The Louisiana Recovery School District's long term relationship to student dropout and achievement

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THE LOUISIANA RECOVERY SCHOOL DISTRICT’S LONG TERM RELATIONSHIP TO STUDENT DROPOUT AND ACHIEVEMENT

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

The School of Social Work

by

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August 2013
I would like to dedicate this dissertation to the memory of my grandparents, Efem Ledet and Lorena Williams Ledet, my uncle, Leroy Ledet, and my Blueberry. You have been guardian angels watching over my life and my work.

I also want to dedicate this project to my family, without whom I would not have been able to begin or complete my work. The path had been paved for me by my uncles, aunts, and cousins who lived during difficult times, with fewer opportunities for educational advancement. During any challenge in my path, I remember that I owe it to you all to do my best to honor your sacrifices. The L. in the initials of my name represents the family name, LEDET. This is their work as much as it is mine.

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ABSTRACT

May 14, 2013 marked the 10-year anniversary of the creation of the Louisiana Recovery School District (RSD), the turnaround intervention for low performing public schools. Since 2003, the RSD has grown to include over 80 schools across the state. The purpose of this multilevel longitudinal study was to examine the relationship of the Louisiana Recovery School District to student and school outcomes including risk of dropout and standardized test scores. The dissertation measured these influences over time (2007-2010). The data collected were derived from Louisiana’s Educational Assessment Program (LEAP) and quantitative data on dropout status from the Louisiana Department of Education Student Information System (SIS) database.

To explore the RSD’s relationship to risk of dropout and student achievement scores over time, two analyses were conducted. First, to examine the relationship between student and school level predictors and the risk of dropout, a multilevel discrete-time survival analysis was conducted. The level 1 analysis included time and student level covariates, while level two included school level covariates. The results of the this analysis indicate that when controlling for student level covariates, RSD students are at a 3.25 times greater risk of dropout than traditional public school students. Next, in the study of the RSD’s relationship to student achievement, a three-level hierarchical linear model was run to account for repeated measures and nested data. The level one analysis examined the influence of time on LEAP/iLEAP scores. The level two analysis examined the influence of student characteristics including race, gender, and free and reduced lunch status on student scores. The third level examined the influence of aggregated school level predictors including school type (RSD versus traditional public school).
on student scores. Results indicate that student characteristics of disadvantage including minority status and low socioeconomic status are linked to lower test performance over time. For Sample A, the school level covariate, school type, was significant in each model, suggesting that even when controlling for student and other school level factors, school type accounted for variation in student scores over time. RSD students performed significantly lower than TPS students in both ELA and math over the 4 year period of the study. The school level covariate, school type, was also significant for Sample B indicating that students in RSD schools perform lower on ELA and Math portions of the LEAP/iLEAP/GEE than their TPS counterparts. When controlling for other school level covariates in Sample B, the effect for school type was no longer significant. No other school level covariates were significant in the models suggesting that variation in outcomes was accounted for by student level characteristics and time rather than by school level characteristics.
CHAPTER 1: INTRODUCTION

As recently as 2012, the Louisiana Recovery School District (RSD) was hailed by the Brown Institute as having a choice and competition index letter grade of A. This was the only A awarded to any school system in the country. A study from Thomas Fordham Institute in 2012 echoed the same information, with summaries of the percentage increases in achievement for RSD schools in New Orleans (Smith, 2012). Press releases from the Louisiana Department of Education hail the “incredible gains” for New Orleans Recovery School District students. As recently as 2011, the Ohio State Board of Education chose to model its school reform efforts after the Louisiana RSD. Several other reports tout the school improvement efforts of the Louisiana RSD and how these efforts can and should be used as a model for other states in addressing educational equality in their public school systems. While these reports use snapshots of data (Buras, 2012), the current study goes farther than previous work and is the first to examine the longitudinal effects of the RSD on student outcomes of risk to dropout and student achievement.

The educational equality gap has been classified as the largest civil rights issue of the 21st century by politicians and scholars alike (Khazei, 2009). It describes the persistent divide between economically disadvantaged, people of color and White, and economically stable populations (McKinsey & Company, 2009) in several educational areas. The gap manifests itself largely in access to prenatal healthcare, quality pre-kindergarten, resourced schools, educational achievement, and highly qualified teachers (McKinsey & Company, 2009). Some argue that “the gap” is as old as the nation itself. From those remotely interested in educational policy and practice to those deeply involved, this phenomenon is so widely known that it has become a cliché: commonplace and enduring, despite the plethora of efforts to reduce it.
Scholars, politicians, educators, and researchers generally frame educational inequality by associating it with levels of student achievement. In this way, inequality in education manifests in academic outcomes for students. These outcomes include letter grades, grade point averages, graduation rates, and standardized test scores (Farrell, 1999). The term that collectively describes these outcomes and the differences in groups’ scores is the “achievement gap.”

Though the majority of research focuses on academic outcomes when investigating the achievement gap, Farrell (1999) offers a broader context to the measurement of educational inequality by giving three areas where inequality manifests itself. His framework, labeled “levels of equality,” operationalizes the concept of equality in education (Farrell, 1999). These levels include two key areas, namely equality of access and equality of survival (Farrell, 1999). Equality of access refers to the ability of students to enroll in all levels of schooling. Because schooling in kindergarten-12th grade (K-12) is compulsory, researchers suggest that smaller inequities exist at this level but suggest that one can observe the largest discrepancy in access at the postsecondary, or collegiate level (Farrell, 1999). Completion rates compose Farrell’s (1999) second level of equality, known as the level of survival in education. This is often measured by graduation and/or dropout rates. In addition to graduation and dropout rates, scholars also use measures such as grade point averages and standardized test scores, which influence graduation and/or dropout rates. Finally, in addition to Farrell’s levels the literature also examines the equality of school resources, which include financial, material, and human resources (Alliance for Excellent Education, 2008).

**Scope of the Problem**

Society cannot avoid witnessing the consequences of the gap. The gap has been linked to numerous negative outcomes including the following: lower lifetime earnings, lower rates of
graduation from high school and college, poorer healthcare, and higher rates of incarceration for the disadvantaged populations caught in its divide (Alliance for Excellent Education, 2009). For larger society it also poses great financial risk. McKinsey and Company (2009) characterize the gap as an imposition “on the United States [that is] the economic equivalent of a permanent national recession” (p.5). As children progress through the American education system many face challenges that lead to low achievement, drop out, or participation in negative behavior. According to the Alliance for Excellent Education (2009), student achievement correlates directly with the United States’ economic stability. The Alliance (2009) reports that if all of the dropouts from the “class of 2009 had graduated, the nation’s economy would have benefited from nearly $335 billion in additional income over the course of their lifetimes” (p. 1). In addition to these high costs for the larger society, failure to graduate from high school correlates with an increase in crime related expenses and incidents (Page, Petteruti, Walsh, & Ziedenberg, 2007). The incidents, then, destroy safety within communities, while the expense of crime control puts a strain on an already burdened economy (Alliance for Excellent Education, 2009; Page et al., 2007). The demonstrated link between educational achievement or lack thereof, and positive and negative outcomes for society necessitate action to ensure educational equality for all children (Alliance, 2009).

In each of Farrell’s (1999) previously named educational levels, inequality exists according to ethnic, economic, regional, and/or gender differences. These negative outcomes are differentiated by subgroups of the population, which creates inequality within the education system and leaves high costs to children, families, communities, and the larger society. The majority of the education literature addresses Farrell’s (1999) survival level of educational equality. Where race and socio-economic status intersect, low-income minorities living in the
United States face exacerbated problems at the survival level of education (Page et al., 2007). For example, the Alliance for Excellent Education (2009) reports that, “about 55% of Hispanic students and 51% of Black students will graduate on time with a regular diploma, compared to 79% of Asian students and 76 percent of White students” (p.3). In addition, it reports that high school students of low-income families drop out of high school at six times the rate of their peers from high-income families (Alliance for Excellent Education, 2007). Also, Carey (2005) reports that only 40.5% of African American students and 47% of Latino students graduated from college within six years as opposed to 59.5% of whites. Regional differences in the survival level of educational equality categorize the country into high performing and low performing regions. In 2007, for example, while only 36.4% of the 16-24 year old population lived in the South, 42.1 percent of all dropouts lived in the South (Cataldi, Laird, & KewalRamani, 2009). The West also had a higher percentage of dropouts than its total population aged 16-24 (Cataldi et al., 2009). In comparison, the Midwest and Northeast had lower percentages of dropouts than their 16-24 year old populations (Cataldi et al.). Lastly, though the gender gap is decreasing, it still exists. According to Cataldi et al. (2009), males ages 16–24 dropped out of high school at a 9.8% rate compared to females at 7.7%.

At the access level, where students gain entrance into school systems, post-secondary inequality manifests in low minority and socio-economic status college enrollment. As discussed earlier, K-12 enrollment is compulsory, so the inequality of enrollment at those levels is minimized. The National Center for Education Statistics (NCES) (2009) reports that in 2007 “sixty-four percent of the college population was White compared to 13% Black, 11% Hispanic, and 7% Asian/Pacific Islander” (p. 94). Its reports are based on data from 2 year and 4-year for profit and not for profit institutions of higher learning. As compared to all other students in all
institutions, the percentage of Black students in public and not for profit two-year institutions was higher (14% and 19%). Likewise, sixteen percent of Hispanic students at public two-year institutions was higher than the percentage of Hispanics at all institutions. Also from this report, Planty, Hussar, Snyder, Kena, KewalRamani, et al. (2009) found that along gender lines, female undergraduate enrollment increased at 26% compared to an increase of only 23% for males.

In addition to Farrell’s levels (1999) the literature also examines large gaps that exist in the resource level or level of human capital in education. When addressing human capital, the National Center for Education Statistics (2004) reports that in high schools with a student body of at least 75% African Americans, teachers of math and science are either uncertified or out of their field three times more than higher income schools. Its results are drawn from previous NCES survey data from the national student and staffing survey conducted in 1999-2000. When examining financial resources, schools with the highest minority populations receive an average of $877 less per student than those schools with lowest minority populations (Alliance for Excellent Education, 2008). In the annual NCES report “Condition of Education,” Planty et al. (2009) describe the intersection of race and socio-economic status, with its data showing that “33% of Black, 35% Hispanic, and 25% of American Indian/Alaska Native students enrolled in high poverty schools compared to 4% White and 13% Asian/Pacific Islander” (p. 64).

**Theoretical Frameworks**

Despite the perpetual effort by scholars, educators, and politicians to decrease the achievement gap, all continue to debate the best methods to address the problem. A major point of contention stems from theories of the underlying causes of the gap. Many of the unsuccessful attempts at education reform result from incorrect identification of the causes of this gap.
Theories offered in the literature to explain the persistence of the achievement gap range from individual deficiencies to societal dysfunction.

A popular explanation for the achievement gap between minorities and whites offered in the 1960s was the innate intellectual inferiority of minorities as evidenced by early performance on IQ tests. Jensen (1969) supported biological determinism as a viable explanation for the gap after he concluded that 80% of the variance in IQ scores had a genetic basis and that environmental factors such as inferior schools and poorly qualified teachers only accounted for an 18-point difference in IQ. His explanation of IQ in relation to minorities was viewed as faulty due to the lack of minority participants in his study. Likewise, Moynihan (1965) considered structural deficiencies within the black family as key contributors to the academic divide between Blacks and Whites. His report produced for the federal government in 1965 highlighted the large number of Black families that were headed by single parents, impoverished, and prone to having out-of-wedlock births. These were underlying reasons for their lower academic performance and success in school.

Biological determinism has been widely challenged as unethical and amoral, although this premise resurfaced in the book “Bell Curve” by Hernstein and Murray (1994), who also found innate racial differences in intellectual capacity. Other criticisms of the IQ theories include the lack of context offered in IQ testing and the cultural biases inherent in the test (Senna, 1973). For example, when psychologist, Robert Yerkes, tested 1.75 million army recruits (Carson, 1993), he developed two different tests for those who could read and those who could not read. Testing outcomes between races of recruits varied greatly, including differences between Blacks and whites. Although Yerkes claimed that the recruits' innate intelligence explained differences
in performance on these tests, many researchers argued that these test were culturally biased (Senna, 1973).

In his application of determinism to the current social order of his time, Spencer (1896) coined the phrase “survival of the fittest” when describing the current strata of groups within society. His theory has also been called social Darwinism, in which groups within society evolve over time, resulting in a natural hierarchy of status. Spencer’s (1896) theory thus necessitated no action from the government or larger society at addressing societal ills or educational inequalities, since the current grouping or achievement levels were a product of survival of the fittest demonstrating their superiority.

Another theory of the contributing factors to the achievement gap are offered by John Ogbu, namely, oppositional culture theory. Through observations and interviews of American minorities, Ogbu (1991) claimed that minorities could be categorized into voluntary and involuntary groups that correspond to their level of adaptation and eventual social status in American society. Voluntary immigrants are those groups who interpret American society as a place full of opportunities when compared with opportunities in their native countries. These minorities then wholeheartedly engage in the American education system, yielding successful achievement and subsequent high levels of social status. According to Ogbu (1991) minority groups that migrate to the United States involuntarily, however, do not perceive higher levels of opportunity in America and are resentful of being forced to migrate. He reported that African Americans compose a large percentage of this group. Ogbu (1991) therefore, proposed that African Americans develop a culture that opposes white-dominated institutions including the education system. Thus, their efforts at academic achievement and subsequent status in society are less than other voluntary minorities or whites.
Harris (2006) is among scholars that have disputed Ogbu’s (1991) theory. Harris used a dataset that included variables on Maryland adolescents to test the hypothesis that Blacks resist school more than Whites. Using a stratified random sample of middle school students, (N=1480), he examined student effort over time from the year students entered middle school until 3 years post-high school. His findings from the pooled cross sectional analysis revealed that there were no significant differences between Blacks and whites on educational expectations or time spent on homework. This contrasts Ogbu’s premise that involuntary immigrants, particularly African American’s, fail to engage completely in the American education system.

