. Thus, after eliminating those participants who did not have data at Wave III or sampling weights, following *Add Health*'s recommended procedures, the full sample contained 14,322 participants, and the ninth-grade cohort comprised 2,477 participants (Chen & Harris, 2020).

Variables

Grade

Time was treated discretely in the analysis versus continuously. The treatment was selected due to the nature of the data and the focus of this study. Although, as noted above, educational attainment is a process which implies a continuous time structure, data regarding educational attainment are generally collected at discrete time points or intervals. This procedure facilitates comparison across groups within studies, is consistent with how attainment is treated in the extant research, and how attainment is commonly discussed outside of academic circles. For example, it is more common to hear statements like, "I dropped out in tenth grade," instead of "I dropped out on November 23, 2003," in which the former implies a discrete time structure of grades and the latter implies a continuous time structure across a calendar year.

As there were several time-varying predictors evaluated along with the outcome, educational attainment/dropout, it was important that a consistent time structure was utilized to ensure that the time-varying covariates would appropriately correspond with the outcome times. Thus, grades were selected as the discrete time interval.

Educational Attainment/Dropout

Educational attainment was selected as the event of interest and was coded as a dichotomous outcome at each grade from zeroth through twelfth grade. A value of zero indicated a student had completed that grade level, and one indicated that (s)he dropped out during that grade, i.e., (s)he completed the previous grade level, but (s)he did not complete the current one.

Educational attainment was determined by recoding the response to a question from Wave III: "What is the highest grade or year of regular school you have completed?" as described above. This question was selected in place of other options, such as another from Wave III, "What degrees or diplomas have you received?", because it allowed for a more accurate representation of the educational attainment process by indicating when a person left formal education. The question regarding degrees and diplomas is also problematic because it is possible for a person to not complete their formal high school education but still earn a high school equivalency credential, such as a General Educational Development (GED) credential (McFarland, et al., 2018).

In the full analysis sample, 1,764 students (12.32%) did not complete high school by Wave III. Of the ninth-grade cohort, 389 students (15.70%) dropped out by Wave III. As noted above, by Wave III, respondents were 18-26 years old, thus most of the ninth-grade cohort was 21-24 years old. Nationally, the status dropout rate in 2002 was 10.5% (McFarland, et al., 2018). Comparing the *Add Health* full sample status dropout rate and ninth grade cohort status dropout rate to the national status dropout rate and to each other using a two reveals that neither the full sample nor the ninth grade cohort is statistically different from the national sample ($\chi^2 = 0.165$, $p = 0.686$; $\chi^2 = 1.188$, $p = 0.28$, respectively) or each other ($\chi^2 = 0.474$, $p = 0.491$).

Residential Mobility

To determine the frequency and timing of residential mobility along a participant's educational history, items from Wave I and Wave II regarding residential mobility from birth to tenth grade were aggregated to create an event history of residential mobility. Items from Wave III were excluded from this process because the one item that referenced residential mobility in that wave did not adequately specify the frequency and timing of events (i.e., "Since the beginning of June 1995 at how many (other) addresses have you lived?").

Frequency and timing of residential mobility from the Wave I and II items were determined through a multistep process. First, participants' ages at the time of their in-home interview at Wave I were calculated by creating date variables for the date of birth from the month and year of birth (day was not asked) and the interview date from the month and year of the interview. To ensure a complete date was created, I set everyone's birth date to the first of the month. In addition, though the interview day was known, for consistency, I also set the interview date to the first of the month. Next, I subtracted the difference between the two and rounded the ages down to the nearest whole number, which resulted in each participant's age at the time of the interview. As all the residential mobility related questions in Wave I and II were in reference to age or year, not grade, calculating age at the time of the interview was an important first step to approximate the age/grade of residential mobility.

There were three questions that allowed me to determine residential mobility. Two were from Wave I: "How old were you when you moved here to your current residence?" and "In what month and year did you first move to the United States?", and one was from Wave II: "Have you lived here since [the last interview date]?" Unfortunately, these questions did not allow for a complete residential mobility event history to be formed, but I was able to determine whether a move happened in a grade. I chose not to count whether there were multiple moves in a grade because of the possibility of counting the same move twice. For example, the move to the current residence in Wave I could also have been the same move to the United States.

Like my procedure for calculating age at the Wave I in-home interview, I converted the residential mobility questions from Wave I to dates (when appropriate) and used the participant's birthdate (when necessary) to calculate the age of the move. After determining the ages of the moves, I subtracted the age of the move from the age at the time of the Wave I interview to determine the grade when the move occurred. For the ninth-grade cohort, a difference of zero implied the move occurred in ninth grade, a difference of one implied the move occurred in eighth grade, and a difference of nine or more was treated as "grade zero," implying moves before the youth began school.

Following the grade-age pattern described for the Wave I questions, the responses to the Wave II question were reverse coded, so that a code of "1" indicated that the student did move, and a code of "0" indicated that (s)he did not. This question was then used to account for residential mobility in tenth grade for the ninth-grade cohort. Unfortunately, residential mobility could not be tracked past tenth grade for the 9th grade cohort using this method and due to the lack of an appropriate question in the later waves of the study, as noted above.

This age/grade matching method was determined to be the best approximation for the student's grade at the time of their moves. However, it did not account for birthdays during the school year, thus age changes in the school year. In addition, this method did not account for any participants who skipped or repeated grades, as it assumed traditional grade advancement, this was potentially problematic as 21.88% of the ninth-grade cohort said that they had repeated a grade, but only 2.67% said that they skipped a grade.

School Exclusion History

School exclusion was captured for out-of-school suspension and expulsion separately. Event histories were created based on responses to questions regarding when school exclusion occurred: "What grade was the last time you received an out-of-school suspension?" and "What grade were you in the last time you were expelled from school?" from Wave I, "[If SCHOOL YEAR:] During this school year/{If SUMMER:} During the 1995-1996 school year {HAVE YOU RECEIVED/DID YOU RECEIVE} an out-of-school suspension from school?" and "[If SCHOOL YEAR:] During this school year/{If SUMMER:] During the 1995-1996 school year {HAVE YOU BEEN/WERE YOU} expelled from school?" from Wave II, and "From what level of school have you been expelled?" from Wave III. To not over count school exclusion events, the question from the earliest time point was favored when creating the event history. Thus, any responses to the Wave III question regarding expulsion in first through tenth grade, were not counted in favor of responses to the questions from Wave I and Wave II.

Due to the phrasing of the questions, I was not able to capture the frequency of school exclusion within a grade. In other words, I could not determine if there were multiple suspension events in a single grade or multiple expulsion events in a single grade. I was also limited in my ability to account for repeated school exclusion events across grades as the questions in Wave I asked for the last time that the event occurred. Finally, the response options to these questions limited the time span of the event histories created.
That is to say, based on the available options, suspensions were counted for first through tenth grade and expulsions were only counted for third through twelfth grade for the ninth-grade cohort.

Additional Predictors of Educational Attainment/Dropout

To explore the relationships between predictors outlined in Rumberger and Lim's (2008) conceptual model and their impact on educational attainment/dropout, several other predictors were evaluated along with out-of-school suspension, expulsion, and residential mobility. Items were selected to represent each individual-level factor and the institutional -level factor of families in the model. All predictors were selected from Wave I of the *Add Health* survey based on the responses of students. In addition, to reduce the number of variables in the model and the randomness in the sample, variables with moderate to high missingness (20% or more) were excluded, unless they were deemed theoretically important to be included. Finally, for groups of variables that were theoretically related, principal components analysis (PCA) was performed.

Based on the results of the PCAs, those items that loaded onto unique factors were combined to create composite scales. These scales were treated as summed indices because the response structures for the items in each index were identical to one another. Thus, standardization of scales was not deemed necessary. In addition, items on the scales were evaluated for their internal consistency using Cronbach's alpha (see Table 3.1).

The final scales included the three-item resident mother's participation in school activities scale (talking about school in the past four weeks, working on a school project in the past four weeks, talking about other things that the student is doing in school in the past four weeks); the two-item college expectations scale (wanting to go to college and likelihood of going to college); the three-item trouble in school scale (getting along with others, getting along with teachers, and paying attention); the five-item school attachment and perceptions of school scale (feeling close to others, being happy at school, feeling the teachers treat students fairly, feeling as a part of the school, and feeling safe in school); the five-item self-esteem scale (liking oneself, feeling accepted, feeling loved and wanted, feeling that (s)he is doing things right, having a lot to be proud of); the seven-item social support scale (feeling that adults/parents/teachers/friends care about her/him, feeling that her/his family understands her/him, feeling that her/his family has fun together, and feeling that her/his family pays attention to her/him); and the fifteen-item scale asking about delinquent behavior (e.g., fighting, stealing, vandalism, using drugs, etc.)

In addition, there were several single item predictors including questions about students' ninth grade academic performance (English/Language Arts, Math, History/Social Studies, and Science grades at the last marking period), trouble completing homework, desire to leave home, frequency of excused and unexcused absences in the ninth-grade school year, hours worked during a typical non-summer week, and school mobility between ninth and tenth grade. Finally, an additional event history was created from students' history of grade retention (i.e., instances of repeating first through ninth grades).

Finally, demographic variables as reported by the student were included in the analysis. These included the sex of the student (1 = female), dummy coded variables for race (Black, Native American, Asian, Other Race, Multiracial, with White as the reference category), Latinx ethnicity (1 = Yes), immigrant status (1 = born in the United States), resident mothers' receipt of public assistance (1 = Yes), and resident mothers' education (code from 0, never went to school, to 9, professional training beyond a four-college or university).

Resident mothers were used as proxies for parents in the current analysis because the majority of the resident parents who completed the parent questionnaire for the ninth-grade cohort were mothers (biological, step, adoptive, foster, grand, etc.) or another female parental figure (77.47%), though items from that questionnaire were not used here. In addition, approximately 28% of resident father-related questions in the student questionnaires were not answered and coded as "legitimate skips" implying that those students did not have a resident father to reference.

Analytical Strategy

All data analysis was completed using R. The first step in analysis was data cleaning, during which time items for analysis were selected based on the criteria described above, PCA run to reduce the number of variables included in modeling, and additional variables were created based on the available data. The variables created during this time included recoding existing variables, creating the composite scales of the predictors, and extracting the event indicators by grade, including creating filler variables for the missing grade event indicators.

Finally, a dummy variable was also added to the dataset to identify those cases that would be included in the analytic subset. Following *Add Health*'s suggestions, only those students in the ninth-grade cohort with complete responses on each variable were identified to be included in the analysis. This reduced the analytic subset of the ninth-grade cohort to 1182 students (47.72% of the full ninth-grade cohort; Chen & Harris, 2020). (Further discussion of missing data in this study and their potential implications on analysis is included below.)

After variables were selected and created, univariate descriptive statistics were evaluated for all variables in the full ninth-grade cohort and the ninth-grade analytic (complete case) sample. In addition, Pearson correlation coefficient matrices were created based on the ninth-grade analytic sample to evaluate the bivariate relationships between the variables included in the analysis. Finally, the final analytic dataset was transformed from the "wide" format in which there was one row per person to the "long" format, a.k.a., a person-period format, in which there is one row per grade per person. The person-period format was necessary to facilitate discrete time survival analysis (DTSA) because of the discrete nature of the time variable and to accurately incorporate the effects of time in predictive modeling (Broström, 2012, p. 117; Mills, 2011, p. 184).

Table 3.1 presents the mean, standard deviation and valid n (i.e., the number of cases, less missing values, that were evaluated to determine the mean and standard deviation) of each variable from Wave I included in the study for the ninth-grade cohort and the ninth-grade complete case subsample. Tables 3.2 and 3.3 present the variables from Waves II and III, respectively. In addition to the variables in the analysis, means, standard deviations, and valid ns were presented for time-varying summary variables indicating whether an event occurred in the time span covered in the wave. These variables were created for the time-varying predictors of suspension, expulsion, residential mobility, and grade retention in Wave I and the outcome of dropout in Wave III to summarize these event histories. For example, the variable “Grade Retention – Any Grade 9 or Less” indicates whether students repeated those grades, but it does not indicate the frequency of the repeats or which grade students repeated. The variables that follow, for example, “Grade Retention – Grade 1” indicates whether a student repeated first grade, and the subsequent variables allow for students to indicate whether those grades were repeated, as well, because of how the question in *Add Health* was phrased.

Survey Package in R

In order to effectively incorporate the sampling weights and produce both “unbiased estimates of parameters for the entire population as well as [the] subpopulation, and unbiased estimates of variance and standard errors” (Chen & Harris, 2020). Functions in the “survey” package in R were used to evaluate the data. The *svydesign* function allowed for the survey design to be specified including the stratification, clustering, and weight variables. In addition, the *subset* function allowed for the analytic subsample of the ninth-grade cohort to be evaluated while keeping the original design information. Finally, DTSA was completed using the *svyglm* function, so that the design and subpopulation specifications were incorporated into the analysis (Lumley, 2020).