Sociological theories explaining social stratification in society have often been applied to education. Three major theories include structuralism, conflict theory, and symbolic interactionism. These theories outline the nature of the processes that lead to the current hierarchy of racial and class groups in society based on status, wealth, and power.

Davis and Murray (1945) explained the functional nature of American education in their theory, which proposes societal demands dictate the current educational needs, focus, and outcomes. A prominent example of functional theory is the industrial or technological changes in society over time that necessitated changes in educational curriculum. The changes in education also created a framework for subsequent occupation. The logic was that workers will have to be trained at school or have innate skills to rise to the challenges of a more industrial and technological society. According to this theory, then, the gaps in educational achievement would be a result of societal needs for workers at different status levels, with those in lower levels either not learning necessary skills at school or not possessing the innate capability to perform higher job functions.
Conflict theory also proposes an explanation of the processes in society that lead to stratification. Max Weber (1978) from his study of education in Prussia suggested that society is composed of groups that share values, norms, and culture that lead them to distinguish themselves from other groups in society. These groups compete for power and wealth within society, with the resulting dominant group dictating many of the structures in society including the educational system. Once the dominant group is established, educational and societal norms mimic the norms of that group. This leads to educational content in schools, for example, that does not include other minority perspectives. Likewise, the dominant group may be able to dictate the current measures of success in schooling and in the occupational world.

Lastly, the sociological theory of symbolic interactionism offers insight into how people make sense of the world around them. The process includes meaningful interaction between individuals and groups of individuals that create learning about one’s place in society (Cooley, 1902). The dominant group interacts with subgroups in ways that perpetuate their dominant status. Thus, teachers and students in schools learn from each other about proper roles in society.

The influence of the dominant group in perpetuating its norms and expectations in society is characteristic of another category of theories about institutional effects on student academic success. In 1965, Aronowitz and Giroux explored the concept of institutional racism in society. They defined institutional racism as the consistent allocation of resources to certain groups in society that privileges these above other groups. From their definition, education scholars have since applied these concepts to educational stratification and educational inequality. Scholars suggest that institutional racism is often not a conscious choice to discriminate against certain groups, but may manifest in the persistent assignment of minority students to low performing
and dilapidated schools (Taylor & Clark, 2009) or the matching of non-highly qualified teachers or leaders to minority schools.

Recently, Taylor and Clark (2009) examined qualitative data from principal and teacher interviews and observations in a large urban school district to determine whether institutional racism was present and whether or not it resulted in a sabotage of school improvement efforts. The district in their study was under a desegregation suit that involved busing students to schools across the district in an effort to integrate schools. The school from which data was collected was 97% Black, although the district was only 60% black. The school received over $350,000 for qualifying as a Title I school, which is an impoverished school in need of improvement and granted money from the federal government. The researchers determined that institutional racism was present in the school and evidenced by the assignment of a less than qualified interim principal to the already failing school. The actions of this principal resulted in a sabotage of school improvement efforts at the school, failure to advance student learning and few opportunities for students to use higher order thinking skills.

This type of allocation of such unqualified teachers and leaders is well documented in the educational inequality literature. Fram, Miller-Cribbs and Van Horn (2007) for example, drew subsets of Black, White, and Hispanic data from the early childhood longitudinal survey-kindergarten cohort in the fall of 1998. The sample size of students was 3,501. The researchers examined the effects on reading skills assessments of school, child and family, and classroom variables included in the survey. Parent and family variables included race, gender, age, and parent education level; classroom variables included teacher ethnicity, years of employment, and certification type; school variables included rural or urban location and the percentage of students that qualify for free and reduced lunch. The researchers found that high ethnic minority
schools differed from low ethnic minority schools significantly in that the classrooms were less adequately staffed, the teachers had significantly less years of education, and lower certification levels.

Likewise, Orfield and Lee (2005) reported demographics of high poverty schools including statistics revealing that 50% of Black and Hispanic students attend high poverty schools compared to 30% Asian and 18% white students. The problems of high poverty schools outlined by Fram, Miller-Cribbs, and Van Horn (2007) are thus experienced by a higher percentage of Black and Hispanic students. Orfield and Lee (2005) also reported that between 73% to 77% of Black and Latino students attend schools that are mainly made of minority students. This data is concerning considering that freshmen in schools that are majority minority are five times less likely to graduate than those in non-majority minority schools (Orfield & Lee). Similarly, (Alliance for Excellence in Education, 2008) reports that in schools that are at least 75% minority, the teachers of math and science are three times more likely to be uncertified or teaching out of their field of expertise. The plethora of examples in the literature of poor allocations and corresponding poor outcomes are demonstrations of the persistent distribution of “resources” in a way that privileges other groups over these high minority groups and schools.

A final theory has also demonstrated substantial support in the literature: Bordieu’s (1973) theory of the forms of capital. Becker (1964), Bowles and Gintis (1975), and Coleman (1968) defined human capital as the tangible resources including wealth, skills, and knowledge possessed by an individual that when accumulated can provide social power. For individuals, this manifests in assets, accumulated wealth, level of education, and how many degrees earned. For schools and districts, this can manifest in the amount of accumulated skills, knowledge, and certifications possessed by the teaching staff and leadership (Becker, 1964; Bowles & Gintis,
Human capital has been linked to greater academic outcomes for those who possess it in adequate amounts as evidenced in the findings of Fram, Miller-Cribbs, and Van Horn (2007) and Orfield and Lee (2005). Those with high levels of human capital have access to a wider variety of educational options including private schools or quality neighborhood schools that are a reflection of residential choice (Hansen, 2008). Hansen (2008) argues that the educational achievement and socioeconomic status of parents influences their student’s level of educational attainment because wealthier families can purchase better education even during times of financial instability. Thus lower socioeconomic groups whose parents have low levels of education attainment will be limited in their subsequent achievement.

Another form of capital that influences status in society and educational outcomes is social capital. Social capital is the accumulation of networks and connections outside of the immediate family that give individuals and groups social energy or advantage over other groups (Bourdieu, 1973). Parental linkages and inclusion in powerful networks manifests in access to more resourced schools with highly qualified teachers and staff. It allows families to move into neighborhoods with others of shared values or who are in the social network. Within the school system, students with high amounts of social capital have access to more variety of opportunities due to their connections (Coleman, 1968; Pfeffer, 2008). Limitations of social capital serve as barriers or roadblocks to low-socioeconomic status and ethnic minority students who are seeking upward mobility within the education system (Coleman, 1968; Pfeffer, 2008). Whereas social capital can manifest in numerous opportunities for students to witness successful completion of high school and college, limited social capital can serve as a blinder to the many opportunities due to lack of connections to demonstrate such success. Schools and districts can also be privy to the benefits of social capital when seeking funding or consideration for new reforms or projects.
Some schools and districts with limited social capital find it difficult to secure support from those outside of their established networks.

Lastly, cultural capital refers to the store of knowledge, norms, artifacts, and expectations that allow cultures to distinguish themselves from others (Bourdieu, 1973). This manifests in education as expectations for high school and college completion from family members, as well as the involvement of family members in student education, that influences the likelihood of students accomplishing these outcomes. Likewise, the standard for academic success while in school can be set through cultural capital. The dominant groups with the most cultural capital yield sway in society on which norms and values are taught and what is considered success. Those with limited cultural capital often do not perceive the same level of expectations for success in schooling or in subsequent job acquisition as those with high levels of cultural capital. Bourdieu (1973) emphasizes how these forms of capital present students with a “head start” in schooling and in their eventual outcomes, whereas disadvantaged students, those without high levels of these forms of capital start at a different level.

**Which Theory Best Explains the Persistence?**

The achievement gap is a manifestation of a larger gap referred to as the educational equality gap. The education equality gap includes differential access to prenatal healthcare, quality pre-kindergarten programs, resourced schools, and highly qualified teachers. Though the reform emphasis often fails to address these larger systemic issues, they are a key to understand which factors perpetuate the divide. Theory extending beyond an explanation of differences in achievement levels is necessary to address the larger systemic issues that affect educational outcomes. Bourdieu’s (1973) theory of the influence of forms of capital on education and social
reproduction and Aronowitz and Giroux’s (1965) theory best address the many facets of educational equality, while also demonstrating empirical support.

The literature demonstrates the persistent resource deficits faced by high minority, high poverty schools and resulting low academic outcomes. There is a consistent demonstration that low poverty, majority white schools have more highly qualified teachers and staff, larger budgets, and thereby better academic outcomes. This persistent misallocation points to the institutionalization of these processes, which according to Aronowitz and Giroux (1965) is indicative of institutional racism. These same deficiencies that are indicative of institutional racism are manifestations of lack of capital. Dominant groups who have higher levels of human capital (highly qualified teachers, resourced schools, high parental socioeconomic status, high parental educational attainment), social capital (linkages to outside support and funding), and cultural capital (knowledge and expectations of how to achieve, parental involvement) achieve better academic outcomes. Those individuals, groups, and schools who have limited amounts of capital experience the negative outcomes detailed in the literature. Thus, these two theories interface to address factors that have been consistently shown to influence the achievement gap, despite efforts to address it.

**Contribution to Social Science**

Educational policy must address the institutional and capital issues faced by disadvantaged schools and districts in order to facilitate increases in achievement. Current policy appears to mimic the fallacy cautioned by Bourdieu (1973) of denying the value of the head start provided by high levels of human, social, and cultural capital. This has been a major criticism of No Child Left Behind (Lagana-Riordan, 2009). Taylor and Clark (2009) also warn that policies, not people are the underlying cause for most acts of institutional racism because being in
compliance with the current educational law, may actually lead a person to make decisions that disadvantage certain groups, such as the implementation of ineffective interventions that have not been studied for effectiveness.

It appears that some of the trends in the achievement gap coincide with federal and local efforts to decrease the gap by addressing systemic issues beyond achievement. Barton and Coley (2010) reviewed data from the National Educational Assessment Program (NAEP) from the years 1970-2002 to determine what trends of achievement have emerged. These assessments are given every four years in the areas of reading and math to random samples of students across the country. From their review they determined that the achievement gap between minorities and whites narrowed between the 1970s and 1980s, then became stable again until 1999 when it narrowed again until 2004. The 1950s and 60s were characterized by federal intervention in local schools and districts specifically for the purposes of addressing educational equality for disadvantaged populations. Supreme Court rulings on Brown vs. the board of education of Topeka, Kansas called for desegregation, but states had been slothful in implementing it. Most of its implementation occurred in the mid-to late 1960s and early 1970s. Also, in the 1965 Elementary and Secondary Education Act, the federal government gave money specifically to impoverished and underprivileged schools for the first time in history and mandated that if a school was to receive federal money, there must be a non-discrimination clause at the school.

**Purpose of the Study**

The purpose of this study is to examine the longitudinal relationship between the Recovery School District (RSD) and a matched set of traditional public schools (tps) on decreasing the achievement gap between advantaged and disadvantaged students in public schools in Louisiana. The objectives of the study include exploring which student and school
factors are related to the variation in dropout risk and student achievement scores over time. A central objective is to determine the extent of differences on the two student outcomes according to type of school (RSD versus TPS) a student attended. The LA-RSD is identified as Louisiana’s turnaround zone and should demonstrate its ability to decrease the gap.

**Research Questions**

1. What is the likelihood that a student will drop out of RSD schools compared to a matched set of traditional public schools at a given time?

2. Do student characteristics influence the risk of students dropping out of school at a given time?

3. Do school characteristics influence the risk of students dropping out of school at a given time?

4. Do standardized test scores vary by school type (RSD schools versus traditional public schools) in Louisiana?

5. Do student characteristics account for the variation in standardized test scores in state takeover and traditional public schools?

6. Do school characteristics account for the variation in standardized test scores between recovery schools and traditional public schools?
CHAPTER 2: LITERATURE REVIEW

Beginnings of Public Education

Public education and school reform follow an inextricably linked pattern in American history. Reform measures enacted by local, state, and federal agencies as early as the 1800s, helped shape the current structure and operation of the public school system. Even the compulsory nature of today’s public school system evolved over time as a result of reform policies. According to Schneider and Kessler (2007) compulsory education did not exist in colonial America. Students attended school for short periods of time and did so sporadically. In the 1800s, states enforced compulsory attendance laws modeled after the Massachusetts Compulsory School Act, and by 1918, forty-eight states had them in place (Allen-Meares, 2004). At that time, local governments managed public schools, and public education centered on religious teachings (Butts & Cremin, 1953). By 1850, public education systems offered entry to all citizens, excluding slaves, and had a state office of the superintendent (Salmone, 2000). The federal department of education did not exist, nor did the state office of the superintendent do anything more than facilitate local education affairs (Schneider & Kessler, 2007). These preliminary developments in public education served as precursors to larger and more comprehensive changes over recent decades. This paper addresses subsequent state and federal policies developed to reform the public education system and preliminary results of their effectiveness.

Setting the Stage for Reform

Once state education systems formalized their schooling practices, distinct inequalities manifested. Racial inequities manifested across the country’s schools, particularly in southern states. Black students and white students attended separate schools, with Black schools having
fewer resources and housed in dilapidated buildings (Butts & Cremin, 1953). In a segregated South that relegated Blacks to back door entrances and back seats on busses, Blacks sought equal access in education. Within the larger struggle for civil rights, the Supreme Court ruled that segregation met constitutional guidelines provided that the separate facilities were of equal condition. This landmark case is known as Plessy versus Ferguson (1896).

Disability status also garnered discrimination in the early public education system. Schools turned away disabled students by classifying them as “uneducable” if they had disabilities that the school lacked resources to address. This practice occurred as late as 1969 (Allen Meares, 2004). According to Altshuler and Kopels (2003), over 1 million children faced complete exclusion from public schools, and those who enrolled often failed to receive adequate educational services.

Gender based inequality manifested in public education, in addition to disability and racial inequalities. According to the National Coalition for Women and Girls in Education (NCWGE) (2002), females accessed training courses in high schools and vocational schools at a much lower rate than their male counterparts. Women also encountered exclusionary policies when attempting to participate in sports other than cheerleading. This left them without access to college athletic scholarships, among other challenges.

As immigration increased in the United States, language surfaced as another major source of bias in public education. Twenty eight million US citizens born in countries outside of the US speak native languages other than English (Allen-Meares, 2004). In early public education systems, some states declared that English was the exclusive language of education in schools (Allen-Meares, 2004), not allowing for students to be educated in their native languages.
Review of Major Educational Legislation

Major legislation tackling these inequalities as well as the organization of the public school system, originated in 1852 and continues today. Allen-Meares (2004) classifies education reform into two categories. She suggests that when evaluating the goals of an educational reform policy, it falls into either the achievement-based or equality-based category. Equality-based reform addresses gaps in achievement, access, and resources experienced by people on the basis of their ethnicity, disability, gender, and native language. Achievement-based reform, on the other hand, focuses on academic outcomes such as test scores, attendance, and graduation rates. In addition to these two categories, this author selects the categories of standards-based reforms and control-based reforms to address reforms aimed at quality of education and what types of authorities govern educational systems.

Achievement-based Reform

Achievement-based school reform policy includes adjustments to school structures, systems, and purpose in an effort to raise academic outcomes. This is especially true of early educational reforms. As mentioned, the 1852 compulsory school act in Massachusetts changed the attendance structure of public schools from non-compulsory to compulsory. As school attendance became compulsory, education shifted purpose from religious training to social skills training in order to create an educated population that would eventually lead the nation, post-Civil War (Butts & Cremin, 1953). The National Educational Vocation Act of 1917 encouraged high schools and colleges to train skilled workers, another shift in educational purpose. A debate about whether or not high schools should be trade schools or academic prep schools was a main focus of debate in the 1920s. Schneider and Kessler (2007) coin the term “progressive” education when describing 1930s educational purpose characterized by cooperation between
teachers and students towards learning positive living principles. In the 1940s and 1950s educational purpose shifted back to intellectual rigor and more traditional patterns of education and evaluation within schools. In the 1930s public school systems also established structural changes by adding “kindergartens, night classes, adult classes, trade schools, and extracurricular activities as part of reform strategies” (Allen-Meares, 2004, p.3). In 1957, congress passed the National Defense Education Act to address the need for excellence in math and science. Even after the 1900s, legislation refocused educational purpose on making the USA first in math and science around the world (Goals, 2000). These changes aimed at increasing achievements in attendance, grades, and completion rates for students.

A shift to increased accountability and measurable outcomes of educational initiatives came in response to a famous report in the field of education: A Nation at Risk (National Commission on Excellence in Education, 1983). This report detailed the impact that low academic performance of American students would have on the nation if not corrected. It categorized risks in several areas including low literacy rates; decrease in standardized tests scores and the scholastic aptitude tests (SAT); dilution of curriculum content; lowered educational expectations of students; and weak teacher education programs. The report cited many of the ways the nation would not be able to compete in a newly competitive age with computer and other advanced technology. The report reasoned that the potential to make dramatic shifts in these trends was to tap into the storehouse of wealth the nation already has.

The most recent educational reform, the 2001 No Child Left Behind (NCLB) Act, served as one of the most comprehensive achievement-based reforms to date. The NCLB Act (2001) built on the Elementary and Secondary Education Act of 1965 and established stringent accountability requirements for schools receiving federal funds, including a minimum yearly
progress score to indicate whether a school is passing or failing (Rosenbaum, 2005). It addressed many areas of educational success including closing the achievement gaps between successful and failing students, who are “poor, limited in English, disabled, migratory, under juvenile court jurisdiction, or members of other at-risk groups” (Rosenbaum, 2005, p. 5). It afforded states and districts options to use creative measures to improve scores, but also requires widespread restructuring for persistently failing schools and districts. Likewise the Obama administration’s Race to the Top (2011) centers on improving student outcomes by increasing teacher accountability and linking teacher outcomes to student progress.

**Equality-based Reform**

Equality-based reform manifested as the country moved into a struggle for civil rights, focusing on equality of access and services for all citizens. According to Allen-Meares (2004), “children whose primary language is not English, children who are ethnic and racial minorities, and female students had been denied access to certain programs offered by schools” (p. 249). The federal government’s passage of legislation to address racial inequalities is hallmarked by one of the most famous Supreme Court decisions in 1954, *Brown versus the Board of Education I*, a ruling passed by the U.S. Supreme Court in 1954, stated that separate schools could not be equal, which in effect repealed the *Plessy versus Ferguson* decision of 1896. While the Supreme Court ruled on this in 1954, states were given some time to act upon it, leading to the 1955 Brown II decision that called for compliance with the first Brown decision. As states used their own discretion to enforce federal mandates of desegregation, the federal government enacted more legislation including the 1971 case of *Swann v. Charlotte-Mecklenburg Board of Education* to facilitate compliance with laws. The first of many “busing” cases, Swann became the first to mandate that desegregation had to include schools beyond the neighborhood. The 1974 Milliken
v. Bradley case contrasted the Swann ruling by prohibiting suburban communities from being included in mandatory segregation. Congress became directly involved in addressing the plight of the disadvantaged by passing the 1965 Elementary and Secondary Education Act, which was the first time the federal government directly allotted funds to improve the situation of poor and disadvantaged children (Allen Meares, 2004). This legislation created the Head Start program to provide “underperforming disadvantaged kids with preschool not available in the community environment” (Allen Meares, 2004, p.3).

Similar equality-based reforms occurred for students with disabilities in public education. In 1970 the Education of the Handicapped Act gave funding to special education programs. The 1973 Rehabilitation Act Section mandated that any agency, including schools receiving federal funding, could not discriminate based on disability. The 1975 Education for all Handicapped Children’s Act: Public Law 94-142 (IDEA) guaranteed handicapped students a right to education. IDEA was ideal legislation because it also promoted handicapped rights against discrimination through “guidelines, federal funding, and local accountability measures” (Allen-Meares, 2004, p. 4). It has since been recast as the Individuals with Disabilities Education Improvement Act in 2004, which has brought about many controversial changes including reducing parental rights in the process (Rosenbaum, 2005).

The major federal legislation addressing gender bias in education came through the 1972 Title IX of the 1972 Education Amendments. Title IX prohibited sex discrimination for any program receiving federal funding. Many lawsuits and cases have arisen that question practices of schools and agencies in admissions and particularly in the sports arena. Similar legislation prohibiting discrimination against non-native English speakers passed congress in the 1970s. The 1974 version of Lau v. Nichols ruled that schools must provide native language teaching to non-
native English speaking students. The 1978 Bilingual Education Act ruled that a child’s native language should be used to educate him/her as much as needed to make him/her competent in education.

**Control-Based Reforms**

The controversy over who should control public education has always been at the forefront of the educational reform dialogue. In the colonial period, churches and individual teachers controlled their own private schools. If a colonial legislature set up a public school, it still required payment as if it was a private school, but it delegated the administration of the school to a group of individuals (Butts & Cremin, 1953). The idea that public education should be provided by the public free of expense was foreign during this time, since economic prosperity was the main goal (Butts & Cremin, 1953). There were further debates about centralization and decentralization of schools, leading to decentralization of tasks such as school funding and staff monitoring to districts or town committees by the end of the 18th century. By 1812 there were the first state departments of education and state superintendents, a move away from free market theory to centralization in state government. Fierce battles over the role of the federal government emerged after the Civil War, battles that have resurfaced in the context of free market education reforms. Ultimately government regulation of the American education system has remained stalwart since the Civil War, even as school choice became the dominant paradigm in education reform. Since then, school choice has become the most popular method to place control of schooling in the hands of parents. These include the advent of magnet schools, school choice transfer, charter schools, and vouchers.
Standards-based reforms

Standards-based reforms developed in tandem with achievement-based reforms as reformers questioned topics such as the purposes of education, curriculum, and staff qualifications. The original purpose of education in church-authorized schools was to teach moral principles and religious doctrine. This purpose dominated most of the colonial period of education. As the colonies sought freedom from England, the purpose of education mimicked their spirit of patriotism. Schooling was seen as a means to build a democratic citizenry that would contribute to society. The 1852 compulsory school act in Massachusetts changed the attendance structure of public schools from non-compulsory to compulsory. As school attendance became mandatory, education shifted purpose from religious training to social skills training in order to create an educated population that would eventually lead the nation, post-Civil War (Butts & Cremin, 1953; Schneider & Kessler, 2007).

Curriculum challenges also emerged alongside changes in purpose. During colonial times, elementary education focused on reading, writing, and arithmetic as children had no other need for education (Butts & Cremin, 1953). Secondary schools were for higher-class students to study philosophy. Around 1875, public education curriculums centered on manual training for elementary students and on industry, health, and trade for secondary school students. The National Educational Vocation Act of 1917 emphasized the preparation of students for skilled jobs, another shift in educational purpose (Schneider & Kessler, 2007). A debate about whether or not high schools should be trade schools or academic prep schools was a main focus of debate in the 1920s. In the 1940s and 1950s educational purpose shifted back to intellectual rigor and more traditional patterns of education and evaluation within schools. In the 1930s public school systems also established structural changes by adding “kindergartens, night classes, adult classes,
trade schools, and extracurricular activities as part of reform strategies” (Allen-Meares, 2004, p.3). Despite the creation of these structures, differential access to these structures persisted through the late 1960s and early 1970s, limiting the early effectiveness of such reforms. Although access to these structures have been expanded to previously excluded groups, gaps still exist in curriculum and who should be learning what (Butts & Cremin, 1953; Schneider & Kessler, 2007).

**Historical Context of Market-based Reforms**

Currently, a major field of study in American public education and school social work is the effectiveness of reforms sanctioned by NCLB. No Child Left Behind pushed for sanctions-based accountability reform in state, district, and school educational systems. Each state was required to create an accountability system based on high stakes assessments of students in schools. Schools that consistently perform under the national requirements for adequate yearly progress, face the mandate to engage in any number of interventions to address specific contributions to their failure.

Among these interventions are the increasingly popular market based reforms. These reforms refer to the body of interventions that emphasize the ability of a free market economy to increase performance of schools as schools seek to meet the demands of children and families. The main types of market-based reforms include magnet schools, school choice, charter schools, and voucher programs (Mathis, 2009). Magnet schools came into existence in the early 1980s to late 1990s to address school desegregation mandates across racially segregated districts. These schools allowed specialized focus on arts, math, and sciences that would attract middle class white students as well as allow black student who met the entrance requirements to attend as well. Magnet schools still exist today, but have not seen the initial increase or rise since their
inception in the 1980s. School choice refers to the sanction meted out to low-performing schools that aims to give parents of those students attending low performing schools “choice” of whether to remain or leave their current low-performing school. School choice is implemented differently across states, but its main premises are that any student shall be allowed to attend another school if their school of residence does not meet accountability standards as designated by the state department of education. There are two distinct forms of school choice enacted variably across states: within district choice and inter-district choice. Within-district choice allows students eligible for choice to transfer to other higher performing schools within their district. Inter-district choice allows students and parents more options of schools by allowing for the transfer to a school within another district. Charter schools are the newest wave of market-based reforms that both offer choice and stronger autonomy for schools (Mathis, 2009). Charter schools are public schools that receive local, state, and federal funding and participate in accountability system, but have leeway in establishing school structure and meeting accountability standards. On the spectrum of free market based reforms, school vouchers are the most extreme case of free market principles, allowing students not only the choice to attend other public schools within district or in another district, but also to attend non-public schools. Students are funded with public money to attend private schools of their choice if they do not find suitable public schools to attend. The vouchers are applied to the tuition of the private school and parents have to pay any outstanding balances.

Of the current market based reforms, an increasingly popular choice is charter schools. There are currently more than 1.5 million students enrolled in over 5,000 charter schools across 39 states (Allen & Consoletti, 2010). Charter schools are public schools of choice that operate under a contract between the school, school district, and external management organization.
These management organizations range in scope from universities, businesses, and school boards to state boards of education. They are considered schools of choice because families utilize the option of attending or not attending charter schools (Allen & Consoletti, 2010). Unlike in traditional public schools, charter student attendance is not dictated by student residence (Allen & Consoletti). Charter schools possess increased flexibility and autonomy in making decisions about school structure, culture, and standards (Allen & Consoletti). Because they are public schools that receive state and federal funding, however, they must also subscribe to accountability mandates such as standardized testing (Allen & Consoletti).