Discrete Time Survival Analysis (DTSA) and Model Fitting

DTSA is a form of survival analysis, also known as event history modeling. This class of analytic procedures is an extension of regression modeling for which the outcome of interest is not only if, but when, an event occurs. Thus, in survival modeling, time functions as a covariate along with other continuous and categorical variables. In DTSA, as the name implies, time is treated in a discrete manner. This treatment could be due to the decision to divide continuous time into prescribed intervals for analytic purposes or could be due to the nature of data

Table 3.1 Description and Summary Statistics for Variables Analyzed from Wave I

	Full Ninth Grade Sample			Ninth Grade Complete Case Sample		
Variable	**Mean**	**Standard Deviation**	**Valid n**	**Mean**	**Standard Deviation**	**Valid n**
Female	0.52	0.50	2477	0.54	0.50	1182
Black	0.20	0.40	2473	0.19	0.39	1182
Native American	0.01	0.11	2473	0.01	0.10	1182
Asian	0.04	0.21	2473	0.05	0.21	1182
Other Race	0.06	0.24	2473	0.05	0.22	1182
Multiracial	0.05	0.22	2473	0.04	0.20	1182
Latinx Ethnicity	0.14	0.35	2473	0.13	0.34	1182
U.S. Born	0.92	0.28	2000	0.93	0.26	1182
Public Assistance	0.10	0.30	2347	0.11	0.31	1182
Parental Education	5.50	2.40	2262	5.49	2.36	1182
Suspension – Any Grade 9 or Less	0.29	0.45	2474	0.28	0.45	1182
Suspension – Grade 1	0.00	0.02	2465	0.00	0.00	1182
Suspension – Grade 2	0.00	0.00	2465	0.00	0.00	1182
Suspension – Grade 3	0.00	0.05	2465	0.00	0.04	1182
Suspension – Grade 4	0.00	0.05	2465	0.00	0.05	1182
Suspension – Grade 5	0.01	0.09	2465	0.01	0.09	1182
Suspension – Grade 6	0.02	0.13	2465	0.01	0.12	1182
Suspension – Grade 7	0.04	0.19	2465	0.04	0.19	1182
Suspension – Grade 8	0.06	0.24	2465	0.07	0.25	1182
Suspension – Grade 9	0.16	0.36	2465	0.15	0.36	1182
Expulsion – Any Grade 9 or Less	0.04	0.20	2476	0.03	0.18	1182
Expulsion – Grade 3 (or Less)	0.00	0.04	2474	0.00	0.03	1182
Expulsion – Grade 4	0.00	0.00	2474	0.00	0.00	1182
Expulsion – Grade 5	0.00	0.03	2474	0.00	0.04	1182
Expulsion – Grade 6	0.00	0.06	2474	0.00	0.06	1182
Expulsion – Grade 7	0.01	0.08	2474	0.01	0.07	1182
Expulsion – Grade 8	0.01	0.10	2474	0.01	0.10	1182
Expulsion – Grade 9	0.02	0.14	2474	0.01	0.12	1182
Residential Mobility – Grade 0 (before Grade 1)	0.21	0.41	2457	0.27	0.45	1182
Residential Mobility – Grade 1	0.05	0.21	2457	0.09	0.29	1182
Residential Mobility – Grade 2	0.05	0.22	2457	0.09	0.29	1182
Residential Mobility – Grade 3	0.05	0.21	2457	0.08	0.27	1182
Residential Mobility – Grade 4	0.06	0.24	2457	0.08	0.28	1182
Residential Mobility – Grade 5	0.06	0.23	2457	0.09	0.29	1182
Residential Mobility – Grade 6	0.08	0.27	2457	0.12	0.32	1182
Residential Mobility – Grade 7	0.10	0.30	2457	0.14	0.34	1182
Residential Mobility – Grade 8	0.13	0.33	2457	0.14	0.34	1182
Residential Mobility – Grade 9	0.07	0.26	2457	0.10	0.30	1182

Note: All statistics presented in this table are based on the unweighted data.

Table 3.1 Description and Summary Statistics for Variables Analyzed from Wave I (cont.)

	Full Ninth Grade Sample				Ninth Grade Complete Case Sample			
Variable	**Cron-bach's α**	**Mean**	**Standard Deviation**	**Valid n**	**Cron-bach's α**	**Mean**	**Standard Deviation**	**Valid n**
Parent Participation in School Activities Scale	0.59	1.32	0.98	2369	0.61	1.34	0.99	1182
College Expectations Scale	0.84	8.51	2.06	2459	0.84	8.67	1.94	1182
English/ Language Arts Grade		2.71	0.99	2410		2.78	0.99	1182
Math Grade		2.65	1.06	2418		2.66	1.05	1182
History/Social Studies Grade		2.83	1.04	2117		2.89	1.03	1182
Science Grade		2.76	1.04	2276		2.82	1.03	1182
Trouble in School Scale	0.61	3.12	2.27	2474	0.61	3.10	2.22	1182
Trouble Completing Homework		1.23	1.11	2475		1.20	1.09	1182
School Attachment & Perceptions Scale	0.76	18.43	3.74	2474	0.76	18.47	3.73	1182
Students at School Prejudiced		3.09	1.21	2468		3.17	1.22	1182
Self-Esteem Scale	0.83	20.27	3.14	2461	0.83	20.47	3.08	1182
Social Support Scale	0.77	27.99	4.05	2441	0.76	28.14	3.90	1182
Desire to Leave Home		2.06	1.19	2455		2.03	1.17	1182
Excused Absences		1.57	0.87	2474		1.56	0.87	1182
Unexcused Absences		1.74	7.53	2469		1.32	5.91	1182
Delinquency Scale	0.84	4.63	5.47	2435	0.84	4.49	5.38	1182

Note: All statistics presented in this table are based on the unweighted data.

Table 3.1 Description and Summary Statistics for Variables Analyzed from Wave I (cont.)

	Full Ninth Grade Sample			Ninth Grade Complete Case Sample		
Variable	**Mean**	**Standard Deviation**	**Valid n**	**Mean**	**Standard Deviation**	**Valid n**
Hours Worked per Non-Summer Week	4.35	8.70	2450	4.54	9.41	1182
Grade Retention – Any Grade 9 or Less	0.22	0.41	2470	0.20	0.40	1182
Grade Retention – Grade 1	0.06	0.24	2474	0.06	0.23	1182
Grade Retention – Grade 2	0.03	0.18	2474	0.03	0.18	1182
Grade Retention – Grade 3	0.03	0.17	2474	0.02	0.15	1182
Grade Retention – Grade 4	0.02	0.13	2474	0.02	0.13	1182
Grade Retention – Grade 5	0.01	0.09	2474	0.01	0.09	1182
Grade Retention – Grade 6	0.01	0.11	2474	0.01	0.08	1182
Grade Retention – Grade 7	0.02	0.14	2474	0.01	0.12	1182
Grade Retention – Grade 8	0.01	0.11	2474	0.01	0.11	1182
Grade Retention – Grade 9	0.04	0.20	2474	0.04	0.20	1182

Note: All statistics presented in this table are based on the unweighted data.

Table 3.2 Description and Summary Statistics for Variables Analyzed from Wave II

	Full Ninth Grade Sample			Ninth Grade Complete Case Sample		
Variable	**Mean**	**Standard Deviation**	**Valid n**	**Mean**	**Standard Deviation**	**Valid n**
Suspension – Grade 10	0.12	0.33	2006	0.11	0.31	1182
Expulsion – Grade 10	0.01	0.11	2004	0.01	0.10	1182
Residential Mobility – Grade 10	0.09	0.28	2104	0.10	0.30	1182
School Mobility – Grades 9 to 10	0.02	0.13	2105	0.01	0.10	1182

Note: All statistics presented in this table are based on the unweighted data.

Table 3.3 Description and Summary Statistics for Variables Analyzed from Wave III

	Full Ninth Grade Sample			Ninth Grade Complete Case Sample		
Variable	**Mean**	**Standard Deviation**	**Valid n**	**Mean**	**Standard Deviation**	**Valid n**
Dropout – Any Grade 9 to 12	0.16	0.36	2475	0.13	0.33	1182
Dropout – Grade 9	0.00	0.06	2475	0.00	0.04	1182
Dropout – Grade 10	0.03	0.16	2475	0.02	0.14	1182
Dropout – Grade 11	0.06	0.23	2475	0.05	0.21	1182
Dropout – Grade 12	0.07	0.26	2275	0.06	0.23	1182
Expulsion – Grade 11	0.02	0.13	2477	0.02	0.13	1182
Expulsion – Grade 12	0.01	0.10	2477	0.01	0.10	1182

Note: All statistics presented in this table are based on the unweighted data.

collection, implying that time is truly discrete in that context (Broström, 2012; Mills, 2011; Singer & Willet, 2003).

To model the effects of time, subjects are included in the analysis until they experience the event outcome (in this case, dropout) or the observation period of the study ends (right censoring – discussed below under "Missing Data"). By eliminating cases as time progresses, the primary models of survival analysis are the hazard function and the survival function. The former depicts the risk of event occurrence in each discrete time period and is "the conditional probability that individual *i* will experience the event in time *j,* given that he or she did not experience it in any earlier time period" (Singer & Willett, 2003, p. 330). The latter depicts the cumulative period-by-period risks of event nonoccurrence "to assess the probability that a randomly selected individual will 'survive' – will *not experience the event*" (Singer & Willett, 2003, p. 334, emphasis original). Typically, these functions are presented with the logit-transformation to facilitate interpretation of the findings and address the limitations of probabilities or odds ratios. Thus, the general model for discrete-time survival analysis is the transformed hazard function presented in (3.1), for which X_{Pij} represents individual i's values for the *P*th predictor in time period j, D_{Jij} represents the dummy variables for each *J* when an event can occur, and the β's represent "the shift in the baseline logit hazard function corresponding to unit differences in the associated predictors" (Singer & Willett, 2003, p. 371).

$$\text{logit } h(t_{ij}) = [\alpha_1 D_{1ij} + \alpha_2 D_{2ij} + \cdots + \alpha_J D_{Jij}] + [\beta_1 X_{1ij} + \beta_2 X_{2ij} + \cdots + \beta_P X_{Pij}] \quad (3.1)$$

Equation (3.1) is often referred to as the general form of the discrete-time logit model and is evaluated as a binomial regression model with a logit specification (Mills, 2011, p. 185).

Once the data was in a person-period format, I began fitting the data to the discrete-time logit model by first evaluating the effectiveness of alternative specifications for the time covariate (in my analysis, grade). As Singer & Willett (2003) state, the benefits of exploring alternative specifications for time are that the general model in (3.1) lacks parsimony and produces "fitted hazard functions that can fluctuate erratically across consecutive time periods" (p. 408).

The alternative time specifications evaluated included the constant model without time as a predictor, the linear model, the quadratic model, the cubic model, and the quartic model. In each case, no additional predictors were included, and time was treated as different order polynomials from zeroth to fourth, respectively. In addition, the hazard functions were plotted for each specification and compared visually as well as based on their differences in Akaike

Information Criterion (AIC) and deviance residuals. Selection of an appropriate time specification was based on these criteria and the general guideline from Singer & Willett (2003): "*If a smooth specification works nearly as well as the completely general one, appreciably better than all simpler ones, and no worse than all more complex ones, consider adopting it*" (p. 417, emphasis original). Once the time specification was selected, the full model, with all predictors, was run.

Missing Data

Censoring. Survival analysis generally assumes that all participants will experience the event of interest at some point in time, even if it is not during the study period. For example, the event of interest may be cancer recurrence after treatment or recidivism after release from incarceration. In any case, the theory is that if a participant does not experience an event during the study period, then they are lost to follow-up, but the event will be experienced after the study ends. This individual is considered to be a right-censored case (Broström, 2012, p. 5-6; Mills, 2011, p. 5-6; Singer & Willett, 2003, p. 315-324).

Although the theory often stipulates that those who are lost to follow-up will experience the event after the study ends, there are many examples, as in the present study, when an individual never experiences the event (i.e., the cancer never returns; the person never reoffends). In these cases, the individual is still considered a right-censored case for the purpose of the study in question because the event was not experienced during the observed time period of the study. They are also maintained in the analysis because they provide valuable information regarding the frequency and timing of the event (Broström, 2012, p. 5-6; Mills, 2011, p. 5-6; Singer & Willett, 2003, p. 315-324).

In this study, the majority of students in the ninth-grade cohort and the analytic subset are considered right-censored cases (84.70% and 87.48%, respectively) because they did not experience dropout. As noted above, the percentage of right-censored cases, conversely the percentage of status dropouts, in the ninth-grade cohort was not statistically different from the percentage of status dropouts in the full *Add Health* sample or the national statistic. Turning to the analytic subset of ninth graders, the percentage of status dropouts in this subset was also not statistically different than the national statistic ($\chi^2 = 0.200$, $p = 0.655$), the full *Add Health* sample ($\chi^2 = 0.002$, $p = 0.966$), or the ninth-grade cohort ($\chi^2 = 0.417$, $p = 0.518$).