The three significant types of charter schools include start-ups, voluntary conversions, and forced conversions, also known as state takeover charters (Arkin & Kowal, 2005; Zimmer & Buddin, 2005). Start-up charters are schools opening for the first time with new facilities and staff. Conversion charters, in contrast, are pre-existing public schools that become charter schools and retain their current building and much of their staff. A third form of charters exists under No Child Left Behind (2002), known as state takeover charters. These are created through forced conversions of pre-existing public schools due to their failing academic performance over a sustained length of time (NCLB, 2001). In a forced conversion, the state department of education or other centralized agency is responsible for establishing a charter contract between the school and an external management organization (NCLB). Emerging research suggests that when examining charter school outcomes it is important to distinguish between these types of charters (Krop & Zimmer, 2005; Lacireno-Paquet, 2006; Zimmer & Buddin, 2005).

There is a current lack of research, however, that attempts to make this distinction. This is due in part to the new adoption of the state takeover process by states, and the limited research on the effectiveness of state takeover as an intervention for failing schools.
**Success of Other Education Reforms**

Research is mixed on whether these reforms effectively created the promised change of their written language. For example, most research evaluating the effects of the Brown decision considers it a failure in comprehensive integration of schools, while acknowledging that schools are slightly more integrated than in 1954 (Borman et al., 2004; Ladson-Billings, 2004; Toppo, 2004).

Similarly, evaluation of the IDEA (2004) in its reauthorization presents challenges when compared to the 1991 version. These include making it easier to expel from school students with disabilities and limiting parental rights in the disability identification, evaluation, and hearing processes (Rosenbaum, 2005). Some declare that these changes are antithetical to the original purpose of IDEA (Rosenbaum, 2005).

NCLB also receives both positive and negative reviews from researchers. Since its recent implementation, several studies demonstrate its effectiveness in closing the achievement gap between low-performing and high performing students and schools. Fusarelli (2004) found that NCLB has forced schools to face issues of underachieving students, so that schools can no longer hide the achievement of subgroups within schools such as minorities or students with disabilities. This is due to reporting requirements instituted in NCLB of subgroup performance. Diamond and Spillane (2004) also praise NCLB for its facilitation of improvements in quality leadership in schools because school leaders are highly responsive to high stakes accountability tests, which are mandated by NCLB. Their interviews and observations of four Chicago elementary schools revealed that the low or high performing status of the school influenced how much principals paid attention to high stakes testing, with more low-performing schools focused strictly on the testing and compliance standards than higher performing schools. Likewise, Kober, Chudowsky,
and Chudowsky (2008) in their comparison of state standardized tests to NAEP trends found that while some standardized test scores increased in several states, those same states did not have an increase in NAEP scores. In 184 instances of test score trends across all states, they found that the achievement gap narrowed, increased in 56 instances, and that scores remained the same in 30 instances.

Reviews that criticize the success of NCLB are also plentiful, arguing that it has failed to close key equality gaps and its detrimental effects on students and schools. In their report on the condition of education in the United States, Planty et al., (2009) reported that national indicators reveal poor urban schools and children in at-risk subgroups continue to severely underperform nationally and in comparison to white affluent students. While some research suggests that NCLB guidelines have improved student achievement other scholars research demonstrates that NCLB actually penalizes the most disadvantaged schools that need assistance by imposing stringent rules and penalties without offering comparable support (Hodge, Harrison, Burden, et al., 2008). Koski and Weis (2004) found that schools start on various levels and have pre-existing quality gaps before engaging in NCLB accountability. These inequalities facilitate the schools receipt of sanctions under NCLB strict standards. Dworkin (2005) reported that accountability systems are increasing problems such as grade retention and dropout rates for minority students. Other criticisms leveled at NCLB include that states individually implement NCLB requirements lacking uniformity and ability to measure across states. One major criticism is NCLB’s lack of intervention for social-personal and family abuse and lack of supervision and family mobility, which all affect achievement.

Whether deemed effective or lacking, the American public education system continues to incorporate local, state, and federal reform policy since its inception. American educational
reforms have largely concentrated on improving academic achievement of students and schools and creating equal access for all groups that face discrimination within the educational system.

**Historical Context of State Takeover Reforms**

The No Child Left Behind Act (2001) claims to improve outcomes for students, schools, and families by turning around low-performing schools through giving students access to effective and challenging scientifically based instruction, and affording parents the opportunity to participate in the development of their children. This resembles the concepts in human capital theory of increasing resources for students. States and districts have chosen any number of the options with mixed results. To accomplish this, NCLB affords states and school districts creative options to address educational inequalities, but also requires widespread restructuring for persistently failing schools and districts (Steiner, 2005). Of the restructuring options employed by states, state takeover of individual schools is the most recent and scarcely utilized option (Steiner, 2005). Currently, twenty-three states possess the legislative power to take over individual schools, but only five of the 23 states have exercised this power (Steiner, 2005). There is potential for this number to grow, however, as states face increasingly stringent federal mandates to address low achievement (Institute on Education Law and Policy, n.d.). Despite states’ current implementation of state takeover as an intervention for failing schools, state takeover is a politically volatile option that involves stripping the local school board’s authority over an individual school and subsequently transferring that authority to a state entity (Steiner, 2005). Schools that are placed in state takeover often face humiliation, loss of resources from their districts, and the political risk of angry workers and teachers’ unions within their communities (Institute on Education Law and Policy, n.d.; Miron, 2008).
Of these options, states utilize the takeover of individual schools the least. It is highly volatile and is usually hostile, involving passionate opposition from stakeholders in takeover schools. It labels a school as failing and then removes authority and funding from its local school boards, who then face social stigma as a result (The Advocate, 2003; Wong & Shen, 2003). It is only available, if the state law permits it (NCLB, 2002). In 23 cases, the state law permits this, but only Maryland, Rhode Island, Louisiana, Alabama, and Massachusetts implemented it (Steiner, 2005). Descriptive summaries of the processes by which these states takeover individual schools are provided in several articles (Steiner, 2005).

**Takeover of Entire School Districts**

While No Child Left Behind (2002) expanded the authority of states to takeover individual schools, state and mayoral takeover of entire school districts occurred since 1988 (Steiner, 2005). Twenty-three states allow state or mayoral takeover of entire school districts, and nineteen of those states and the District of Columbia run a takeover district (Burns: 2003; Steiner, 2005; Wong & Shen, 2003). In these cases, states, mayors, and mayor appointees manage the entire school district through state or local governing bodies (Wong & Shen, 2003, p. 16). Districts in cities such as Chicago, Boston, Detroit, Cleveland, and Newark are examples of cities whose entire school district is state operated. Although, district takeover has occurred in more states than individual school takeover, both numbers are meager compared to alternative state efforts to address educational inequalities within their systems (Burns, 2003; Steiner, 2005). Given this fact, the same questions arise about outcomes for states and students in states that choose to takeover schools (Cibulka, 1999; O’Day, & Smith, 1993).
Effectiveness of Takeover as Education Reform

Limited research exists on the effectiveness of state takeover of individual schools as occurs in Louisiana and four other states. Research is growing however, on the evaluation of district takeover by the state that sheds light on the potential for turning around low-performing schools through state takeover reform.

One comprehensive study done by the RAND Corporation examined the Philadelphia school district’s experience with state takeover in 2002 (Gill, Zimmerman, Christman, & Blanc 2007). All of the schools in the Philadelphia school district were taken over under a diverse provider model, which ensured that various agencies including the schools themselves got the option to manage and provide educational services to the students of the city. Gill et al. (2007) examined these models to determine which model was able to increase student achievement the most when compared to other schools throughout the state and schools managed through other models. The sample of 86 schools, listed according to provider model included the following: 45 schools under private management from any schools under self-management, and four schools under charters. The four schools transferred into charters were not evaluated in this study. The authors utilized a fixed effects model for information from 10 different student cohorts covering 2001-2006. The data had student identifier information to be able to follow throughout the time period. The dependent variables in the study included standardized test scores. They also used a fixed effects model for the school characteristics that make schools more likely to be low performing. The results demonstrated that the percentage of elementary and middle school students that achieved proficiency in reading in district managed schools increased by 10% points and by 20% points in math over the 5 year period (Gill et. al, 2007). After three years of intervention, district managed schools demonstrated statistically significant gains in grade 5 and
8, but the 4\textsuperscript{th} year of intervention saw only 8\textsuperscript{th} grade reading scores demonstrated statistical gains (5\% points) (Gill et al., 2007). Other gains in their analysis were not statistically different from other schools throughout the state or the other provider models, leading to the conclusion that none of the provider models are superior in raising student achievement.

Wong and Shen (2003) also examined the takeover of school districts from the period of 1992-2000. The dependent variables under consideration were higher quality teaching and learning; improved management; and increased public confidence. This descriptive analysis was based on evidence from the US Department of Education, Bureau of Labor Statistics, state departments of education, and local school districts in the areas of demographics, partisanship, management, school quality, and student achievement. After compilation and synthesis across districts, Wong and Shen (2003) used standardized assessments to determine the level of public confidence in the school districts and the nature and frequency of tests per year. Teacher quality linked to student achievement aggregated to the district level. They conducted a school level analysis in Boston, Chicago, Lawrence, and Compton that yielded results demonstrating mayoral takeover in Chicago and Boston was associated with increases in elementary school student achievement. Gains in non-elementary grades for Chicago and Boston were smaller than gains made by all other elementary schools. They also found that when state takeover causes political and administrative issues, student achievement suffers using data from Lawrence state tests in 1997-1999, grades fell during that time. They concluded that increased accountability led to increased public confidence in the state takeover districts. Lastly, they found that mayoral control dictated financial and administrative reallocation of school funds.

A review of the progress of New Orleans public schools done in 2010 by the Tulane University Cowen Institute examined the performance growth between the various types of
schools in New Orleans compared to the rest of Louisiana. This includes differences between the organizations that run each type of traditional school and charter school. It delineated types of schools into schools run by the Orleans parish school board and recovery school district, as well as charters run by the Orleans parish school board, the board of secondary an elementary education, and compared each of these types to all Louisiana schools. Their review lacked statistical analyses, but includes a summary of trends in performance data for New Orleans public schools. From the compiled data, Cowen (2010) highlights differences between charter types and associated growth in school performance scores as rated by the Louisiana state department of education accountability system. Their main findings include the following: school leaders report improved school cultures; plans are in place to increase spending on facilities; academically unacceptable status as of 2009 when compared to 2005; more stable leadership at local, state, and school levels; shaky financial stability due to budget restraints; lack of clarity about the governance of schools; limited data access and transparency; strained relationships between the RSD and Orleans Parish School Board (Cowen, 2010).

The single study examining outcomes for Louisiana charter schools within the Recovery School District was conducted by the Center for Research on Educational Outcomes (2010). Its larger study examined 16 different states, including Louisiana. It utilized available standardized testing data from the years 2001-2008 and provides a strong longitudinal picture of charter school student performance compared with virtual student matches of traditional public school (tps) students. Their student sample from Louisiana includes 34,479 charter school students with an 85% virtual student match. Their outcome variable of interest was academic growth on standardized tests in reading and math for this amount of time. The authors utilized OLS regression and found that Louisiana charter school students as a whole outperform their
traditional public school counterparts in both reading and math. They found that blacks (.13 pts) and Hispanics (.09 pts) in charters do significantly better than traditional public school students in math. Students in poverty also do better than their counterparts in public schools in reading (.05pts) and math (.04pts). Special education students are not significantly outperforming their counterparts. Retained students perform more poorly when in charter schools than tps students. These relative growth measures are seen only in students enrolled for longer periods of time in charters.

Reports and studies that specifically focus on the Louisiana Recovery School District are growing in number since its origin in 2003. According to these studies, there appears to be as much praise as there is criticism of the RSD’s influence on student outcomes like dropout and achievement. Whitehurst and Whitfield (2012) of the Brown Center on Education Policy at Brookings are among the most recent authors to laud the success of the LA-RSD. In their ratings of United States public school districts, they award letter grades based on the amount of choice and competition within each district. They awarded their only “A” to the LA-RSD due to its near 100% random choice for parents selecting schools for their children, rather than assignment by neighborhood. Another work praising the model, governance, and structure of the RSD was written by Smith (2011). In his work, Smith (2012) applied lessons from the LA-RSD to the Ohio public school system. Buras (2012) critiques Smith’s (2012) work, citing its lack of data and data analysis on the increase of the student performance as merely summaries of the data.

**Limitations of State Takeover Evaluation Literature**

The Louisiana Recovery School District has recently been touted as a highly performing, highly successful school district that offers quality choice and charter achievement (Hill & Murphy, 2011; Smith, 2012). The underlying reasons for these claims include a decrease in
dropout rate, an increase in standardized test scores, improved choice for parents, and increased innovation and autonomy. Indeed, the RSD model is being co-opted by other states like Illinois, whose school system is now run by a former RSD official. What is lacking in these research claims is a detailed longitudinal picture that focuses solely on the RSD compared to other similar schools. This is what the principal investigator offers in this dissertation. It is being summoned forth as a way forward for dealing with the education equality gap, a decades old problem in America’s public schools. The author categorizes the gaps in literature into limitations of content and design.

**Content Limitations**

Lack of research on state takeover. State takeover schools are characteristically different from traditional schools (Wong & Shen, 2004). However, there are a severely limited number of studies that examine the nature of state takeover schools. This lack masks the true influences of charter types on achievement. States exercising takeover, commonly target schools that are failing, have high minority enrollments, and highly impoverished students. These factors are compounded by the stigmatization inherent in the state takeover process due to being labeled “underperforming.” The nature of the state takeover process curbs the ability of schools to operate with autonomy and instead encourages heavy bureaucratic influence. Thus, state takeover public and charter schools lack the autonomy and choice inherent in theoretical assumptions of charter school success. Descriptive data in the literature must be extended beyond startup and voluntary conversions for states with state takeovers like Louisiana.