Unlike the theoretical definition of right censoring, the persons considered to be right censored are not truly right censored because they did not experience dropout during the study period, and they did not after their observation ended. Instead, they are treated as right-censored because they completed at least twelfth grade (i.e., graduated high school). Following the traditional theory of right censoring, these persons are also considered to have data missing because the event did not occur in the observed time period. However, as demonstrated here, they are not truly cases experiencing this form of missingness.

What is potentially possible with this sample is that students who experienced dropout (i.e., ended their formal education before the completion of twelfth grade) may have completed high school after the study period ended. This could be because at Wave III, they were still in high school or because after Wave III data were collected, they returned to complete their degree. Both cases are representative of how educational attainment is a process that can take on a variety of forms. However, for the purpose of this study, both cases are treated as instances of dropout due to the scope and nature of the analysis, which may mean that the dropout rate observed is inflated and implies a potentially unknown level of missingness.

Truncation. Another common form of missingness in survival analysis is due to truncation. The most common form of truncation is left truncation in which participants enter the study after the onset of risk, not before as is expected in survival studies. In this study, since the study period was set back to begin before entering first grade, this form of truncation is not present. No one is genuinely at risk of dropout before they begin school. However, another form of truncation is present in this study (Mills, 2011, p. 6-7).

Interval or gap truncation occurs when there is data missing for a participant during period of time when participants are being observed. This gap in data collection results in missing data that could introduce bias to the results Mills, 2011, p. 7). In the ninth-grade cohort, there were 372 students (15.02%) who were not interviewed during Wave II but were interviewed during Wave I and Wave III.

Other Forms of Missing Data. In addition to right censoring and interval truncation, other forms of missing data in the *Add Health* dataset include item non-response. There were five main forms of non-response that were generally treated as missing data.

1. Items were left blank for a student.
2. The student's response was coded as refused to answer the question.
3. The student replied with "don't know."
4. The question was coded as a "legitimate skip."
5. The question was coded as "not applicable."

The first three forms of non-response were automatically treated as missing data. The fourth and fifth forms were treated as missing data only in the cases when the questions they were in response to were truly not applicable to the student. For example, when constructing the event history for suspension, there were two relevant questions in Wave I. Responding "yes" to the first, “Have you ever received an out-of-school suspension?”, resulted in the interviewer asking the second, “What grade were you in the last time you received an out-of-school suspension?” If a student said “no” to the first question, then the second question was coded as “legitimate skip” for all response options. In this instance, the “legitimate skips” were not considered missing data. Instead, they were treated as instances that the event did not occur in the event history. However, in other instances, such as the Wave I question, “Were you born in the United States?”, 477 (19.26%) responses were coded as “legitimate skips” in the ninth-grade cohort. As there were no questions preceding this one that appeared to relate to immigration status and there were no comments in the codebook regarding this coding, those cases were recoded as missing data (Harris, 2009).

Handling of Missing Data. As noted above, following *Add Health*’s suggestions, only complete cases in the ninth-grade cohort were analyzed. This reduced the analytic subset of the ninth-grade cohort to 1182 students (47.72% of the full ninth-grade cohort). While the sample size decreased, this also decreased the randomness in the analysis and makes it possible to more easily compare results from these models with models of different subsets (Chen & Harris, 2020, p. 29), though generalizability could be reduced due to the nature of the missingness (i.e., if it is not at random or completely at random).

In addition, several variables, as noted above, were created to ensure that each event history variable matched in length of time. To preserve the completeness of the data for analytic purposes, those variables were coded as 0 for all students. This was a truly accurate response for several items, such as whether a student dropped out in first grade, because that student would not have been included in this study had (s)he dropped out before entering ninth grade. In other cases, this value was chosen to be the most likely response based on the distribution of responses on other items within the timespan. In other words, because the frequency of residential mobility, suspension, expulsion, and grade retention at each grade in the timespan skewed heavily towards non-occurrence (code = 0), zero was chosen as a viable dummy code. In fact, the highest frequency of occurrence on any of these variables in the ninth-grade analytic subset, was 13.54% for residential mobility in seventh and eighth grade, with a mean response value of 0.14 (*SD* = 0.34), further supporting the zero imputations.

However, it should be noted that by imputing each time-filler variable with a value of zero, the overall rates of residential mobility, suspension, expulsion, and grade retention across the timespan are likely lower than reality. For instance, though it may be accurate that no students were suspended, expelled, or retained in zeroth grade (If they attended school, this would be equivalent to preschool and kindergarten years.), it is entirely possible that a reasonable number of students experienced these events in later years. Therefore, since data for suspension in eleventh and twelfth grade, expulsion in first and second grade, and grade retention in tenth, eleventh, and twelfth grades are not available for this subsample, imputing the values for those timepoints with zero (no occurrence), likely underestimates the actual proportion of students who experienced those events.

CHAPTER 4

RESULTS

Patterns of School Exclusion, Residential Mobility, and Dropout

As demonstrated in Tables 3.1, 3.2, and 3.3, the distributions of the variables in the full ninth-grade cohort and the ninth-grade complete case sample were largely similar. However, there were notable differences in the means and standard deviations of several variables. For example, all students in the complete case sample experienced residential mobility, whereas only a subsample of the ninth-grade cohort did. This resulted in the ninth-grade complete case sample presenting higher means and standard deviations on all residential mobility variables in comparison to the ninth-grade cohort. The notable exception was the distribution of residential mobility in eighth grade (cohort: $M = 0.13$, $SD = 0.33$; complete case: $M = 0.14$, $SD = 0.34$).

Other notable variables that showed marked differences between the cohort and the complete case sample include the college expectations scale (cohort: $M = 8.51$, $SD = 2.06$; complete case: $M = 8.67$, $SD = 1.94$), English/Language Arts grades (cohort: $M = 2.71$, $SD = 0.99$; complete case: $M = 2.78$, $SD = 0.99$), History/Social Studies grades (cohort: $M = 2.83$, $SD = 1.04$; complete case: $M = 2.89$, $SD = 1.03$), Science grades (cohort: $M = 2.76$, $SD = 1.04$; complete case: $M = 2.82$, $SD = 1.03$), school attachment & perceptions scale (cohort: $M = 18.43$, $SD = 3.74$; complete case: $M = 18.47$, $SD = 3.73$), belief that students at school are prejudiced (cohort: $M = 3.09$, $SD = 1.21$; complete case: $M = 3.17$, $SD = 1.22$), unexcused absences (cohort: $M = 1.74$, $SD = 7.53$; complete case: $M = 1.32$, $SD = 5.91$), delinquency scale (cohort: $M = 4.63$, $SD = 5.47$; complete case: $M = 4.49$, $SD = 5.38$), hours worked per non-summer week (cohort: $M = 4.35$, $SD = 8.70$; complete case: $M = 4.54$, $SD = 9.41$), and dropout (cohort: $M = 0.16$, $SD = 0.36$; complete case: $M = 0.13$, $SD = 0.33$). These findings indicate that the complete case sample may underrepresent dropout in the ninth-grade cohort and that those who are represented in the complete case sample may have been academically stronger students who viewed their schools more positively, except in terms of prejudiced peers. In addition, these students appeared less likely to engage in delinquent behavior, including missing school, and worked more during the school year.

Focusing on the complete case sample, the last instance of suspension between first and ninth grade occurred in ninth grade for the largest number of students ($M = 0.15$, $SD = 0.36$). As discussed in Chapter 3, this does not mean that those students were not suspended in earlier grades, just that ninth grade was the last time they had been suspended as of their Wave I interview. This distribution was also greater than the number of students suspended in tenth grade ($M = 0.11$, $SD = 0.31$). In contrast, expulsion remained relatively rare across the all grades, with a slight increase in eleventh grade ($M = 0.02$, $SD = 0.13$). In addition, residential mobility was most frequent in grade 0, before first grade ($M = 0.27$, $SD = 0.45$), but it was also notably frequent for students in the middle school and junior high school years (sixth grade: $M = 0.12$, $SD = 0.32$; seventh grade: $M = 0.14$, $SD = 0.34$; eighth grade: $M = 0.14$, $SD = 0.34$). Finally, the frequency of dropout increased over time with the highest frequencies occurring in eleventh grade ($M = 0.05$, $SD = 0.21$) and twelfth grade ($M = 0.06$, $SD = 0.23$). To examine the relationship between these and the other variables in the study, Pearson correlation coefficients were calculated for each bivariate combination in the complete case sample.

Relationships between the Predictors of Dropout and Dropout

Pearson correlation matrices are presented in Appendix A, Table A.1, and B, Table B.1, for the variables in the complete case sample. Table A.1 includes the time-varying summary variables described in Chapter 3 and presented in Tables 3.1 and 3.3 for dropout, suspension, expulsion, residential mobility, and grade retention. Table B.1 includes the event history variables for dropout, suspension, expulsion, residential mobility, and grade retention (i.e., the variables are presented per grade) and only includes the demographic predictors.

From Table A.1, the only strong correlations were between Other Race and Latinx ethnicity ($r = 0.525$), English/Language Arts grade and History/Social Studies grade ($r = 0.507$), and the trouble in school scale and trouble completing homework ($r = 0.522$). All of these coefficients were significant at the $p < 0.05$ level.

There were several more moderately strong correlations in Table A.1. Of particular note were the relationships between suspension and dropout ($r = 0.345$), the college expectations scale and dropout ($r = -0.303$), and grade retention and dropout ($r = 0.314$). All these correlations were significant at the $p < 0.05$ level, and the direction of these correlations is as one would expect based on the literature.

Residential mobility was not correlated with any other variable in Table A.1 because residential mobility was a constant variable: all students in the complete case sample experienced residential mobility.

Turning to Table B.1, suspension – grade 1, suspension – grade 2, and expulsion – grade 4 were not correlated with any other variables as these were constant variables with zero occurrences of the events. In addition, there were no variables that were moderately or strongly correlated with dropout. Of the weak correlations, there were some relationships worth highlighting.

In terms of suspension and dropout, suspension – grade 8 and dropout – grade 10 ($r = 0.124$), suspension – grade 8 and dropout – grade 11 ($r = 0.190$), suspension – grade 9 and dropout – grade 10 ($r = 0.120$), suspension – grade 9 and dropout – grade 12 ($r = 0.178$), suspension – grade 10 and dropout – grade 11 ($r = 0.156$), and suspension – grade 10 and dropout – grade 12 ($r = 0.188$) were all significant correlations at the $p < 0.05$ level. These findings are reflective of the moderate correlation between suspension and dropout in Table A.1, in that as occurrence of suspension was associated with increased occurrence of dropout.

Regarding expulsion and dropout, expulsion – grade 9 and dropout – grade 10 ($r = 0.135$), expulsion – grade 9 and dropout – grade 12 ($r = 0.163$), expulsion – grade 10 and dropout – grade 11 ($r = 0.131$), and expulsion – grade 12 and dropout – grade 12 ($r = 0.116$) had significant relationships at the $p < 0.05$ level. This too was consistent with the findings in Table A.1 regarding expulsion and dropout in that as expulsion events increased, so did dropout events, though there, as here, the correlations were weak ($r = 0.256$, $p < 0.05$).

Finally, of the demographic predictors, public assistance and dropout – grade 12 ($r = 0.175$), parental education and dropout – grade 10 ($r = -0.108$), parental education and dropout – grade 11 ($r = -0.111$), and parental education and dropout – grade 12 ($r = -0.127$) were notable significant correlations at the $p < 0.05$ level. The relationship between public assistance and dropout indicates that those who receive public assistance are associated with increased occurrences of dropout during twelfth grade. Regarding parental education, increases in levels of parental education were associated with decreased occurrences of dropout in grades 10, 11 and 12.

To further explore the relationship between the timing of events and dropout, discrete time survival analysis (DTSA) was used to model the relationship between the predictors.

Discrete Time Survival Analysis

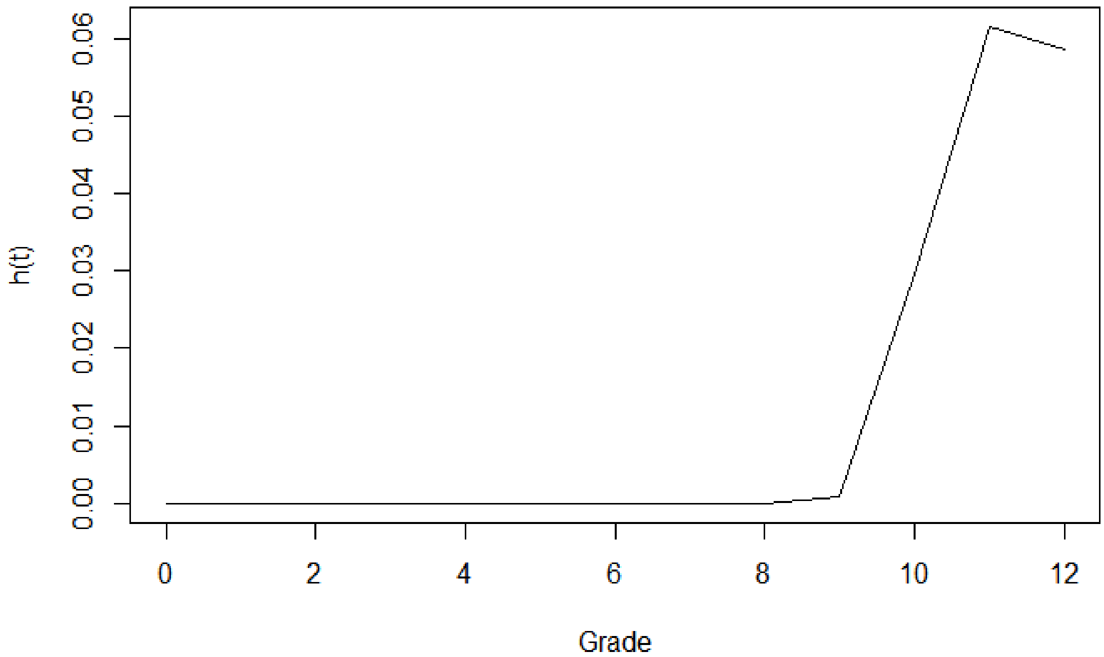
To begin DTSA, I first created a life table to depict the frequency of dropouts per grade. In addition, the table also depicts the hazard functions and the probability functions at each successive grade. As can be seen in Table 4.1, the number of students who dropped out increased by more than twelve times from ninth to tenth grade and then more than doubled from tenth to eleventh grade. These changes resulted in large increases in the hazard function and corresponding decreases in the survivor function. The hazard function is also graphically depicted in Figure 4.1.

Next I began to test the alternative specifications for time to best fit the data. I started by fitting the general model in (4.1), followed by the constant model in (4.2), the linear model in (4.3), the quadratic model in (4.4), the cubic model in (4.5), and the quartic model in (4.6). For each model, ONE is a constant equal to one for every case in the person-period dataset (Singer & Willet, 2003, p. 411).

Table 4.1 Life Table Describing the Educational Attainment of Ninth Grade Students (n=1182)

	Number			Proportion of	
Grade	**Enrolled at the Beginning of the Year**	**Who Left During the Year**	**Censored at the End of Year**	**Hazard Function**	**Survivor Function**
1	1182	0	0	0.000	1.000
2	1182	0	0	0.000	1.000
3	1182	0	0	0.000	1.000
4	1182	0	0	0.000	1.000
5	1182	0	0	0.000	1.000
6	1182	0	0	0.000	1.000
7	1182	0	0	0.000	1.000
8	1182	0	0	0.000	1.000
9	1182	2	0	0.002	0.998
10	1180	25	0	0.021	0.977
11	1155	55	0	0.048	0.931
12	1100	66	1034	0.113	0.825

Figure 4.1 Discrete Time Hazard Function for 9th Grade Cohort Dropout



$$\text{logit}\, h(t_j) = \alpha_1 D_1 + \alpha_2 D_2 + \cdots + \alpha_J D_J \tag{4.1}$$

$$\text{logit}\, h(t_j) = \alpha_0 ONE \tag{4.2}$$

$$\text{logit}\, h(t_j) = \alpha_0 ONE + \alpha_1 (TIME_J - c) \tag{4.3}$$

$$\text{logit}\, h(t_j) = \alpha_0 ONE + \alpha_1 (TIME_J - c) + \alpha_2 (TIME_J - c)^2 \tag{4.4}$$

$$\text{logit}\, h(t_j) = \alpha_0 ONE + \alpha_1 (TIME_J - c) + \alpha_2 (TIME_J - c)^2$$

$$+\alpha_3 (TIME_J - c)^3 \tag{4.5}$$

$$\text{logit}\, h(t_j) = \alpha_0 ONE + \alpha_1 (TIME_J - c) + \alpha_2 (TIME_J - c)^2$$

$$+\alpha_3 (TIME_J - c)^3 + \alpha_4 (TIME_J - c)^4 \tag{4.6}$$

Then, I plotted all six hazard functions as shown in Figure 4.2. The general, cubic, and quartic models all very closely overlap, so the general and cubic models are not visible. In addition, several model characteristics are presented in Table 4.2.

Table 4.2 corroborates much of the evidence in Figure 4.2, namely that each specification of time is superior to the previous model at fitting the data, except for the quartic, but the differences in deviance are much smaller for the cubic and quartic polynomials. However, when comparing the differences to the general model, the quadratic model is the first that is not significantly different from the general model at $p < 0.05$. The quadratic model does not appear to fit as well as the cubic or quartic, based on Figure 4.2. However, following the advice of Singer & Willett (2003, p. 417), the quadratic model works nearly as well as the general one and much better than the simpler ones, and no worse than the more complex ones, so it was selected as the time parameterization for the discrete-time hazard model.

After the time parameterization was selected, the discrete-time logit model was run with all the predictors included to test the conceptual model of dropout from Rumberger & Lim (2008). Namely, since the conceptual model depicts the potential relationships between predictors and educational attainment and predictors were selected as representatives of the individual factors and the institutional family factor, the discrete-time logit model with all the predictors was evaluated to see how strongly the predictors were related.

As shown in Table 4.3, the significant predictors were residential mobility history, parental education, the college expectations scale, math grade, excused absences, and grade retention history. Each of which were significant at the $p < 0.05$ level or lower.

Figure 4.2 Hazard Function from Different Time Parameterizations

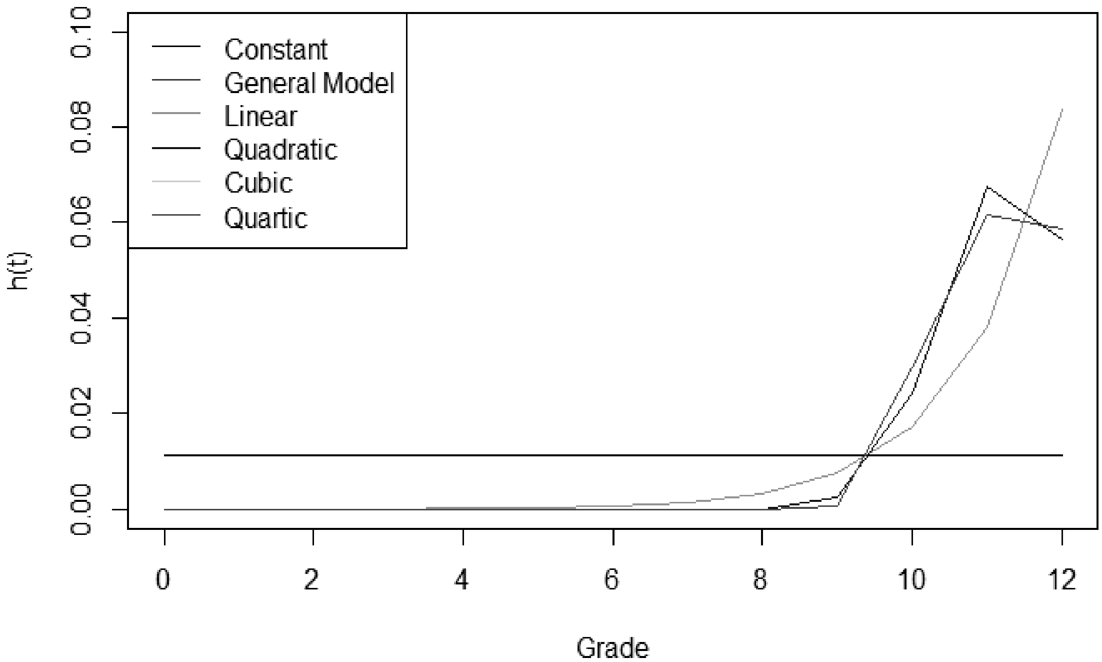


Table 4.2 Comparison of Alternative Time Specifications for the Main Effect of TIME in a Baseline Discrete-Time Hazard Model

Represen-tation of TIME	n parameters	Deviance	Difference in Deviance in Comparison to Previous Model	Difference in Deviance in Comparison to General Model	AIC	BIC
Constant	1	1866.650	-----	**508.868** (12)	1845.448	1871.762
Linear	2	1420.744	**445.905** (1)	**62.963** (11)	1409.001	1430.968
Quadratic	3	1361.949	**58.795** (1)	4.168 (10)	1350.318	1377.285
Cubic	4	1357.782	**4.167** (1)	2.43e-04 (9)	1348.723	1378.230
Quartic	5	1357.782	-4.50e-04 (1)	6.935e-04 (8)	1350.724	1383.342
General	13	1357.781	-----	-----	1366.723	1424.237

Note: (x) represents degrees of freedom for χ^2 log likelihood test, and **bold** numbers represent significant values at $p < 0.05$.

These findings indicate that, controlling for the effects of all other predictors, at each grade from zero to twelve, the odds of dropout increase by 154.441% for a student who experienced a concurrent or previous instance of residential mobility. Turning to parental education, the college expectations scale, and grade retention history, controlling for all other predictors, an increase in parental education level decreased the odds of dropout by 12.760% and an increase in score on the college expectations scale corresponded to decreasing the odds of dropout by 17.130%. Regarding grade retention history, controlling for the effects of all other predictors, at each grade from zero to twelve, the odds of dropout increase by 99.999% for a student who experienced a concurrent or previous instance of grade retention. All these findings are consistent with the bivariate correlations presented above, although the correlation between parental education and dropout was low in Table B.1 and the correlations between college expectations and dropout and grade retention history and dropout were both moderate in Table A.1.

Of the other two significant predictors in the model, math and excused absences, each correlated with dropout weakly in Table A.1 ($r = -0.219$, $p < 0.05$ and $r = 0.162$, $p < 0.05$, respectively). For math, controlling for all other predictors, a single letter grade increase in math grade decreased the odds of dropout by 23.456%. In addition, for excused absences, controlling for all other predictors, an increase in excused absences in the school year increased the odds of dropout by 41.397%. The directionality of these findings are also consistent with the correlations in Table A.1.

At the $p < 0.10$ level, there were four other significant predictors in the model: suspension history, science grade, the school attachment and perceptions scale, and school mobility from grades 9 to 10. Controlling for the effects of all other predictors, at each grade from zero to twelve, the odds of dropout decrease by 77.214% for a student who experienced a concurrent or previous instance of suspension. This finding contradicts the findings from the bivariate correlations presented in Table A.1 and several grades in Table B.1 (albeit those correlations were weak) and the existing literature (Arcia, 2006; Caton, 2012; Rumberger, 2011; Stearns & Glennie, 2006; Suh & Suh, 2007). In addition, holding all other predictors constant, increasing science grades by a single letter grade reduced the odds of dropping out by 20.801%. Similarly, holding all other predictors constant, an increase in school attachment and positive perceptions of school corresponded to a decrease in the odds of dropout by 4.574%. Finally, controlling for the effects of all other predictors, changing schools between ninth and tenth grade increased the odds of dropout by 230.356%.