A study done by Arkin and Kowan (2005) delves deeper into the nature of conversion charters and deals briefly with state takeover charters. It reviews methods implemented across states when closing a public school and re-opening it as a charter school. They concluded that
forced conversion charters are new phenomena, but face difficult challenges in terms of performance. In their study, practitioners provided data through telephone interviews. Results demonstrated governance structure, environmental factors, school-level governance, leadership, and organizational factors all become difficult when closing public schools and re-opening them as charters.

**Design Limitations**

Another challenge of measuring state takeover effectiveness is its complex nature. As yet, studies lack sophisticated analytic strategies to evaluate the performance of state takeover districts and schools. Schneider’s (2005) article only offers a description of each state takeover process that occurs in states that employ takeover. Likewise, McDermott (2003) examines the predictors of states choosing to implement takeover as a reform option. Wong and Shen’s (2004) analysis offers a synthesis of several sources of information on mayoral takeover but no statistical analysis. It also does not address state takeover. While the CREDO (2009) study uses a sophisticated regression analysis, it only examines charters and not the entire Recovery School District in New Orleans, which contains schools that are not charters, but that are directly run by the Recovery School District.

**The Louisiana Recovery School District**

Louisiana’s most sweeping reforms also stem from the five options afforded states by NCLB: state takeovers of individual school (NCLB, 2002). The Louisiana State Board of Elementary and Secondary Education (BESE) created a state takeover district, known as the Recovery School District. The Louisiana Recovery School District (LA-RSD), created in 2003, currently operates 71 schools throughout the state (Recovery School District, 2009). In addition to these 71 schools, twenty-nine others face state takeover if they fail to meet agreements for
improved scores (Recovery School District, 2009). Initially, the state assigns a low performing school to the category of academically unacceptable status (AUS) when it falls below school performance score standards, a number based on the combination of school attendance and test scores (LDOE, 2009). After four consecutive years in AUS, the state places schools in the Recovery School District under the authority of BESE, where the schools must remain for a minimum of five years (LDOE, 2009, p. 53).

Despite the stated needs for the LA-RSD in assisting schools to achieve accountability standards, no school that has been placed in the RSD since 2004 has met those standards (The Recovery School District, 2009). When considering the potential effects of the continued underperformance of state takeover schools, it becomes necessary to address the systems that improve outcomes for students, schools, and communities. The categories of achievement necessary for being sanctioned with state takeover are becoming increasingly broader, so that more schools today face possible takeover than one year ago. Although the state takeover process and Recovery School District has not been proven to improve academic outcomes for students and schools, it is being expanded in Louisiana. The state department of education has created another subpart of the Recovery School District, called the Baton Rouge Achievement Zone. The BRAZ consists of public schools in Baton Rouge that are in the RSD, but that have failed to make sufficient academic gains under their charter operators. This is an intervention for the “intervention” of state takeover of these schools (RSD, 2012).

Summary

While the United States’ public education system becomes saturated with market-based reforms spurred on by No Child Left Behind, there is limited information that suggests the unequivocal superiority of such reforms. Under NCLB, states are also beginning to engage in
state takeovers of individual schools, which suffers from an even greater lack of evidenced based research to demonstrate its ability to turn around low performing public schools. These processes combine under the Louisiana Recovery School District state takeover intervention for chronically low-performing schools in the state. Due to the state takeovers in New Orleans, that city’s school system could become the nation’s first school district that is only charters (Buras, 2012), but as yet, there have been no comprehensive examinations of the efficacy of this intervention.

**Implications**

In 2011, representatives from New Jersey, Oklahoma, and Tennessee came to Louisiana to receive briefings and participate in workshops given by the Louisiana Department of Education (LDOE), including RSD staff (Hill & Murphy, 2011). The workshops stressed the success that Louisiana has seen in closing and transforming low performing schools through the RSD. Indeed, Hill and Murphy (2011) assert that the Louisiana RSD is “a vital asset to the state” (p. 2). In a recent presidential mandate, President Barack Obama announced the ability for states to apply and obtain waivers from federal No Child Left Behind policies, due to stringent mandates that states claim have hindered real progress (American Recovery and Reinvestment Act, 2009). Without overwhelming supporting evidence to suggest the efficacy of NCLB, several states have opted out of NCLB policies. Louisiana has not chosen to do so and with the perception of success as given in the above-mentioned reports and papers, the LDOE may never chose to do so. The course of the New Orleans style takeover model is not only being spread to Indiana, Michigan, and Tennessee, but also to places such as Haiti, Chile, and Venezuela by the former RSD superintendent, Paul Vallas (Buras, 2012). With its spread, there is an imperative
that the LDOE conduct sound research to demonstrate the ability of state takeover to improve student achievement and decrease the risk of dropout.
CHAPTER 3: METHODOLOGY

Conceptual Framework

This chapter introduces the research methodology, research questions and design for the current study. Then, operational definitions of key variables and terms are provided. Next, characteristics of the study sample, data collection methods, instrumentation, and internal and external validity are detailed. The chapter concludes with data analyses for the research questions. First, the methodology used for the dropout portion of the study is presented. It will provide a brief overview of the research design and key definitions for the dropout portion of the study. Details about the analysis, including building and testing models, explaining equations will be presented later in this chapter. Then, the methodology used for the achievement outcome will be presented.

Purpose

The author utilized longitudinal administrative data to conduct a retrospective research study examining the efficacy of a federal education reform implemented by the state of Louisiana, the Recovery School District (RSD). This study evaluates the RSD’s relationship to two student outcomes that are central topics in education literature: risk of dropout and student achievement. The dropout outcome was analyzed using a multilevel discrete-time survival analysis to determine the RSD’s relationship to the risk of dropping out between RSD and traditional Louisiana public schools. The second outcome, student achievement, was examined using hierarchical linear modeling to determine whether there was significant improvement in student achievement for RSD schools compared to traditional public schools.
Research Questions

1. What is the likelihood that a student will drop out of RSD schools compared to a matched set of traditional public schools?
2. Do student characteristics influence the risk of students dropping out of school at a given time?
3. Do school characteristics influence the risk of students dropping out of school at a given time?
4. Do standardized test scores vary by school type (RSD schools versus traditional public schools) in Louisiana?
5. Do student characteristics account for the variation in standardized test scores in state takeover and traditional public schools?
6. Do school characteristics account for the variation in standardized test scores between recovery schools and traditional public schools?

Analysis One: Dropout

Operationalization of Study Variables

Dependent Variables

Dropout status. A key student outcome addressed by federal and local education reform is the percentage of students who fail to graduate with a high school diploma. Successful completion of high school is a key component of the survival level of the academic achievement gap according to Farrell (1999). The survival level describes students’ success in terms of how long they remain in school and the height of their education attainment. Not only does dropout increase negative outcomes for those students who are affected by it (Page et al., 2007), dropout also poses great financial and social risks to larger society, which is why many interventions
have focused on decreasing the United States’ dropout rate (Alliance for Excellent Education, 2009). This focus is also a central element of the state takeover reform in Louisiana. While dropout is a significant national concern, few evaluations of the effect on dropout rates of takeover schools have been conducted. For the purposes of this study, dropout is a dichotomous variable, which will be coded 1 for dropout and 0 for not dropping out in each year. In a discrete-time survival analysis, the focus of the drop out variable is not simply only whether the student drops out, but when the students drop out to that researchers can identify grades in which students are most at risk of dropping out.

**Independent Variables**

Since this is a multilevel survival analysis, there will be two levels of independent variables: the student level, which is nested in the second level, the school level. The student level analysis will include the following variables: free and reduced lunch status, race, and gender. Each of these variables have been identified as correlates of lower academic performance, higher dropout rates, and slower grade progression in studies of other public school populations (Alliance for Excellent Education, 2007; Carey, 2005; Page et al., 2007), thus their inclusion in this study will reveal whether Louisiana students have comparable experiences to those of other students in the nation.

**Time Invariant Variables**

Time-invariant variables are characteristics of individuals that do not change during the course of a study (Singer & Willet, 1991). Race is designated by the ethnic group to which students in schools belong. The majority of the public school students in Louisiana are African American including those in the Louisiana Recovery School District (). This study aims to identify whether the educational plight of the African American public school majority is similar
to the pattern of the rest of the nation. As discussed in this paper, minorities experience far poorer educational outcomes including graduation rates and promotion rates than their white counterparts (National Center for Education Statistics, 2004). Minority status was coded 0-non-African American, 1-African American.

Another student characteristic linked to educational outcomes is gender (National Center for Education Statistics, 2004), which in this study was coded 0-female, 1-male. This will also be included as a level-one covariate.

At the school level the only time invariant variable was school type. The two types of schools included in the analysis are Recovery School District Schools and traditional public schools. The coding scheme for this variables is as follows: 0=traditional public school, 1=Recovery school district school.

**Time Variant Variables**

Time-variant values can fluctuate over time (Singer & Willet, 1991). Free and reduced lunch status is a time-variant variable often cited in school effects literature. It is a national measure of poverty that correlates to low scores and outcomes for students (McKinsey & Company, 2009). This variable is coded as 0-Full Price Lunch, 1-Free Lunch, 2-Reduced Lunch. The majority of African American students in Louisiana’s public schools receive free and/or reduced lunch. Averages of school level variables served as independent variables at level 2 of the model. These variables included mean measures of each school’s free and reduced lunch and minority student population. In addition to these variables, the school level analysis will include variables mean % of highly qualified teachers, and school type (Recovery School District or traditional public school). Schools in the LA-RSD have 90-100% of their student populations qualifying for free and reduced lunch status. The percentage of minority students in the school is
linked to achievement; those with higher minority percentages perform lower than those with lower minority percentages (Carey, 2005). Similarly, the percentage of highly qualified teachers in a school is linked to student achievement (National Center for Education Statistics, 2004). High minority, high poverty schools tend to have a lower percentage of highly qualified teachers, which correlates to lower achievement rates (NCES, 2004).

**Definition of Key Terms**

The following are central definitions to understanding the multilevel discrete-time survival analysis.

**Survival Analysis**: Survival analysis was popularized in medical studies of death and have since been expanded to the social sciences to study the occurrence of various events including student drop out from school (Willet & Singer, 1991; Willet & Singer, 1993). A survival analysis examines the likelihood that a subject under study will experience a given event and when that subject is most at risk to experience the event. Thus, the dependent variable is the “time to event” or time until an event occurs (Bradburn et al., 2003). Survival analysis is able to deal with continuous and discrete independent and dependent variables. Although similar to logistic regression, it goes farther than logistic regression in examining the “longitudinal progression of the probability that an event occurs (Muthen and Masyn, 2003) by addressing time, rather than disregarding time as in logistic regression.

**Discrete-time survival analysis**: Discrete time is measured in large intervals, such as months, semesters, or years, rather than as a continuous variable (Hox, 2010). In the current study of dropout, the discrete time interval was years, since public school dropout data is reported in yearly time intervals. While, the drop out process may be a continuous process, meaning a student may drop out at any time during the year, the measurement is discrete, occurring only
once each year. Discrete-time survival analysis is applied to data that is categorized into several time points.

**Hazard rate:** The hazard rate is the probability that a student will experience an event, such as dropout at time \( t \) when the individual is at risk of experiencing the event. Regarding dropout, the hazard rate is the total expected number of dropout events per person per year for the entire sample of individuals. Having a high hazard rate corresponds with a low survival rate. The dropout hazard rate would tell us the chances of dropping out today, given a student was enrolled at the start of the year (Hox, 2010).

**Hazard function:** The hazard function is the hazard rate expressed as a function of survival time and is denoted by the formula \( h(t) \) where \( h \)=the hazard and \( t \)=the time period. It is the instantaneous rate of occurrence of the event (Willet & Singer, 1995).

**Discrete time hazard function:** This function demonstrates the probability that a given student experiences the hazard event during the current interval, given that she did not experience the event in an earlier time period (Singer & Willet, 1993). As a probability it is bounded by 0 and 1.

**Survivor Function:** The survivor function is derived from the hazard rate and gives the probability of surviving (avoiding dropout) beyond time \( t \). In other words, it is the chronological pattern of survival probabilities over time (Willet & Singer, 1993). In the current study it would be the probability that student has not dropped out at time \( t \) and would be denoted by the formula \( S(t) \), where \( s \)=the survivor function and \( t \)=the time period.

**Censoring:** Censoring is the occurrence of incomplete observations of the event. In any study of human life, a number of subjects may not experience the event of interest and the survival time will not be known as a result (Barber, Murphy, Axinn, & Maples, 2000; Hox, 2010; Willet & Singer, 1991). In the current study, some students may not have experienced drop out by the end
of the 2011-2012 school year. There are several reasons that censoring may occur including the following: a student is lost to attrition; a student experiences a different event like death or moving to another city that makes follow up impossible (Clark, Braburn, Love, & Altan, 2003). Researchers have tried to implement several methods to address censoring in survival analysis. One method of addressing censoring in the literature involves selecting only subjects who have knowingly experienced an event to build the study sample (Willet & Singer, 1993). This method biases the mean estimates of the survival length (Singer & Willet, 1993). Likewise, others have used imputation of an event time for censored data at the end of the observation period (Singer & Willet, 1993). This is biased as well because it creates an event where none actually occurred. In the case of dropout, this would be equivalent to labeling a student as a dropout at the end of the study, even though that student graduates after the study is over.

Fixed right censoring: Fixed right censoring is the most common type of censoring and occurs when the study period ends without observing the event (dropout) for a given subject. It is assumed that the subject could possibly experience the event after the observation period ends (Willet & Singer, 1993). This study will utilize fixed right censoring which can be interpreted as those students who do not experience dropout before the end of the 2011-2012 school year (end of the study) could still dropout after that year.