Table 4.3 Coefficients for DTSA Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-8.531e+01	1.998e+01	-4.270	7.06e-05 ***
Grade	1.506e+01	3.708	4.061	1.44e-04 ***
I(Grade^2)	-6.656e-01	1.704e-01	-3.905	2.42e-04 ***
Suspension History	-1.479	7.584e-01	-1.950	0.056 .
Expulsion History	-1.270e-01	6.007e-01	-0.211	0.833
Residential Mobility History	9.339e-01	4.277e-01	2.183	3.29e-02 *
Female	8.301e-02	1.782e-01	0.466	0.643
Black	2.615e-01	2.671e-01	0.979	0.331
Native American	-2.589e-01	8.510e-01	-0.304	0.762
Asian	-8.139e-01	1.296	-0.628	0.532
Other Race	-2.678-01	6.920e-01	-0.387	0.700
Multiracial	-2.131e-01	4.404e-01	-0.484	0.630
Latinx Ethnicity	9.614e-02	3.581e-01	0.268	0.789
U.S. Born	4.329e-01	7.264e-01	0.596	0.553
Public Assistance	3.005e-01	2.454e-01	1.225	0.225
Parental Education	-1.365e-01	5.827e-02	-2.342	0.023 *
Parent Participation in School Activities Scale	-1.038e-01	1.256e-01	-0.826	0.412
College Expectations Scale	-1.879e-01	4.658e-02	-4.034	1.57e-04 ***
English/ Language Arts Grade	-1.781e-01	1.255e-01	-1.419	0.161
Math Grade	-2.673e-01	8.957e-02	-2.984	4.11e-03 **
History/Social Studies Grade	-5.406e-02	1.216e-01	-0.445	0.658
Science Grade	-2.332e-01	1.196e-01	-1.950	0.056 .
Trouble in School Scale	-5.271e-02	6.092e-02	-0.865	0.390
Trouble Completing Homework	1.209e-01	1.124e-01	1.075	0.287
School Attachment & Perceptions Scale	-4.682e-02	2.507e-02	-1.867	0.067 .
Students at School Prejudiced	-8.661e-04	1.078e-01	-0.008	0.994
Self-Esteem Scale	5.851e-02	4.365e-02	1.340	0.185
Social Support Scale	-5.414e-03	3.143e-02	-0.172	0.864
Desire to Leave Home	1.860e-02	9.679e-02	0.192	0.848
Excused Absences	3.464e-01	1.331e-01	2.603	0.012 *
Unexcused Absences	9.887e-03	9.008e-03	1.098	0.277
Delinquency Scale	2.328e-02	1.564e-02	1.489	0.142
Hours Worked per Non-Summer Week	7.974e-03	9.309e-03	0.857	0.395
School Mobility – Grades 9 to 10	1.195	6.950e-01	1.720	0.091 .
Grade Retention History	-1.206e+01	6.292e-01	-19.165	< 2e-16 ***

Note: Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

CHAPTER 5

DISCUSSION AND CONCLUSIONS

The aim of this study was to outline the patterns of school exclusion, residential mobility, and dropout over the study period, examine the relationships between predictors of dropout and dropout, and explore the effects of the frequency and timing of residential mobility, school exclusion, and other predictors on attainment. A subsample of complete cases from the ninth grade cohort were examined in the main findings of the study, which was consistent with the recommendations of the *Add Health* research team, only those students with complete responses to the study variables were included in the analysis (Chen & Harris, 2020). As discussed in Chapter 4, the differences between the entire ninth grade cohort and the complete cases sample was not appreciably different on many of the variables. However, there were noticeable differences between the two groups on several items that led the impression that the complete cases sample analyzed potentially underrepresented the percentage of students who dropped out and created a sample that was in general academically stronger than full ninth grade cohort, consisted of only individuals who experienced residential mobility, had more positive perceptions of and attachments to their schools, except for in regards to perceived prejudices by other students, and were less engaged in delinquent behavior. These differences potentially skewed the findings in this analysis, so it is important to be aware of these differences.

Regarding the patterns of school exclusion, residential mobility, and educational attainment data during the study period. The findings on suspension trends is consistent with the general trends found nationally, namely that more students are suspended in high school versus elementary school. However, expulsion rates were not broken down by grade nationally, though as expected from the national data, the rates of expulsion were considerably lower compared to the rates of suspension in the sample (Losen, Hodson, Keith, Morrison, and Belway, 2015).

The trends in residential mobility were also consistent with trends in that the number of students who experienced residential mobility before entering first grade was higher than that in any other grade. After that, the closest frequencies in residential mobility only occurred in sixth, seventh and eighth grades years (sixth grade: $M = 0.12$, $SD = 0.32$; seventh grade: $M = 0.14$, $SD = 0.34$; eighth grade: $M = 0.14$, $SD = 0.34$), but even then the means were nearly half of that at grade 0 ($M = 0.27$, $SD = 0.45$). This increase in movers in the middle school/junior high school were not consistent with national trends asdu elementary-aged children have the next highest rate of movers (U.S. Census Bureau, 2019). These findings likely reflect the fact that only a small subset of the full sample was analyzed in this study, and this complete case sample, as indicated in Table 3.1 and Chapter 4, demonstrated differences from the larger ninth grade cohort that could be affecting the findings. In addition, the national rates are only representative of a single cohort at one time, unlike the longitudinal nature of the data here.

Regarding dropout trends, the findings indicating that dropout increased over time provides new information regarding when dropout occurs. As previously noted, educational attainment is not often treated as a process in the literature (Lessard, et al., 2008; Rumberger, 2011); thus, dropout is treated as an event. In fact, the U.S. event dropout rate is defined as “the percentage of 15- to 24-year-olds in grades 10-12 who left school between the beginning of one school year and the beginning of the next without earning a high school diploma or alternative credential” (McFarland, et al., 2018, p. 4). Therefore, it is not feasible to compare the national event dropout rate or even status dropout rate to the trends across grade presented in this data.

However, it can be said that the increasing trend in dropouts between grades ten and twelve may be reflective of the effects of compulsory education laws across states which set the age requirements during “which a student is required by law to attend school or an equivalent program defined by law” (Diffey & Steffes, 2017, p. 1). During those age ranges, which, depending on the state, end at 16 to 19 or the completion of tenth or twelfth grade, students are legally required to attend school. Since most youth are approximately 16 years old in tenth grade, it is not surprising that those who do dropout do not begin to do so until tenth grade and that the grades of dropout increase from there. However, once more due to the nature of educational attainment as a process (Lessard, et al., 2008; Rumberger, 2011), it should also be noted that because of the way that *Add Health* asked the question regarding educational attainment in Wave III, students could have experienced cycles of dropping out and reenrolling in school between Waves II and III culminating in the dropout experience captured in Wave III. Though not necessarily the case in all instances of dropout, this could have reflected the experience of some students who did not complete high school by Wave III.

Turning to the relations between predictors and dropout, many of the findings were unexpected in this context. For example, the only strong correlations found in Table A.1 was between Other Race and Latinx Ethnicity, English and History grades and the trouble in school scale and trouble completing homework. Despite the surprise that these were the only strong relationships, the findings do not seem unreasonable.

The correlation between Other Race and Latinx ethnicity likely is indicative of the fluid nature of race and ethnicity for many people of Latinx descent. In other words, many people of Latinx descent will identify as racially Black or White, but there are others who do not, preferring to either identify as racially Latinx (versus simply ethnically Latinx) or with no racial group at all as they identify with only their Latinx ethnicity (Fergus, 2016). The correlation between English Language/Arts and History/Social Studies grades is likely due to the necessity to apply similar skill sets in both courses, such as reading texts and writing essays. Finally, the correlation between the trouble in school scale and the trouble completing homework variable is likely due to the fact that if a student is struggling with some aspects of school, then they are likely struggling with others. In other words, if a student is struggling getting along with teachers and other students and paying attention in school, it is not unreasonable to expect that s(he) would also be struggling with completing homework.

The moderate correlations in Table A.1 appeared to also be consistent with the literature. Increased occurrences of suspension are correlated with the occurrence of dropout, though I expected this finding to be more strongly correlated (Arcia, 2006; Caton, 2012; Rumberger, 2011; Stearns & Glennie, 2006; Suh & Suh, 2007). In addition, greater desire to and believed likelihood that the student will go to college (the college expectations scale) are correlated with fewer instances of dropout as students planning for college demonstrate the value they place on continuing their education. Finally, increased occurrences of repeating grades are correlated with more dropout, which is also consistent with the literature (Rumberger & Lim, 2008).

Regarding the correlations in Table B.1, though they were all weak, these findings may imply potential critical moments for when to intervene based on when events occur, some of which are consistent with previous findings. For example, suspension in late middle/junior high school or early high school (grades 8-10) have been shown to be strong predictors of dropout, particularly in the early high school years (Arcia, 2006; Caton, 2012; Chu & Ready, 2018; Rumberger; 2011; Stearns & Glennie, 2006; Suh & Suh, 2007). In addition, expulsion during high school has also been found to be predictive of dropout, likely in part because some expulsions require enrollment in a new school district/system and while others can be accompanied by a transfer to an alternative school in the same district, which means that some students are more burdened to seek a new educational institution than others and may remain out of school (Losen & Gillespie, 2012; Skiba, et al., 2014; Theriot, et al., 2010)

However, despite these consistent findings with previous research, the correlations in the current study were not as strong as expected across several relationships. In addition, there were no correlations between residential mobility at any grade and dropout at any grade that exceeded $r = \pm 0.1$. These low correlations could be indicative of the significance of residential mobility as a predictor in models of dropout being reliant on its combined effects with other predictors in the models or be an artifact of the data due to the analytic sampling set creation method.

When exploring the effects of frequency and timing of residential mobility, school exclusion, and other predictors on attainment, the findings of the results of the DTSA analysis like those of the correlations were also somewhat unexpected and, at times, inconsistent with the existing literature. The fact that a concurrent or previous occurrence of suspension (p = 0.0558), which was nearly significant at the $p < 0.05$ level, decreased the odds of dropout by 77.214% when controlling for the effects of all other predictors, at each grade from zero to twelve was particularly surprising. As noted in Chapter 4, this finding contradicts the findings from the bivariate correlations in Table A.1 and several of the grades in Table B.1 along with the existing literature (Arcia, 2006; Caton, 2012; Rumberger, 2011; Stearns & Glennie, 2006; Suh & Suh, 2007).

One explanation for these results could be the nature of the sample. As discussed above regarding the complete case sample in comparison to the full ninth grade cohort these findings could be reflective of a sample that was not representative of the population due to the nature of the missingness present in the eliminated cases. In addition, though the sample size was still large (n = 1182), there were potential power issues due to the large number of variables included in the model, even after the dataset was converted to the person period format and the number of variables reduced.

The nature of the data, in terms of the questions asked, may have been another contributor to these findings. As previously discussed in Chapter 3, to create the person-period dataset for DTSA, the timelines for all the time-varying predictors and the outcome had to match. Since dropout only ran from grades 9 to 12, residential mobility from grades 0 to 10, suspension from grades 1 to 10, expulsion from grades 3 to 12, and grade retention from grades 1 to 9, there were several timepoints for these variables when the imputed value was zero. Though imputing to zero was likely accurate for the missing dropout time points, it likely was inaccurate for the other variables. In addition, the thirteen time points included in the analysis could have also been too long, especially considering there were so many imputed values. The results may have been further skewed by the model having to account for the lengthy timeline, which further corresponds to the large number of variables in the analysis.

It is also entirely possible, but highly unlikely, that these findings could be valid because the effects of time were addressed in this model. In other words, when examined over time, suspension events could deter dropout. However, as previously stated, this likely is inaccurate, particularly when the other inconsistent and unexpected findings are taken into consideration. The coefficients for the race and ethnicity variables (especially Black and

Latinx), one of the SES variables (public assistance), gender (female), immigrant status (U.S. born), and expulsion history (which also appeared to decrease the odds of dropout) were also not significant predictors in this model. As previously noted, these findings could reflect reality since time is incorporated as a covariate in this model, these predictors may behave differently in longitudinal modeling like this. However, once more, that conclusion is highly improbable. More than likely the reasons outlined above contributed to these nonsignificant findings, as well.

There is also one final possibility for these unexpected results that is exogenous to statistical explanations. When this data was collected, the Gun Free Schools Act of 1994 (GFSA) had just been enacted into law, so its effects were likely not experienced by students in this study. The GFSA essentially mandated all schools receiving federal education dollars to enforce zero tolerance disciplinary policies for bringing weapons to school. Though the act only specified that a minimum one-year expulsion was required for any student who brought a firearm to school, and it allowed for administrative discretion in the enforcement of these disciplinary policies, a significant proportion of schools across the U.S. began to adopt zero tolerance disciplinary policies across the board, resulting in oftentimes severe, and disproportionate punishment for relatively minor offenses that typically relied on suspension, expulsion, or arrest by the police (American Psychological Association Zero Tolerance Task Force, 2008; Sughrue, 2003). In addition, the widespread use of zero tolerance policies in schools continued to dominate under the No Child Left Behind Act (NCLB) of 2001 (Dupper, 2010). However, the effects of these policies were likely not felt to the degree that students five to ten years later experienced them. For this reason, there may be a cohort effect that is reflected in this data, which is attenuating the relationships between suspension, expulsion, and dropout over time. Even though strong relationships have been found in research using data before the enactment of GFSA and NCLB (Losen, et al., 2015) once more, those studies did not account for the effects of time longitudinally as was done here.

Despite these shortcomings, many of the other findings in the DTSA model were consistent with previous research regarding predictors of dropout, such as residential mobility (South, et al., 2007; Swanson & Schneider, 1999). However, this finding is limited by the fact that each student in the complete case sample experienced residential mobility, reducing the variance of the predictor, though the residential mobility experienced was not all at the same grade. In addition, the effects of SES, as accounted for by parent education, college expectations, grade retention, math grades, excused absences, science grades, school attachment and perceptions of school, and school mobility between ninth and tenth grade were all affected the odds of dropout in expected ways (Rumberger, 2011).