** Dropout Data **

** Individuals **

This study utilized secondary administrative data. The data are located in the Louisiana state department of education student information system (SIS). Individual scores for each student on dropout are published annually and housed at the Louisiana Department of Education. Each student is assigned a student identification number by the LDOE, for all of their state
education records. Student demographic information included the schools attended, achievement data, demographic data, discipline data, and other enrollment information such as dropout status and grade progression. The dropout variable in the LDOE database is coded as 7, which is one of the multinomial response options for exiting a school. This author recoded the data into two dichotomous options for each year, 0=no dropout, 1=drop out. In order to utilize this information for the current study, the author downloaded all relevant files from EXCEL documents housed within the LSU Office of Social Service Research and Development.

Schools

The secondary data available for the school level variable is also collected and housed at the Louisiana Department of Education. However, it is available to the public through the LDOE website. The data is aggregated to the school level on each of the independent and dependent variables in this study and published annually by the LDOE. Each school in the state is issued a site code that is linked to the school name, school district name, and percentages of the student population that qualify for free and reduced lunch program, percentages of highly qualified teachers, and percentages of the student population that is minority.

Dropout Method and Procedures

Sample

Matching

The population from this study includes all of the schools in the Recovery School District (RSD) each school year from 2007-2010. It also includes a matched comparison group of traditional public schools in Louisiana from the same school years. The match was performed at the school-level and was gathered through a stratified sample of schools. The stratification criteria included urbanicity, grade structure, mean percentage Black students, and mean
percentage free and reduced lunch population. Urbanicity in this study refers to the physical location of schools within large urban areas of the state. The majority of RSD schools are in New Orleans, Louisiana, which is a very large urban area. The only other two comparable areas in terms of population in Louisiana are Baton Rouge and Shreveport. The parishes and school districts encompassed by the cities are East Baton Rouge Parish and Caddo Parish. These two were chosen because they are the other two largest Louisiana parishes in terms of population: Caddo (257,051) and East Baton Rouge (441,438). The next largest parish, Calcasieu Parish, only had a population of 192,758.

The grade structures varied more within the RSD population of schools. Most common grade structures were K-5, K-4, K-8, 7-12, and 9-12, whereas almost all traditional public schools have grade structures of K-5, 6-8, and 9-12. This made the matching process on this variable more difficult. Race is represented by the aggregation of the Black student population in schools.

Once the school level matched was performed, a propensity score match was performed based on race and free/reduced lunch status. The match was performed and yielded a matched comparison sample of schools (n=74). The population of RSD schools for the study (N=71) yielded a total school level sample of (n=145). Demographics of schools and students are included in Table 1.

**Matching in School Effects Literature**

The CREDO (2011) study of charter schools is one of the most recent studies of charters and includes Louisiana charters. The researchers examined the effect of school attendance at charter versus traditional public school (tps) on standardized reading and math growth score for each student. After selecting the entire population of charters, they stratified comparison schools into
“feeder”/“non-feeder” schools before including them in the matched sample of traditional public schools. The researchers identified all the traditional public schools that had students who transfer from the traditional public school to a given charter school and labeled them “feeder schools.” Once they identified the feeder schools, all the students in the feeder schools became potential matches for the charter school student sample. In this study, the researchers pooled all the student records from all the feeder schools to create a source for creating virtual student matches with charter school students.

Like the matching strategy in the current study, the stratification methods are enhanced in recent charter school studies by the utilization of propensity matching. In their study of California charters, Zimmer and Buddin (2007) created a propensity score that denoted the probability of a school with certain characteristics being either a traditional public school or charter school. The quasi-experimental study was designed to examine how student achievement varied between 352 charter schools and traditional public schools by identifying how the school structure and operation influenced student achievement. The dependent variable under investigation was the student percentile test score. Next, Zimmer and Buddin (2007) fit a logistic regression equation to identify the charter status of schools as a function of schools’ percentage ethnicity, percentage of free and reduced lunch students, and percentage of English language learners. Then, the researchers created predicted values for charters and traditional public schools in that area. Finally, they determined the distance between schools by the difference in propensity scores.

Also like the current study, several of the more recent charter school effects studies also create a matched student sample, in addition than a school sample. Instead than including all students within the matched group sample of schools, some researchers have utilized propensity
matching to create student matches for charter school students. The CREDO (2011) study utilized virtual matching of students in charter and traditional public schools. This matching only occurs after a stratified sample of “feeder” traditional public schools is gathered. The researchers used student records in feeder schools in the year prior to the test year of interest. Their study was an attempt to create “mirror” images of charter school students within traditional public schools, so that the only differences between students were the type of school they attended. The match characteristics for the virtual student matches were as follows: Grade-level; Gender; Race/Ethnicity; Free or Reduced Price Lunch Status; English Language Learner Status; Special Education Status; and Prior test score on state achievement tests.

**Pros of Matching Strategy in Current Study**

There are several methods used in the literature to further decrease sampling error that are not utilized in the current study. Propensity matching, as used in Zimmer and Buddin (2007) study increases the likelihood that one can attribute the results of an analysis to school level characteristics. It can reduce group differences on observed variables (Shadish and Cook, 2005). Since the current study examines between school differences, a propensity match would enhance the likelihood that conclusions about school effects could be exclusively attributed to the school differences.

**Cons of Matching Strategy in Current Study**

The virtual control record is another matching strategy that uses an initial stratification a higher level, but goes further and creates a match for disaggregated data, in this case at the student level. The match used in the CREDO (2011) study created a mirror image “virtual twin” of each charter school student in the population. According to the researchers, the only difference between the charter school student and virtual match, then becomes type of school the student
attends. Without this type of matching, there may still be extraneous factors that contribute to the outcome of interest besides the school characteristics. Lastly, selection bias cannot be completely eliminated through stratification or matching because not all variables pertinent to the study are used in matching (Shadish & Cook, 2002). Thus, in the current study, only utilizing three matching variables (urbanicity, mean percentage Black students, and mean percentage free and reduced lunch students) may reduce but not eliminate selection bias.

**Student Level Sample**

The student level sample for the study was 11,501. The data were provided by the Louisiana Department of Education in an agreement with the Louisiana State University Office of Social Service Research and Development. These data allow the researcher to access individual and group level data from each school within the state of Louisiana.

In the 2007-2010 school years, approximately 76.7% of students qualified for free lunch. Fifty-one percent of the student population was female, and 49% male. Also, approximately 88% of the student sample is African American, and 11.8% is non-African American.

**School Level Sample**

At the school level, the mean percentage of students who qualify for free and reduced lunch for all years is 88.11% (s.d.=50.25). The mean percentage of African American students is 95.36% (s.d.=8.84), and the mean percentage of highly qualified teachers is 50.97% (s.d.=25.52).

**Representativeness**

The matched comparison sample is a non-probability sample that limits generalizability to the study sample. The population of RSD schools (N=71), however, includes each school within the RSD, and may be generalized to other state takeover systems like the Louisiana RSD and to the rest of the schools that within the LA-RSD that will open in years to come. The new
school performance score that is necessary for schools to achieve in order to avoid state takeover has risen to 75 over the last year. This will increase the number of schools eligible for takeover because schools that had previously avoided takeover by achieving a score of 65, could now fall below the new target to avoid takeover, 75. The student population in the RSD schools is matched with similar students in Louisiana public schools and, thus, can be generalized to that sample of public schools.

**Protection of Human Participants**

This secondary data analysis may present social risks to schools in the LA-RSD because of their inclusion as RSD schools. While the data do not include names of the schools, the site codes are available and public information. The general results may present social stigma to the category of schools classified as being in the LA-RSD, however, due to the low performing nature that characterizes these schools. The data is confidential property of the Louisiana Department of Education and includes student identifier information, which could pose risks if released. No schools were contacted for this study and student identifier information was not linked to student names. Also, in the results of this analysis schools are identified by a school site code rather than a name. Likewise, the LSU Office of Social Service Research and Design has taken measures to ensure the integrity of the data, by securing the data on hard drives locked in a password protected safe. The data may only be used at the LSU OSSRD office, must be signed in and out, and must be used on a computer that does not allow internet access to its users. In March 2012, approval was granted by the LSU Institutional Review Board to conduct this study.

**Dropout Research Design**

The examination of the relationship between school and student level characteristics and dropout status was conducted using a multilevel discrete-time survival analysis.
Issues of Validity

Validity

Internal validity of a research design refers to the confidence a researcher can have that the independent variable has an effect on the outcome variable. This is of concern in experimental and quasiexperimental designs. The criteria for establishing causality, whether a variable caused the outcome, include the following: temporal order; empirical correlation between the independent and dependent variables; and lack of spuriousness. Temporal order suggests that the independent variable preceded the outcome variable. Empirical correlation refers to a relationship between the variables, when there is a change in one variable there is also a change in the other. Lack of spuriousness refers to the absence of other variables that are able to explain away the relationship between the independent and dependent variables.

Several key threats to internal validity are present in this study. Although the comparison groups will be comparable on several key characteristics, all characteristics are not measured in this study, which increases the likelihood of spuriousness. The threat of history affects a study when extraneous factors in society have the potential to influence outcomes on the dependent variable. In the case of schools within the LA-RSD, all schools in New Orleans were affected by the natural disaster, Hurricane Katrina in 2005. This is especially true in the case of the LA-RSD because not all schools were taken over at the same time. There are several schools, for example, that were taken over in 2008. Another threat to history occurs when subjects are exposed to different amounts of the intervention, which is the case for schools in the LA-RSD due to the different dates that they were taken over.
Construct validity

Administrative data have both strengths and limitations in regards to validity and reliability. Threats to the reliability of administrative data include the human input error that may occur at both the school and state database levels. Staff from local public schools input data on students including enrollment data, discipline data, and demographic information. This information is then provided to the state department of education for input into its database. There is potential for misinformation and improper coding to occur due to human error. In terms of construct validity, the data are not often gathered according to a theoretical framework, but instead are based on what information would be easiest to collect. Therefore the measures available may not accurately measure the concept that the research wants to measure. Likewise, when using previously coded administrative data, the study design is limited to the variables already included in the database. This also refers to the underlying meaning of the variables, the range of categorical variables, and the interpretation of the variables. Researchers may not be measuring what they intend to measure which is the definition of validity.

Mode of Observation

Measurement

This study utilized secondary education data. Student dropout data is recorded in the yearly school data as well as in each student individual file. While a student may drop out of school at any given time during the school year, that information is only reported discretely, once per year. The data are located in the state department of education database within the accountability department. Individual student scores and aggregate school scores on the dropout variable are published annually and housed within the Department of Education. Each school in the state is issued a site code that is linked to the school name, school district name, percentages
of the student population that qualify for free and reduced lunch program, percentages of highly qualified teachers, and percentages of the student population that is minority. In order to utilize this information for the current study, the author downloaded all relevant files into EXCEL or STATA.

**Instrumentation**

All data from this study were gathered using the Louisiana Student Information System (SIS). All local school districts report student information to the Louisiana Department of Education’s SIS. In the East Baton Rouge Parish school district, this system called EschoolsTac. In Caddo Parish this system is Jpams. In the RSD various systems are used by charter and state operated schools. There is not uniform student management system in the RSD. The current federal policy of No Child Left Behind requires states to monitor dropout data. Unfortunately, the lack of uniformity in the system confounds instrumentation for this variable.

**Validity of Dropout Measure**

The lack of uniformity in instrumentation brings into question the validity of the dropout data. Within each enrollment system, student dropout is a valid measure, as evidenced by the multinomial options available to label a student who does not return to his home school. For example, the East Baton Rouge Parish student information system, EschoolsTac, allows school administration to enter one of several labels including transferring schools; moving to another parish or state; and other circumstances that allow dropout to be clearly identified as a student who is not attending school at all. A label of dropout actually means that the student is not attending school anywhere, even outside of the city or state. Throughout each district school system it is clear when a student does not dropout, but instead transfers to another school based on the specific option selected for school exit. Bias may come in when a student does indeed
drop out, but the information is incorrectly documented. Barbara Ferguson (2009) is among several researchers that suggest that schools try to avoid the selection of students as dropouts by selecting the exit reason code “unknown.”

**Reliability of Dropout Measure**

Reliability of administrative data is also subject to threats due to human error. Because staff at public schools and the department of education change, the outcome variable, dropout status, may not be coded similarly over time. The student information systems used by parishes also vary, although the state dropout data takes on one form. East Baton Rouge uses an information system called Teacher Access Center (TAC), Caddo uses a similar system known as JPAMS and the RSD uses a combination of both as determined by the chartering agency. All school district information is then input into the Student Information System (SIS) housed at the Louisiana Department of Education. There are over 20 exit reason codes, including item 7: dropout and never returning to school (Ferguson, 2009). This focus of this study is on students who are categorized by item 7, meaning they have not attended school elsewhere. Thus, item 7 was the single item used to code dropouts in the current study. The response items in the SIS was recoded as 1=dropout, 0=no dropout in the current study.