Limitations

Several of the potential limitations of this study were previously addressed in this chapter, but there are a few more that are worthy of noting, especially in the context of possible future research. First, this study is limited by the data available through *Add Health. Add Health* is a public health dataset that was not designed with education research in mind. Therefore, there are limits to what analysis is possible (as, of course, there is with any longitudinal dataset). However, *Add Health* was the only longitudinal dataset that addressed school exclusion, residential mobility, and high school educational attainment. After reviewing several other possible nationally representative, longitudinal datasets, including education datasets, I chose to work with *Add Health* because all others were missing important variables for my study because it is a uniquely robust dataset. In addition, within *Add Health* it is not possible to determine the distance between each move, the time spent at each residence, or the full life history of mobility. Further, the frequency of school exclusion events per grade, the duration of each exclusion event, nor the specific type of exclusion experienced in each instance can be fully determined from this data across students' entire education career. Finally, the relative timing of life events, such as which came first in a single grade, residential mobility or school exclusion, cannot be analyzed. Addressing these concerns in future research would, however, require time to be treated continuously to truly capture their effects, but that brings its own potential limitation if the timespan, as it was here, is too long, resulting in the dataset to be too complicated. The end result may be having to rely on discrete time analysis once more. Despite these limitations, the *Add Health* dataset is one of the most comprehensive and recent dataset which contains variables related to these phenomena. In addition, the original data were not collected with my study in mind nor for the purpose that I am proposing to use it.

Future Research

This work was a first step in a burgeoning direction for educational attainment research. Therefore, it should be replicated and expanded upon to address its shortcomings and to allow for the greater growth in the field. More specifically, based on these findings, future research could address the limitations in the data itself, which would ideally address the other statistically endogenous limitations present here. For example, more complete data will open possibilities for more accurate and applicable findings. In addition, future studies should expand their analyses to incorporate different grade cohorts and more aspects of Rumberger and Lim's (2008) conceptual model to see if the findings here are limited to the subset of ninth graders analyzed here, which often represents the new cohort in a high school, and thus presents students with a host of challenges. Also, by evaluating the contributions of different variables at different levels to attainment, the models produced in future studies could better reflect reality. Further, it is worth exploring comparative models for different grade cohorts to see if these findings hold for different groups of students at different points in their educational careers and/or if results that are more consistent with the large body of research on dropout are found.

Finally, to better understand the complex nature of dropout, future research should not only be done at the national level, as this was, but also at the school, district, and state level. By doing so, opportunities open to be able to evaluate whether the process of attainment is consistent. In other words, not only can grade cohort comparisons improve theoretical understandings of the process of dropout, cross-geographic studies can as well. By comparing results on vertically and laterally, a richer understanding of the experiences of students can be learned to better meet and support their needs through school. This is why I believe that beyond further quantitative analyses, qualitative analysis will also be important to better inform and test the validity of the models from quantitative research by introducing richer student narratives into the work and better allow researchers to further interrogate the influence of the timing of events.

Significance of the Study

In conclusion, this study has both empirical and practical implications on future work to address high school dropout. By contributing to the necessary examination of the effects of time on the process of attainment, new possibilities continue to open for future research and for interventions to address students' needs at potentially critical junctures in their academic careers. In addition, by focusing on two time-varying predictors that have not been examined together in previous research and by utilizing the conceptual framework of Rumberger & Lim (2008) as a theoretical framework, this work pushed the boundary in the evaluation of predictors of dropout by including several variables across different dimensions at the individual and familial level that had not been evaluated together before allowing for a new perspective on how these predictors affect attainment.

From the practical side, these results and more nuanced analyses in the future have the potential to inform high school dropout prevention interventions that could improve life course outcomes for all students. The introduction and evaluation of time allows for increased possibilities to understand the paths students take in the process of attainment. This will allow for dropout intervention programs to be developed that do not rely on a "one-size-fits-all" mindset but are designed to serve the needs of the individual at their greatest moment of need. Conversely, the inclusion of more institutional predictors in future work can also be used to help inform teachers and school and district administrators on how they contribute to student dropout so that institutional practices and culture can be altered to improve the learning environment for all students.

Despite large bodies of work on educational attainment, residential mobility, and school exclusion, there are still pronounced disparities in student attainment across racial and socioeconomic lines (McFarland, et al., 2018). Though this study was not able to clearly address the disparities across racial lines, the work here was both comprehensive and specific in its approach to the analysis of educational attainment which can be informative for future research, student-level interventions, and broader policy changes that will only help to address these perpetual flaws in our nation's educational landscape.

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APPENDIX A

PEARSON CORRELATION MATRIX FOR PREDICTORS OF DROPOUT AND DROPOUT WITH TIME-VARYING SUMMARY VARIABLES

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables)

	Dropout	Suspension	Expulsion	Residential Mobility
Dropout	1.000	**0.345**	**0.256**	NA
Suspension		1.000	**0.293**	NA
Expulsion			1.000	NA
Residential Mobility				1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables; cont.)

	Female	Latinx Ethnicity	Black	Native American	Asian	Other Race	Multiracial	U.S. Born	Public Assistance	Parental Education
Dropout	**-0.003**	**0.060**	**-3.09e-4**	-0.015	**-0.059**	-0.016	0.022	**0.024**	**0.163**	**-0.209**
Suspension	**-0.123**	**0.039**	**0.144**	-0.001	**-0.054**	0.055	**0.058**	**0.014**	**0.156**	**-0.171**
Expulsion	**-0.040**	**0.081**	**0.102**	**0.109**	**-0.006**	**0.072**	**0.087**	**-0.068**	**0.149**	**-0.131**
Residential Mobility	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Female	1.000	**-0.021**	**0.025**	0.017	**-0.085**	**-0.021**	0.043	**0.057**	**-0.002**	**-0.073**
Latinx Ethnicity		1.000	**-0.180**	**0.104**	**-0.073**	**0.525**	0.019	**-0.358**	**0.067**	**-0.218**
Black			1.000	-0.051	**-0.107**	**-0.111**	**-0.102**	**0.108**	**0.156**	**0.093**
Native American				1.000	**-0.023**	-0.024	-0.022	**-0.035**	**-0.011**	**-0.048**
Asian					1.000	-0.051	-0.046	**-0.269**	**-0.077**	**-0.008**
Other Race						1.000	-0.048	**-0.256**	**-0.005**	**-0.099**
Multiracial							1.000	**-0.024**	**0.075**	**0.005**
U.S. Born								1.000	**0.032**	**0.156**
Public Assistance									1.000	**-0.231**
Parental Education										1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables; cont.)

	Parent Participation in School Activities Scale	College Expectations Scale	English/Language Arts Grade	Math Grade	History/Social Studies Grade	Science Grade
Dropout	**-0.061**	**-0.311**	**-0.287**	**-0.219**	**-0.242**	**-0.264**
Suspension	**-0.024**	**-0.303**	**-0.365**	**-0.279**	**-0.291**	**-0.316**
Expulsion	**-0.058**	**-0.191**	**-0.188**	**-0.154**	**-0.162**	**-0.142**
Residential Mobility	NA	NA	NA	NA	NA	NA
Female	**0.032**	**0.100**	**0.120**	**0.012**	**0.061**	**0.038**
Latinx Ethnicity	**0.006**	**-0.083**	**-0.055**	**-0.121**	**-0.083**	**-0.050**
Black	**0.020**	**0.028**	**-0.115**	**-0.110**	**-0.125**	**-0.119**
Native American	**0.008**	**-0.046**	**0.041**	**-0.035**	**-0.004**	**-0.046**
Asian	**-0.001**	**0.064**	**0.078**	**0.101**	**0.080**	**0.140**
Other Race	**0.011**	**-0.039**	**-0.053**	**-0.060**	**-0.046**	**-0.042**
Multiracial	**0.004**	**-0.042**	**-0.040**	**-0.018**	**-0.084**	**-0.014**
U.S. Born	**0.034**	**0.032**	**0.016**	**-0.026**	**-0.006**	**-0.032**
Public Assistance	**-0.018**	**-0.159**	**-0.126**	**-0.105**	**-0.188**	**-0.100**
Parental Education	**0.068**	**0.250**	**0.161**	**0.108**	**0.197**	**0.176**
Parent Participation in School Activities Scale	1.000	**0.086**	**0.070**	**0.038**	**0.071**	**0.051**
College Expectations Scale		1.000	**0.354**	**0.258**	**0.354**	**0.318**
English/Language Arts Grade			1.000	**0.434**	**0.507**	**0.466**
Math Grade				1.000	**0.381**	**0.377**
History/Social Studies Grade					1.000	**0.497**
Science Grade						1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables; cont.)

	Trouble in School Scale	Trouble Completing Homework	School Attachment & Perceptions Scale	Students at School Prejudiced
Dropout	**0.176**	**0.148**	**-0.169**	**0.011**
Suspension	**0.274**	**0.194**	**-0.256**	**0.028**
Expulsion	**0.162**	**0.098**	**-0.138**	**0.022**
Residential Mobility	NA	NA	NA	NA
Female	**-0.053**	**-0.071**	**-0.062**	**0.052**
Latinx Ethnicity	**-0.047**	**0.039**	**-0.034**	**-0.063**
Black	**0.001**	**-0.043**	**-0.012**	**-0.200**
Native American	**0.043**	**0.005**	**-0.060**	**0.036**
Asian	**-0.055**	**-0.049**	**0.069**	**-0.051**
Other Race	**-0.036**	**0.032**	**-0.005**	**-0.072**
Multiracial	**0.051**	**0.038**	**-0.073**	**0.032**
U.S. Born	**0.076**	**-0.002**	**-0.035**	**0.044**
Public Assistance	**0.038**	**0.054**	**-0.094**	**-0.009**
Parental Education	**-0.032**	**-0.028**	**0.074**	**0.006**
Parent Participation in School Activities Scale	**-0.070**	**-0.080**	**0.063**	**-0.002**
College Expectations Scale	**-0.237**	**-0.224**	**0.258**	**-0.039**
English/Language Arts Grade	**-0.272**	**-0.286**	**0.197**	**-0.021**
Math Grade	**-0.209**	**-0.272**	**0.203**	**-0.022**
History/Social Studies Grade	**-0.213**	**-0.236**	**0.185**	**0.043**
Science Grade	**-0.222**	**-0.245**	**0.208**	**0.002**
Trouble in School Scale	1.000	**0.522**	**-0.422**	**0.147**
Trouble Completing Homework		1.000	**-0.235**	**0.053**
School Attachment & Perceptions Scale			1.000	**-0.192**
Students at School Prejudiced				1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables; cont.)

	Self-Esteem Scale	Social Support Scale	Desire to Leave Home	Excused Absences	Unexcused Absences
Dropout	**-0.056**	**-0.161**	**0.137**	**0.162**	**0.252**
Suspension	**-0.056**	**-0.198**	**0.144**	**0.125**	**0.342**
Expulsion	**-0.023**	**-0.079**	**0.076**	**-0.015**	**0.188**
Residential Mobility	NA	NA	NA	NA	NA
Female	**-0.137**	**0.043**	**0.102**	**0.105**	**-0.024**
Latinx Ethnicity	**-0.032**	**0.009**	**-0.030**	**0.027**	**0.119**
Black	**0.123**	**0.040**	**0.017**	**-0.122**	**-0.041**
Native American	**-0.021**	**-0.069**	**0.042**	**-0.047**	**0.008**
Asian	**0.013**	**0.002**	**-0.024**	**-0.113**	**-0.058**
Other Race	**-0.004**	**0.051**	**-0.014**	**0.012**	**0.077**
Multiracial	**-0.052**	**-0.029**	**0.041**	**0.002**	**0.041**
U.S. Born	**-0.010**	**-0.049**	**0.058**	**0.090**	**-0.030**
Public Assistance	**-0.041**	**-0.088**	**0.088**	**0.044**	**0.077**
Parental Education	**0.083**	**0.061**	**-0.011**	**-0.067**	**-0.090**
Parent Participation in School Activities Scale	**0.077**	**0.137**	**-0.121**	**-0.024**	**-0.131**
College Expectations Scale	**0.214**	**0.329**	**-0.156**	**-0.087**	**-0.295**
English/Language Arts Grade	**0.038**	**0.163**	**-0.107**	**-0.164**	**-0.266**
Math Grade	**0.064**	**0.132**	**-0.096**	**-0.145**	**-0.239**
History/Social Studies Grade	**0.052**	**0.147**	**-0.097**	**-0.086**	**-0.196**
Science Grade	**0.075**	**0.156**	**-0.112**	**-0.150**	**-0.221**
Trouble in School Scale	**-0.241**	**-0.350**	**0.218**	**0.129**	**0.270**
Trouble Completing Homework	**-0.168**	**-0.254**	**0.193**	**0.141**	**0.226**
School Attachment & Perceptions Scale	**0.330**	**0.388**	**-0.210**	**-0.132**	**-0.199**
Students at School Prejudiced	**-0.048**	**-0.091**	**0.053**	**0.020**	**0.075**
Self-Esteem Scale	1.000	**0.453**	**-0.257**	**-0.083**	**-0.088**
Social Support Scale		1.000	**-0.389**	**-0.097**	**-0.238**
Desire to Leave Home			1.000	**0.091**	**0.141**
Excused Absences				1.000	**0.199**
Unexcused Absences					1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table A.1 Pearson Correlation Coefficients for Predictors and Dropout (Time-Varying Summary Variables; cont.)