**Dropout Data Analysis**

**Power Analysis**

Power refers to the likelihood of rejecting the null hypothesis when it is false. This is known as a Type II error. Cohen (1992) suggests using a power of .80 as a common value for power. Determining power involves addressing the sample size, significance level, and population effect size. Cohen (1992) considers .50 a moderate power level. In *a priori* power analysis, the sample size helps to determine a certain power for a given alpha level and effect size. An increase in sample size can enhance the ability to correctly reject a false null hypothesis.
In survival analyses, power can be calculated with information about the sample size and length of survival time. According to Jozwiak and Moerbeek (2012) the more measurements or time periods in the study, the higher the statistical power will be. As a guideline, Jozwiak and Moerbeek (2012) suggest that having a large sample size and a few periods of time can give sufficient power. Alternatively, having a smaller sample size with a large number of periods can also give sufficient power. As an example, they listed the number of time periods and sample size necessary to achieve a power of .80 for a set of data (Jozwiak & Moerbeek, 2012). For 6 time periods, which is similar to the 5 time periods used in the current study, a sample size of N=1247 was sufficient to yield a power of .80. Thus, considering the large sample at the student level, (N=) and small amount of time periods (t=5), this study should yield sufficient statistical power.

Data Quality

Descriptive Statistics

To determine whether survival analysis is appropriate for the given dropout data, Willet and Singer (1991) suggest several steps including first transforming the data from person-oriented to person-period data. A person-oriented data set is the traditional dataset that includes one entry for every subject with all the time intervals included on the single line entry (Singer & Willet, 1991).

Person-period data is a restructured data set that creates a single line entry for each subject and for every time period in the study. This includes dummy variables for the discrete intervals, information about whether the observation is centered or not, and whether the subject experienced the event at each interval (Singer & Willet, 1991).
Once this is done, next steps are to create a life table that will summarize the sample distribution of event occurrence and create graphs that show the survival function and hazard probability.

**Inferential Statistics**

Although researchers have used survival analysis to study student dropout, according to Willet and Singer (1995) survival analysis has not been used pervasively in the high school dropout literature. Instead, the aggregated dropout rates of students within schools serve as a metric for calculating the dropout rate in schools, across schools, and across districts and states. These types of analyses lack details that allow researchers and policy makers to get to the underlying reasons for dropout that can then be the subject of drop out interventions. For example, studies of the effectiveness of the Louisiana Recovery School District have been conducted over the past five years that indicate its influence on student dropout rate has been positive (Smith, 2012). However, these studies are lacking in attention to student or school level data analysis and instead summarize aggregates of change across schools. Numerous resources are spent on developing programs that are not based on rigorous research that provides an idea of that presents when the risk is greatest for drop out.

**Multilevel Discrete-Time Survival Analysis**

There exists a very small body of research on combining multilevel models with discrete-time hazard models (Reardon, Brennan, & Buka, 2010). There is an even smaller body of research that applies these multilevel survival analyses to high school dropout data. One research study that does make the application was conducted by Ma and Williams (1999). They utilized survival analyses in a multilevel form. The study did not focus on the overall dropout from school but dropout from a mathematics course offered in 9-12th grades. Ma and Williams (1999)
also examined the difference in mathematics dropout rates across schools. Using data from the Longitudinal Study of American Youth between 1987 and 1993, they assessed the influence of student level variables and school level variables on the risk of drop out. The student level variables included the following: gender, socioeconomic status, previous year math achievement, and previous attitude towards math. The school level variables were derived from a teacher questionnaire about several areas included the following: academic press; principal leadership; disciplinary climate; teacher autonomy; teacher commitment; resources for math; support for math; percentage of Black students; percentage of Hispanic students, and percentage of parental visits. Their study demonstrated that there were specific transition periods between 8th and 9th grade and 10th and 11th grade that increased the students’ likelihood of dropping out (Ma & Williams, 1999). Barber et al. (2000) also offer a detailed explanation of building a multilevel discrete-time survival analysis.

Advantages of Discrete-Time Survival Analysis

Several researchers, including Willet and Singer (1991; 1993; 1995) tout the advantages of discrete-time survival analysis. First this analysis is commonly used in education research to analyze event occurrences. Secondly, interpretations of parameters are straightforward and can be fitted using logistic regression. Next, this analysis encourages the examination of the shape of the hazard function unlike Cox regression that only looks at parameter shifts in the covariates under the proportionality assumption. Also, the discrete-time survival analysis avoids cohort effects. This is due to the fixed nature of cohorts in a longitudinal study. The same cohort of students is followed over time. In regards to the current study, this is useful because the dropout rate for a particular grade varies by year due to the cohort shift.
In order to run the model for a multilevel discrete-time survival analysis, several assumptions of the data must first be tested and met. The following are the assumptions for this analysis.

**Model Assumptions for Multilevel Discrete-Time Hazard Model**

1. Uninformative censoring. This refers to censoring that is not related to drop out or any other event. Those lost to follow up should have been just as likely to drop out as those still in study.

2. The linearity assumption. This assumption states that for every unit difference in a covariate, the vertical shifts in the logit hazard are linear (Willet & Singer, 1993). They suggest checking this assumption through graphical methods. The assumption is met if the same differences in the covariates correspond to the vertical shifts in the logit hazard (Willet & Singer, 1993).

3. The no unobserved heterogeneity assumption. This assumption refers to the idea that the observed variance in the covariates are the sole factors that determine the variation in hazard profiles across students.” (Willet & Singer, 1993, p. 184). In other words, the assumption states that some individuals may be more at risk of dropout than others based on factors other than the independent variables already included in the model.

4. The proportionality assumption. According to Willet and Singer (1993) this proportionality assumption states that all logit-hazard profiles share a similar shape, being parallel and only in different vertical locations according to the values of the covariates. Another way to describe this assumption is that the covariates have an identical effect in every time period.

The next section will demonstrate the models to be tested in this analysis including models to test assumptions and hypotheses.
The Models

This section of the analysis involves 7 models. Models 1-4 test assumptions necessary to ensure the survival analysis is appropriate for the data. Models 5-7 examine the research questions.

Person level discrete-time hazard models

Initially, a set of preliminary models were estimated to determine how much variation in dropout there is between schools. This is first accomplished by ignoring nesting at the school level and estimating a simple discrete-time hazard model using logistic regression. In the regression equation we leave out the intercept and include a set of year dummy variables (Reardon et. al, 2010).

\[ \eta_{ijt} = \ln \left( \frac{h_{ijt}}{1-h_{ijt}} \right) - \sum_{t=0}^{5} \alpha_t(\text{year}_{ijt}) \]  

Where
- \( h_{ijt} \) = the hazard of dropout for student \( i \) in school \( j \) at time \( t \)
- \( \text{year} \) = a dummy variable for time \( t \) for student \( i \) in school \( j \)
- \( \alpha_t \) = coefficient that gives the shape of the baseline logit-hazard curve

Secondly, several student covariates are added to the model. This model represents the effects of several time-invariant covariates on the logit-hazard curve without accounting for the type of school attended (Reardon et. al, 2010).

\[ \eta_{ijt} = \sum_{t=0}^{5} \alpha_t(\text{year}_{ijt}) \cdot \beta \cdot X_{ij} \]

Where
- \( X_{ij} \) = vector of covariates, gender, race, and free/reduced lunch status for student \( i \) in school \( j \)

To determine whether or not the failure of model 1 to take school type into account biases the estimates, a conditional logit discrete-time model is developed (Reardon et. al, 2010).
Where

\[ \eta_{jt} = \sum_{j=0}^{5} \gamma_{jt} \cdot (\text{year}_{jt}) + \beta X_{jt} \]  

\[ \forall t \in \{0, 5\} \]

\[ \gamma_j = \text{the school-specific intercept for school } j. \]

\[ \alpha_i = \text{the average within-school differences in student-level independent variables} \]

\[ \beta = \text{coefficient representing the average within school differences in the vector of student level covariates} \]

By comparing a standard logit discrete-time model (model 2) to the conditional logit discrete-time model (model 3) general information can be gathered about how much the relationships between student level characteristics and hazard rates are due to school clustering (Reardon et al. 2010).

**Two-Level Discrete-Time Hazard Models**

The first model examines three proportionality assumptions including the level-1 proportional odds assumption (the effect of the student level covariate on the log odds of dropout is the same each year); the level-2 proportional odds assumption (the effect of the school level covariate \( Z_j \) is the same each year); and the level-2 proportional error assumption (assumption that the school-level error term for school \( j \) is the same each year) (Reardon et al. 2010). These three assumptions are incorporated in the following two-level discrete-time hazard model.

The conditional logit discrete-time model includes the proportionality assumption that states the shapes of the baseline logit-hazard curves are parallel across all schools. To fully examine this assumption, we use a two level discrete-time hazard model (Reardon et al. 2010).

\[ \eta_{jt} = \alpha_{j0} + \sum_{m=0}^{5} \alpha_{jm} (\text{year}_{jt}) + \beta X_{jt} \]

\[ \alpha_{j0} = \gamma_{j01} Z_j + \mu_j \]

\[ \alpha_{j0} = \gamma_{j01} \quad \forall t \in \{0, 5\} \]
X\textsubscript{ij}=time-invariant student level independent variable for student i in school j, gender, race, and free/reduced lunch status for student i in school j
Z\textsubscript{j}=time invariant school-level independent variable for school j.
\alpha_i=the average within-school differences in student-level independent variables

After testing these assumptions and making comparisons, a complete multilevel model of the hazard by the logit link can be developed. This model of logit-hazard for the outcome represents the relationship between independent variables and the log odds of dropout. In this equation, the parameters represent additive effects on the log odds of dropout. The individual level model is the hazard model for student j in school k:

\[
\text{Logit}(p_{ijk}) = \beta_{0k} + \beta_{1k} \text{Gender}_j + \beta_{2k} \text{Race}_j + \beta_{3k} \text{F&RL}_j + \beta_{4k} \text{Time}_j + \beta_{5k} \text{Time}_j^2
\]  

[5]

When allowing \( \beta_0 \) to vary by school, the overall dropout level will be a function of the school the student attends. The school level model was as follows:

\[
\begin{align*}
\beta_{0k} &= \gamma_{00} + \gamma_{01} \text{Schooltype}_k + \gamma_{02} \text{F&RL}_k + \gamma_{03} \text{Race}_k + \gamma_{04} \text{HQT}_k + \in_0k \\
\beta_{1k} &= \gamma_{10} + \gamma_{11} \text{F&RL}_k + \gamma_{12} \text{Race}_k + \gamma_{13} \text{HQT}_k + \in_{1k} \\
\beta_{2k} &= \gamma_{20} + \gamma_{21} \text{Race}_k + \gamma_{22} \text{HQT}_k + \in_{2k} \\
\beta_{3k} &= \gamma_{30} + \gamma_{31} \text{HQT}_k + \in_{3k} \\
\beta_{4} &= \gamma_{40} \\
\beta_{5} &= \gamma_{50}
\end{align*}
\]  

[6]

Where
\in=error that demonstrates any correlation between the timing of dropout by students in the same school.
\beta_{0k}=the overall level of dropout in school k, which varies by percentage of free and reduced lunch population, percentage of black student population, and percentage of highly qualified teachers.
\beta_{1k}=the effect of gender for school k, which varies by free and reduced lunch status, race, and % of highly qualified teachers for school k
\beta_{2k}=the effects of race for school k, which varies by race and percentage of highly qualified teachers for school k
\beta_{3k}=represents the effects of free and reduced lunch status for school k, which varies by percentage of highly qualified teachers for school k
\beta_{4} and \beta_{5} =the effects of duration since beginning of study to duration squared.
This model can be expressed as two separate sets of equations, as noted above, but also as one complete model. To produce this equation the author substituted the level 2 equations for the Bs in the level 1 equation.

\[
\text{Logit} (p_{tjk}) = (\gamma_{00} + \gamma_{01} \text{Schooltype}_k + \gamma_{02} F & RL_t + \gamma_{03} \text{Race}_k + \gamma_{04} \text{HQT}_k + \in 0k) + (\gamma_{10} + \gamma_{11} F \& RL_t + \gamma_{12} \text{Race}_k + \gamma_{13} \text{HQT}_k + \in 1(\text{Gender}_j) + \\
(\gamma_{20} + \gamma_{21} \text{Race}_k + \gamma_{22} \text{HQT}_k + \in 2k) \text{Race}^+ + ((\gamma_{30} + \gamma_{31} \text{HQT}_k + \in 3k) F \& RL_t^+) + \\
\gamma_{40} \text{Time}_{tj} + \gamma_{50} \text{Time}^2_{tj}
\]

[7]

Where

- \(\text{Time}_{tj}\) = number of years since beginning of study (duration)
- \(\text{Time}^2_{tj}\) = number of years since beginning of study, (duration squared)
- \(Y_{tjk}\) = a dichotomous outcome variable that indicates whether student \(j\) in school \(k\) drops out of school during year \(t\).
- \(P_{tjk}\) = the hazard of dropping out for student \(j\) in school \(k\) during year \(t\) (given that he has not dropped out yet)
- \(\text{Race}^+\) = a dichotomous independent variable that indicates whether student \(j\) is Black or non-Black. This is a time-invariant student level variable.
- \(\text{Schooltype}_k\) = a dichotomous independent variable that indicates whether a school \(k\) is an RSD school or a traditional public school at year \(t\). This is a time-invariant school level covariate.
- \(F \& RL_j\) = a dichotomous independent variable that indicates whether student \(j\) is receiving free or reduced lunch at year \(t\). This is a time-varying student level covariate.
- \(F \& RL_{kt}\) = an indicator of the mean school \(k\) percentage of free and reduced lunch student population at year \(t\). This is a time-varying school level covariate.
- \(\text{Race}_{kt}\) = an indicator of the mean school \(k\) percentage of black student population at year \(t\). This is a time-varying school level covariate.
- \(\text{HQT}_{kt}\) = an indicator of the mean school \(k\) percentage of highly qualified teacher population at year \(t\). This is a time-varying school level covariate.