	Delinquency Scale	Hours Worked Per Non-Summer Week	School Mobility – Grades 9 to 10	Grade Retention
Dropout	**0.154**	**-0.004**	**0.058**	**0.314**
Suspension	**0.301**	**-0.003**	**0.086**	**0.286**
Expulsion	**0.179**	**0.036**	**0.041**	**0.143**
Residential Mobility	NA	NA	NA	NA
Female	**-0.063**	**-0.018**	**-0.016**	**-0.053**
Latinx Ethnicity	**-0.001**	**-0.083**	**0.008**	**0.064**
Black	**-0.013**	**-0.121**	**0.032**	**0.098**
Native American	**0.048**	**0.028**	**-0.011**	**-0.029**
Asian	**0.003**	**-0.034**	**-0.023**	**-0.074**
Other Race	**0.046**	**-0.020**	**0.013**	**0.061**
Multiracial	**0.036**	**0.007**	**0.018**	**0.019**
U.S. Born	**0.028**	**0.038**	**-0.003**	**-0.057**
Public Assistance	**0.073**	**-0.022**	**0.041**	**0.113**
Parental Education	**-0.019**	**0.046**	**0.029**	**-0.195**
Parent Participation in School Activities Scale	**-0.058**	**0.045**	**0.004**	**-0.048**
College Expectations Scale	**-0.219**	**0.018**	**-0.032**	**-0.238**
English/Language Arts Grade	**-0.204**	**0.034**	**-0.045**	**-0.218**
Math Grade	**-0.113**	**0.003**	**-0.035**	**-0.214**
History/Social Studies Grade	**-0.161**	**0.032**	**-0.018**	**-0.230**
Science Grade	**-0.166**	**-0.002**	**-0.045**	**-0.189**
Trouble in School Scale	**0.396**	**0.065**	**0.019**	**0.111**
Trouble Completing Homework	**0.277**	**0.006**	**0.037**	**0.121**
School Attachment & Perceptions Scale	**-0.266**	**0.018**	**-0.023**	**-0.115**
Students at School Prejudiced	**0.101**	**0.048**	**-0.053**	**-0.033**
Self-Esteem Scale	**-0.218**	**0.015**	**0.025**	**-0.039**
Social Support Scale	**-0.345**	**-0.014**	**0.015**	**-0.048**
Desire to Leave Home	**0.276**	**0.050**	**0.024**	**0.023**
Excused Absences	**0.110**	**0.007**	**0.035**	**0.065**
Unexcused Absences	**0.299**	**0.007**	**0.123**	**0.163**
Delinquency Scale	1.000	**0.050**	**0.041**	**0.066**
Hours Worked Per Non-Summer Week		1.000	**0.010**	**0.040**
School Mobility – Grades 9 to 10			1.000	**0.075**
Grade Retention				1.000

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

APPENDIX B

PEARSON CORRELATION MATRIX FOR DEMOGRAPHIC PREDICTORS OF DROPOUT AND DROPOUT WITH EVENT HISTORY VARIABLES

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables)

	Dropout - Grade 9	Dropout - Grade 10	Dropout - Grade 11	Dropout - Grade 12
Dropout - Grade 9	1	**-0.006**	**-0.009**	**-0.010**
Dropout - Grade 10		1	**-0.032**	**-0.036**
Dropout - Grade 11			1	**-0.054**
Dropout - Grade 12				1

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Suspension - Grade 1	Suspension - Grade 2	Suspension - Grade 3	Suspension - Grade 4	Suspension - Grade 5
Dropout - Grade 9	NA	NA	-0.002	**-0.002**	**-0.004**
Dropout - Grade 10	NA	NA	-0.006	**-0.007**	**-0.013**
Dropout - Grade 11	NA	NA	-0.009	**0.069**	**0.027**
Dropout - Grade 12	NA	NA	-0.010	**-0.012**	**0.021**
Suspension - Grade 1	1	NA	NA	NA	NA
Suspension - Grade 2		1	NA	NA	NA
Suspension - Grade 3			1	**-0.002**	**-0.004**
Suspension - Grade 4				1	**-0.004**
Suspension - Grade 5					1

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Suspension - Grade 6	Suspension - Grade 7	Suspension - Grade 8	Suspension - Grade 9	Suspension - Grade 10
Dropout - Grade 9	-0.005	**-0.008**	**0.071**	**0.041**	**-0.014**
Dropout - Grade 10	-0.018	**0.003**	**0.124**	**0.120**	**0.024**
Dropout - Grade 11	**0.075**	**0.043**	**0.036**	**0.190**	**0.156**
Dropout - Grade 12	0.033	**0.031**	**0.052**	**0.178**	**0.188**
Suspension - Grade 1	NA	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA	NA
Suspension - Grade 3	-0.005	**-0.008**	**-0.011**	**-0.017**	**-0.014**
Suspension - Grade 4	-0.006	**-0.010**	**-0.014**	**-0.021**	**-0.018**
Suspension - Grade 5	-0.011	**-0.017**	**-0.024**	**-0.037**	**0.032**
Suspension - Grade 6	1	**-0.023**	**-0.033**	**-0.051**	**-0.019**
Suspension - Grade 7		1	**-0.052**	**-0.081**	**0.063**
Suspension - Grade 8			1	**-0.113**	**0.080**
Suspension - Grade 9				1	**0.313**
Suspension - Grade 10					1

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Expulsion - Grade 3	Expulsion - Grade 4	Expulsion - Grade 5	Expulsion - Grade 6	Expulsion - Grade 7	Expulsion - Grade 8
Dropout - Grade 9	**-0.001**	NA	**-0.002**	**-0.002**	**-0.003**	**-0.004**
Dropout - Grade 10	**-0.004**	NA	**-0.006**	**0.093**	**-0.010**	**0.047**
Dropout - Grade 11	**0.132**	NA	**-0.009**	**0.056**	**0.041**	**0.062**
Dropout - Grade 12	**-0.007**	NA	**-0.010**	**0.049**	**-0.017**	**0.015**
Suspension - Grade 1	NA	NA	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA	NA	NA
Suspension - Grade 3	**-0.001**	NA	**-0.002**	**-0.002**	**-0.003**	**-0.004**
Suspension - Grade 4	**-0.001**	NA	**-0.002**	**-0.003**	**0.233**	**-0.005**
Suspension - Grade 5	**-0.003**	NA	**0.233**	**0.162**	**-0.006**	**-0.008**
Suspension - Grade 6	**0.241**	NA	**-0.005**	**-0.007**	**-0.009**	**-0.012**
Suspension - Grade 7	**-0.006**	NA	**-0.008**	**-0.011**	**0.113**	**0.028**
Suspension - Grade 8	**-0.008**	NA	**-0.011**	**-0.016**	**0.028**	**0.114**
Suspension - Grade 9	**-0.012**	NA	**-0.017**	**0.098**	**0.037**	**0.083**
Suspension - Grade 10	**0.084**	NA	**-0.014**	**0.120**	**0.013**	**0.051**
Expulsion - Grade 3	1	NA	**-0.001**	**-0.002**	**-0.002**	**-0.003**
Expulsion - Grade 4		1	NA	NA	NA	NA
Expulsion - Grade 5			1	**-0.002**	**-0.003**	**-0.004**
Expulsion - Grade 6				1	**-0.004**	**-0.006**
Expulsion - Grade 7					1	**-0.007**
Expulsion - Grade 8						1

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Expulsion - Grade 9	Expulsion - Grade 10	Expulsion - Grade 11	Expulsion - Grade 12
Dropout - Grade 9	**-0.005**	**-0.004**	**-0.006**	**-0.004**
Dropout - Grade 10	**0.135**	**0.041**	**-0.020**	**-0.016**
Dropout - Grade 11	**0.044**	**0.131**	**0.062**	**-0.023**
Dropout - Grade 12	**0.163**	**0.080**	**0.107**	**0.116**
Suspension - Grade 1	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA
Suspension - Grade 3	**-0.005**	**-0.004**	**-0.006**	**-0.004**
Suspension - Grade 4	**-0.006**	**0.156**	**0.120**	**-0.005**
Suspension - Grade 5	**-0.010**	**-0.009**	**-0.012**	**0.084**
Suspension - Grade 6	**-0.014**	**-0.013**	**0.038**	**-0.013**
Suspension - Grade 7	**-0.023**	**-0.020**	**0.008**	**0.066**
Suspension - Grade 8	**0.027**	**0.004**	**0.040**	**-0.028**
Suspension - Grade 9	**0.239**	**0.184**	**0.088**	**0.115**
Suspension - Grade 10	**0.077**	**0.277**	**0.118**	**0.068**
Expulsion - Grade 3	**-0.003**	**-0.003**	**-0.004**	**-0.003**
Expulsion - Grade 4	NA	NA	NA	NA
Expulsion - Grade 5	**-0.005**	**-0.004**	**-0.006**	**0.193**
Expulsion - Grade 6	**-0.007**	**0.273**	**-0.008**	**-0.006**
Expulsion - Grade 7	**-0.008**	**0.221**	**0.081**	**-0.008**
Expulsion - Grade 8	**-0.011**	**-0.010**	**-0.013**	**-0.010**
Expulsion - Grade 9	1	**0.058**	**0.040**	**0.128**
Expulsion - Grade 10		1	**0.293**	**0.067**
Expulsion - Grade 11			1	**0.109**
Expulsion - Grade 12				1

Note: Significant Correlation Coefficients at $p < 0.05$ level are bolded. Correlation Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Residential Mobility - Grade 0	Residential Mobility - Grade 1	Residential Mobility - Grade 2	Residential Mobility - Grade 3	Residential Mobility - Grade 4
Dropout - Grade 9	**0.021**	**0.058**	**-0.013**	**-0.012**	**-0.013**
Dropout - Grade 10	**-0.011**	**-0.027**	**-0.027**	**0.021**	**0.061**
Dropout - Grade 11	**-0.063**	**-0.015**	**-0.015**	**-0.022**	**-0.024**
Dropout - Grade 12	**-0.049**	**-0.053**	**-0.053**	**-0.032**	**-0.008**
Suspension - Grade 1	NA	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA	NA
Suspension - Grade 3	**0.021**	**-0.013**	**-0.013**	**-0.012**	**-0.013**
Suspension - Grade 4	**-0.031**	**-0.016**	**-0.016**	**0.047**	**-0.015**
Suspension - Grade 5	**-0.032**	**0.005**	**0.005**	**0.010**	**0.008**
Suspension - Grade 6	**-0.010**	**0.010**	**-0.039**	**-0.036**	**-0.011**
Suspension - Grade 7	**0.033**	**-0.062**	**0.031**	**0.025**	**-0.010**
Suspension - Grade 8	**-0.021**	**-0.040**	**-0.028**	**-0.006**	**0.003**
Suspension - Grade 9	**-0.048**	**-0.028**	**-0.028**	**0.006**	**0.001**
Suspension - Grade 10	**-0.060**	**-0.027**	**0.020**	**-0.004**	**0.011**
Expulsion - Grade 3	**-0.018**	**-0.009**	**-0.009**	**-0.009**	**-0.009**
Expulsion - Grade 4	NA	NA	NA	NA	NA
Expulsion - Grade 5	**-0.025**	**-0.013**	**-0.013**	**-0.012**	**-0.013**
Expulsion - Grade 6	**-0.003**	**-0.019**	**-0.019**	**-0.017**	**0.035**
Expulsion - Grade 7	**-0.044**	**-0.023**	**0.018**	**-0.021**	**-0.022**
Expulsion - Grade 8	**0.020**	**-0.001**	**0.030**	**0.003**	**0.034**

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Residential Mobility - Grade 0	Residential Mobility - Grade 1	Residential Mobility - Grade 2	Residential Mobility - Grade 3	Residential Mobility - Grade 4
Expulsion - Grade 9	**-0.039**	**0.063**	**0.013**	**0.019**	**0.043**
Expulsion - Grade 10	**0.008**	**-0.006**	**-0.006**	**-0.031**	**-0.003**
Expulsion - Grade 11	**-0.010**	**0.001**	**-0.021**	**-0.040**	**-0.018**
Expulsion - Grade 12	**-0.028**	**-0.034**	**0.022**	**-0.031**	**-0.003**
Residential Mobility - Grade 0	1	**0.007**	**-0.032**	**-0.029**	**-0.097**
Residential Mobility - Grade 1		1	**0.208**	**0.161**	**0.101**
Residential Mobility - Grade 2			1	**0.225**	**0.164**
Residential Mobility - Grade 3				1	**0.210**
Residential Mobility - Grade 4					1

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Residential Mobility - Grade 5	Residential Mobility - Grade 6	Residential Mobility - Grade 7	Residential Mobility - Grade 8	Residential Mobility - Grade 9	Residential Mobility - Grade 10
Dropout - Grade 9	**-0.013**	**-0.015**	**-0.016**	**-0.016**	**-0.013**	**-0.014**
Dropout - Grade 10	**-0.007**	**-0.035**	**0.011**	**-0.007**	**0.032**	**0.090**
Dropout - Grade 11	**0.025**	**-0.030**	**-0.052**	**0.089**	**0.037**	**0.035**
Dropout - Grade 12	**0.009**	**0.003**	**0.065**	**0.055**	**0.033**	**0.081**
Suspension - Grade 1	NA	NA	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA	NA	NA
Suspension - Grade 3	**-0.013**	**-0.015**	**0.044**	**-0.016**	**-0.013**	**-0.014**
Suspension - Grade 4	**-0.016**	**-0.018**	**0.029**	**0.029**	**-0.016**	**-0.017**
Suspension - Grade 5	**0.105**	**-0.002**	**0.022**	**-0.035**	**0.037**	**0.037**
Suspension - Grade 6	**-0.039**	**0.022**	**-0.006**	**-0.006**	**0.033**	**0.080**
Suspension - Grade 7	**0.014**	**0.014**	**0.029**	**-0.050**	**-0.002**	**-0.019**
Suspension - Grade 8	**-0.041**	**0.028**	**0.002**	**0.031**	**0.026**	**0.036**
Suspension - Grade 9	**0.003**	**-0.004**	**-0.034**	**0.085**	**0.040**	**0.086**
Suspension - Grade 10	**0.045**	**0.017**	**-0.003**	**-0.003**	**0.034**	**0.041**
Expulsion - Grade 3	**-0.009**	**-0.011**	**-0.012**	**-0.012**	**0.089**	**-0.010**
Expulsion - Grade 4	NA	NA	NA	NA	NA	NA
Expulsion - Grade 5	**-0.013**	**0.049**	**0.044**	**-0.016**	**-0.013**	**0.056**
Expulsion - Grade 6	**0.031**	**-0.021**	**-0.023**	**0.020**	**-0.019**	**0.030**
Expulsion - Grade 7	**0.018**	**-0.026**	**0.041**	**0.007**	**0.017**	**-0.024**
Expulsion - Grade 8	**0.059**	**-0.008**	**0.065**	**-0.013**	**-0.032**	**0.057**

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Residential Mobility - Grade 5	Residential Mobility - Grade 6	Residential Mobility - Grade 7	Residential Mobility - Grade 8	Residential Mobility - Grade 9	Residential Mobility - Grade 10
Expulsion - Grade 9	**-0.013**	**0.003**	**-0.025**	**0.061**	**0.086**	**0.109**
Expulsion - Grade 10	**0.049**	**0.012**	**0.029**	**0.029**	**-0.007**	**0.020**
Expulsion - Grade 11	**-0.022**	**0.011**	**0.022**	**0.022**	**0.021**	**-0.001**
Expulsion - Grade 12	**0.021**	**0.012**	**0.053**	**-0.018**	**-0.007**	**-0.008**
Residential Mobility - Grade 0	**-0.127**	**-0.181**	**-0.192**	**-0.214**	**-0.181**	**-0.080**
Residential Mobility - Grade 1	**0.065**	**-0.017**	**-0.059**	**-0.101**	**-0.065**	**0.002**
Residential Mobility - Grade 2	**0.125**	**0.038**	**-0.033**	**-0.093**	**-0.065**	**-0.027**
Residential Mobility - Grade 3	**0.179**	**0.066**	**4.60E-05**	**-0.063**	**-0.055**	**0.027**
Residential Mobility - Grade 4	**0.192**	**0.079**	**1.30E-02**	**-0.040**	**-0.027**	**-0.019**
Residential Mobility - Grade 5	1	**0.098**	**0.024**	**-0.035**	**0.002**	**0.049**
Residential Mobility - Grade 6		1	**0.002**	**-0.059**	**-0.021**	**0.057**
Residential Mobility - Grade 7			1	**-0.077**	**-0.054**	**0.069**
Residential Mobility - Grade 8				1	**-0.062**	**0.052**
Residential Mobility - Grade 9					1	**0.162**
Residential Mobility - Grade 10						1

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Female	Latinx Ethnicity	Black	Native American	Asian	Other Race	Multi-racial
Dropout - Grade 9	0.038	**-0.016**	**-0.020**	**-0.004**	**-0.009**	**-0.009**	**-0.009**
Dropout - Grade 10	-0.017	**0.048**	**-0.026**	**-0.016**	**-0.032**	**-0.007**	**0.028**
Dropout - Grade 11	-0.004	**0.023**	**0.037**	**0.015**	**-0.011**	**-0.014**	**-0.026**
Dropout - Grade 12	0.004	**0.038**	**-0.014**	**-0.026**	**-0.054**	**-0.005**	**0.040**
Suspension - Grade 1	NA	NA	NA	NA	NA	NA	NA
Suspension - Grade 2	NA	NA	NA	NA	NA	NA	NA
Suspension - Grade 3	-0.003	**-0.016**	**0.033**	**-0.004**	**-0.009**	**-0.009**	**-0.009**
Suspension - Grade 4	0.013	**-0.019**	**0.019**	**-0.005**	**0.069**	**-0.012**	**-0.011**
Suspension - Grade 5	-0.055	**0.024**	**0.082**	**-0.009**	**-0.019**	**-0.020**	**-0.018**
Suspension - Grade 6	**-0.059**	**-0.025**	**0.032**	**-0.013**	**-0.027**	**-0.028**	**0.010**
Suspension - Grade 7	-0.055	**-0.008**	**0.091**	**-0.020**	**-0.021**	**0.038**	**-0.018**
Suspension - Grade 8	-0.040	**0.027**	**0.024**	**0.004**	**-0.012**	**0.031**	**0.061**
Suspension - Grade 9	**-0.079**	**0.023**	**0.107**	**0.024**	**-0.036**	**0.035**	**0.066**
Suspension - Grade 10	**-0.081**	**0.012**	**0.033**	**-0.037**	**-0.012**	**-0.017**	**0.035**
Expulsion - Grade 3	-0.031	**-0.011**	**0.060**	**-0.003**	**-0.006**	**-0.007**	**-0.006**
Expulsion - Grade 4	NA	NA	NA	NA	NA	NA	NA
Expulsion - Grade 5	-0.044	**0.045**	**0.033**	**-0.004**	**-0.009**	**0.085**	**-0.009**
Expulsion - Grade 6	-0.004	**-0.022**	**0.121**	**-0.006**	**-0.013**	**-0.013**	**-0.012**
Expulsion - Grade 7	-0.029	**0.008**	**0.026**	**0.107**	**0.041**	**-0.016**	**-0.015**
Expulsion - Grade 8	-0.016	**0.094**	**-0.002**	**0.159**	**-0.021**	**0.140**	**-0.020**

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Female	Latinx Ethnicity	Black	Native American	Asian	Other Race	Multiracial
Expulsion - Grade 9	-0.023	**0.020**	**0.018**	**-0.012**	**-0.026**	**0.007**	**0.121**
Expulsion - Grade 10	-0.016	**-0.016**	**0.094**	**-0.011**	**0.054**	**-0.024**	**0.018**
Expulsion - Grade 11	-0.029	**0.005**	**0.049**	**0.047**	**0.031**	**0.028**	**0.099**
Expulsion - Grade 12	-0.016	**0.032**	**0.073**	**-0.011**	**0.015**	**-0.024**	**0.018**
Residential Mobility - Grade 0	-0.053	**0.064**	**-0.024**	**-0.010**	**0.063**	**0.034**	**-0.006**
Residential Mobility - Grade 1	-0.018	**0.085**	**-0.081**	**0.022**	**0.123**	**0.047**	**0.005**
Residential Mobility - Grade 2	-0.018	**0.119**	**-0.058**	**0.022**	**0.081**	**0.087**	**-0.024**
Residential Mobility - Grade 3	-0.047	**0.098**	**-0.049**	**-0.002**	**0.140**	**0.060**	**0.045**
Residential Mobility - Grade 4	0.002	**0.091**	**-0.031**	**-0.003**	**0.120**	**0.056**	**-0.019**
Residential Mobility - Grade 5	-0.047	**0.030**	**-0.053**	**0.021**	**0.079**	**0.019**	**-0.025**
Residential Mobility - Grade 6	-0.022	**0.040**	**-0.021**	**-0.013**	**0.120**	**0.013**	**0.015**
Residential Mobility - Grade 7	0.035	**0.068**	**-0.021**	**0.053**	**0.030**	**0.057**	**-0.022**
Residential Mobility - Grade 8	0.015	**0.076**	**-0.002**	**0.029**	**0.042**	**0.080**	**0.015**
Residential Mobility - Grade 9	-0.013	**0.087**	**0.039**	**-0.007**	**0.037**	**0.017**	**0.017**
Residential Mobility - Grade 10	0.015	**0.152**	**-0.007**	**0.020**	**-0.019**	**0.042**	**0.030**

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	Female	Latinx Ethnicity	Black	Native American	Asian	Other Race	Multiracial
Female	1	**-0.021**	**0.025**	**0.017**	**-0.085**	**-0.021**	**0.043**
Latinx Ethnicity		1	**-0.180**	**0.104**	**-0.073**	**0.525**	**0.019**
Black			1	**-0.051**	**-0.107**	**-0.111**	**-0.102**
Native American				1	**-0.023**	**-0.024**	**-0.022**
Asian					1	**-0.051**	**-0.046**
Other Race						1	**-0.048**
Multiracial							1

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.

Table B.1 Pearson Correlation Coefficients for Predictors and Dropout (Event History Variables; cont.)

	U.S. Born	Public Assistance	Parental Education
Dropout - Grade 9	**0.011**	**-0.014**	**-0.035**
Dropout - Grade 10	**-0.006**	**0.043**	**-0.108**
Dropout - Grade 11	**0.029**	**0.039**	**-0.111**
Dropout - Grade 12	**0.009**	**0.175**	**-0.127**
Suspension - Grade 1	NA	NA	NA
Suspension - Grade 2	NA	NA	NA
Suspension - Grade 3	**0.011**	**-0.014**	**0.009**
Suspension - Grade 4	**0.014**	**-0.018**	**-0.003**
Suspension - Grade 5	**-0.014**	**0.063**	**-0.014**
Suspension - Grade 6	**0.033**	**0.003**	**-0.010**
Suspension - Grade 7	**3.44e-04**	**-0.025**	**-0.008**
Suspension - Grade 8	**-0.005**	**0.025**	**-0.045**
Suspension - Grade 9	**0.003**	**0.158**	**-0.157**
Suspension - Grade 10	**0.021**	**0.105**	**-0.062**
Expulsion - Grade 3	**0.008**	**0.083**	**0.031**
Expulsion - Grade 4	NA	NA	NA
Expulsion - Grade 5	**0.011**	**0.052**	**-0.017**
Expulsion - Grade 6	**0.016**	**0.026**	**-0.024**
Expulsion - Grade 7	**0.020**	**0.051**	**-0.040**
Expulsion - Grade 8	**-0.111**	**0.023**	**-0.084**
Expulsion - Grade 9	**-0.025**	**0.123**	**-0.105**
Expulsion - Grade 10	**-0.035**	**0.067**	**-0.039**
Expulsion - Grade 11	**0.012**	**0.015**	**-0.014**
Expulsion - Grade 12	**-0.035**	**0.015**	**-0.039**
Residential Mobility - Grade 0	**-0.226**	**-0.098**	**0.019**
Residential Mobility - Grade 1	**-0.334**	**-0.037**	**-0.046**
Residential Mobility - Grade 2	**-0.345**	**-0.028**	**-0.053**
Residential Mobility - Grade 3	**-0.367**	**0.025**	**-0.063**
Residential Mobility - Grade 4	**-0.285**	**0.030**	**-0.081**
Residential Mobility - Grade 5	**-0.295**	**-0.002**	**-0.040**
Residential Mobility - Grade 6	**-0.209**	**0.016**	**-0.026**
Residential Mobility - Grade 7	**-0.172**	**0.060**	**-0.034**
Residential Mobility - Grade 8	**-0.065**	**-0.012**	**0.002**
Residential Mobility - Grade 9	**-0.090**	**0.024**	**-0.105**
Residential Mobility - Grade 10	**-0.076**	**0.067**	**-0.058**
Female	**0.057**	**-0.002**	**-0.075**
Latinx Ethnicity	**-0.358**	**0.067**	**-0.232**
Black	**0.108**	**0.156**	**0.087**
Native American	**-0.035**	**-0.011**	**-0.046**
Asian	**-0.269**	**-0.077**	**-0.017**
Other Race	**-0.256**	**-0.005**	**-0.110**
Multiracial	**-0.024**	**0.075**	**0.006**
U.S. Born	1	**0.032**	**0.169**
Public Assistance		1	**-0.239**
Parental Education			1

Note: Significant Coefficients at $p < 0.05$ level are bolded. Coefficients all based on unweighted data.