**Analysis 2: Student Achievement**

**Operationalization of Key Variables**

**Dependent Variables**

LEAP test scores. This study examines the nationally accepted data of yearly state standardized test scores for students including grades 3-11. The dependent variable is subdivided into scaled scores for corresponding achievement levels. These achievement levels include
unsatisfactory, approaching basic, basic, mastery, and advanced. The lower boundary point for BASIC or proficient scores in math varies from one test year to the next, as does the proficient scores for English Language Arts (ELA). These vary according to the level of difficulty of test questions. The range for each subject is 0-900, with the proficiency level at 55% of the total testing items.

iLEAP test scores Integrated Louisiana Educational Assessment Program. iLEAP is administered to 3rd, 5th, 6th, 7th, and 9th grade students in Louisiana public schools. It is similar to the LEAP test, administered to 4th, 8th, and 10th grade students. Like the LEAP test it also examines student performance in 4 areas including ELA, Science, Mathematics, and Social Studies. iLEAP scores are less influential on students passing to the next grade, but may be taken into account for placement in specific classes in the next grade.

**Independent Variables**

The independent variables for the second analysis were the same as the first analysis on dropout with

**Definition of Key Terms**

**Nested Data:** Data that can be grouped at a higher level. In the current study, students are grouped within schools.

**Level-One Covariate:** The first level of the HLM is the lowest possible disaggregation of groups. It is usually the individual level or time within individuals.

**Level-Two Covariate:** A covariate for the second level group, the group in which individuals are linked together. Alternatively, the level two covariate can be characteristics of the subjects in the study if level one is time within individuals.
**Level-Three Covariate**: The highest grouping level. These covariates are characteristics of large groups such as neighborhoods, hospitals, and schools.

**Time within Individual**: This is detailed at level one of a three level model of change within individuals. Time is used as a covariate, with the outcome variable regressed onto it.

**Intraclass Correlation Coefficient (ICC)**: This coefficient describes the ratio between group variance to the total variance. In other words, it the percentage of variance in achievement between schools. The ICC assumes that within group data is more similar than between group data.

**Fully unconditional model**: This model includes no predictor variables at any level and is indicative of individual achievement growth for student i in school j at time t.

**Student-level model**: This model demonstrates student achievement as a function of school means plus error.

**School-level model**: This model demonstrates the variability among schools.

**Conditional model**: This model includes predictors plus error at each level of the hierarchical linear model, with student achievement as the outcome.

**Achievement Data**

**Individuals**

This study utilized secondary administrative data. The data are located in the state department of education database within the accountability department. Individual scores for each school and student on LEAP/iLEAP/GEE scores are published annually and housed within the Department of Education. Each student is assigned a student identification number by the LDOE, for all of their state education records. Student information includes the school attended, achievement data, demographic data, discipline data, and other enrollment information such as
drop out status and grade progression. In order to utilize this information for the current study, the author downloaded all relevant files from EXCEL documents and entered data for schools in the study into the STATA database.

Schools

The secondary data available for the school level variables is also collected and housed at the state department of education. However, it is available to the public through the state department to of education website. The data is aggregated to the school level on dropout and LEAP/iLEAP scores and published annually by the LDOE. Each school in the state is issued a site code that is linked to the school name, school district name, and percentages of the student population that qualify for free and reduced lunch program, percentages of highly qualified teachers, and percentages of the student population that is minority.

Achievement Method and Procedures

Sample

Matching

The sample and matching strategy for the student achievement outcome variable are identical to the strategies employed in the Discrete Time Survival Analysis of dropout risk. In order to capture the outcomes for students in schools that have opened after 2007-2008, this sample is divided into two samples: Sample A and Sample B. The majority of the RSD schools in the sample were opened in the 2007-2008 school year and therefore have 4 years of data available. There is a small sample of RSD schools that were opened in 2008-2009, these are the schools that are included in Sample B and followed for 3 years. Methods will be presented for both samples.
Student Sample A

In the fall 2007-2010 school years, the mean ELA score for all students was 292.73 (s.d.=50.22) and the mean Math score for all students was 296.13 (s.d.=55.69). Approximately 91.51% of students qualified for free lunch and 7.02% qualified for Reduced Lunch. Fifty-two percent of the student population was female, and 42.8% male. Also, approximately 90.59% of the student population is African American, and 9.41% is non-African American.

School Sample A

At the school level, the mean percentage of students who qualify for free and reduced lunch for all years is 89.84% (s.d.=8.36). The mean percentage of African American students is 97.7% (s.d.=3.05), and the mean percentage of highly qualified teachers is 48.22% (s.d.=24.37).

Student Sample B

In the fall 2008-2010 school years, females composed 51.87% of the sample and males made up 48.13%. African American students comprised 98.67% of the sample, while non-African American students made up 1.33% of the sample. Students who qualified for Free lunch made up 93.73% of the sample, and those students who qualified for Reduced lunch composed 6.27% of the sample. RSD schools comprised 50% percent of the sample and traditional public schools comprised 50% percent of the sample. The mean percentages of the school level variables were as follows: school percent free and reduced lunch=83.96 (s.d.=8.22); school percent highly qualified teachers=66.02 (s.d.=12.40); and school percentage African American students=98.20 (s.d.=1.65). The mean percentages on the scaled score outcomes were as follows: ELA scaled score=294.31 (s.d.=89.95) and math scaled score=300.96 (s.d.=87.25).
**School Sample B**

At the school level, the mean percentage of students who qualify for free and reduced lunch for all years was 83.96% (SD=8.22). The mean percentage of Black students is 98.20% (SD=1.65), and the mean percentage of highly qualified teachers is 66.02% (SD=12.40).

**Representativeness**

The matched comparison sample is a non-probability sample that limits generalizability to the study sample. The population of RSD schools for Sample A (N=71), however, includes each school within the RSD, and may be generalized to other state takeover systems like the Louisiana RSD and to the rest of the schools that within the LA-RSD that will open in years to come. The new school performance score that is necessary for schools to achieve in order to avoid state takeover has risen to 75 over the last year. This will increase the number of schools eligible for takeover because schools that had previously avoided takeover by achieving a score of 65, could now fall below the new target to avoid takeover, 75. The student population in the RSD schools is matched with similar students in Louisiana public schools and, thus, can be generalized to that sample of public schools.

**Protection of Human Participants**

This secondary data analysis may present social risks to schools in the LA-RSD because of their inclusion as RSD schools. While the data do not include names of the schools, the site codes are available and public information. The general results may present social stigma to the category of schools classified as being in the LA-RSD, however, due to the low performing nature that characterizes these schools. The data is confidential property of the Louisiana Department of Education and includes student identifier information, which could pose risks if released. No schools were contacted for this study and student identifier information was not
linked to student names. Also, in the results of this analysis schools are identified by a school site code rather than a name. Likewise, the LSU Office of Social Service Research and Design has taken measures to ensure the integrity of the data, by securing the data on hard drives locked in a password protected safe. The data may only be used at the LSU OSSRD office, must be signed in and out, and must be used on a computer that does not allow internet access to its users. In March 2012, the LSU Institutional Review Board granted this author permission to conduct this study.

**Achievement Research Design**

Hierarchical linear modeling was employed to examine the influence of student and school characteristics on the continuous outcomes of LEAP/iLEAP/GEE achievement scores. This design was chosen for investigation due to its ability to manage nested data while accounting for within group and between group variation at each level of the analysis (Raudenbush & Bryk, 2002).

**Issues of Validity**

**Validity**

Validity of a research design refers to the confidence a researcher can have that the independent variable has an effect on the outcome variable. This is of concern in experimental and quasiexperimental designs. The validity of the data are the key focus of this research design since it is not experimental or quasi experimental in nature. Administrative data have both strengths and limitations in regards to validity. Threats to the validity of administrative data include the human input error that may occur at both the school and state database levels. Staff from local public schools input data on students including enrollment data, discipline data, and demographic information. This information is then provided to the state department of education
for input into its database. There is potential for misinformation and improper coding to occur due to human error. Also, the data are not often gathered according to a theoretical framework, but instead are based on what information would be easiest to collect. Likewise, when using previously coded administrative data, the study design is limited to the variables already included in the database. This also refers to the underlying meaning of the variables, the range of categorical variables, and the interpretation of the variables. Researchers may not be measuring what they intend to measure which is the definition of validity.

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The threat of instrumentation occurs in this case because the testing instrument, the LEAP, test used to measure the dependent variable changes from the pre-test to the post-test or from year to year. Instrumentation threats decrease the ability to conclude that the outcome has changed because different measurements were used at each data collection point. However, although test is different on each administration, the content standards remain the same from year to year.

The testing threat occurs when subjects react to the testing process. The act of engaging in LEAP/iLEAP testing may be anxiety producing for several students and teachers, resulting in an enhancement or reduction of the quality of subject responses on the outcome measure. This
also refers to conditions of the testing environment that are different from pre-test to post-test, such as a student being ill on the pre-test but not on the post-test. The student’s post-test responses would be different, not due to the treatment or intervention, but because of the differences in testing environment. Lastly, because several students are administered the LEAP/GEE with special accommodations, such as reading the test aloud or delivery in small groups, test administrator behavior may also influence outcomes on the test. For example, a test administrator may either provide too little or too much assistance with test items, biasing the answers as a result.

**Reliability**

Reliability of administrative data is also subject to threats due to human error. Because staff at public schools and the department of education change, the outcome variable, dropout status, may not be coded similarly over time. Similarly, the consistency with which schools collect free and reduced lunch forms and with which staff input the information into the state enrollment system can also affect the reliability of the free and reduced lunch measure. The systems used by parishes also vary, East Baton Rouge uses an information system called Teacher Access System (TAC), Caddo uses JPAMS and the RSD uses a combination of both, determined by the chartering agency.

**Mode of Observation**

**Measurement**

This study utilized secondary education data. The LEAP/GEE tests are administered each spring by teachers in schools and scored by the LEAP testing agency electronically and human scoring of written responses for the English portion of the exam. The data are located in the state department of education database within the accountability department. Individual student scores and aggregate school scores on the LEAP are published annually and housed within the
Department of Education. Each school in the state is issued a site code that is linked to the school name, school district name, percentages of the student population that qualify for free and reduced lunch program, percentages of highly qualified teachers, and percentages of the student population that is minority. In order to utilize this information for the current study, the author downloaded all relevant files into EXCEL or STATA.

**Instrumentation**

All data from this study were gathered using the Louisiana Educational Assessment Program (LEAP), Integrated Louisiana Education Assessment Program (iLEAP), and Graduate Exit Examination (GEE) standardized testing forms or state enrollment data on public school students. The current federal policy of No Child Left Behind requires states to engage in standardized testing attached to high stakes. Louisiana utilizes a criterion referenced testing program developed in 1997. Approved by the Louisiana State Board of Elementary and Secondary Education (BESE) and performed by the Data Recognition Corporation (DRC) and Pacific Metrics, this test is administered to 3rd-9th grade students in subject areas of English language arts, mathematics, science, and social studies. Tenth grade students also take the high school level of this test in English and Math, known as the Graduate Exit Examination (GEE).

The development of the test followed the processes of item writing; committee reviews; revision; field testing; field-test data analysis; operational form selection; operational administration; and operational test data analysis (LDOE, 2010). To develop forms for upcoming years, a pool of operational test items are selected from the previous year’s test; no field test items are used. The DRC utilized the following selection criteria to include items on test forms. The scaling method used by DRC follows the NAEP test Item Response Theory, both estimating a test item’s difficulty and the likelihood of a low performing student answering the question.
directly. This method is used to convert raw LEAP scores to scaled scores to allow for valid comparisons over different versions of the test (LDOE, 2010).

**Validity of LEAP/iLEAP/GEE**

The estimated content validity of the LEAP, iLEAP, and GEE was determined by the degree to which the test aligned with state content standards. This was defined by in-state committees for each subject and grade level. The committees consisted of Louisiana teachers, Louisiana Department of Education curriculum and assessment staff, and an outside consultant.

**Reliability of LEAP/iLEAP/GEE**

The coefficient alpha reliability for each of the grade levels ranges from .59-.66. The Cronbach’s alpha for each grade level test ranges from .85-.93 indicating a strong measure of reliability for the overall test (LDOE, 2010).

**Achievement Data Analysis**

**Power Analysis**

Power refers to the likelihood of rejecting the null hypothesis when it is false. This is known as a Type II error. Cohen (1992) suggests using a power of .80 as a common value for power. Determining power involves addressing the sample size, significance level, and population effect size. Cohen (1992) considers .50 a moderate power level. In *a priori* power analysis, the sample size helps to determine a certain power for a given alpha level and effect size. An increase in sample size can enhance the ability to correctly reject a false null hypothesis. According to Cohen (1992), the study sample size is sufficient for a power analysis of .80.

In regression analyses, Knapp and Campbell (2004) recommend that the number of observations in a given equation should at least equal ten times the number of predictors in the equation. This study considered a maximum of six variables in the second and third level HLM analyses. Thus with n=145 observations at level 3, the number of variables does not present a
problem for this analysis. For Sample B, the level 3 analysis only includes 12 schools, but this was counterbalanced at level 2. The level 2 analysis included 1,106 students, which is more than ten times the number of predictors in the level 2 equation.

**Data Quality**

Using STATA, all cases at the student level with missing values were deleted. The data was screened for outliers. Also, the LEAP/iLEAP tests only begin in 3rd grade, so many schools that don’t have these grade levels were excluded from the analysis. Data were only included if they were linked to student name, ID#, for multiple years. In STATA this is a search for duplicates, to match the students with each year of data.

**Descriptive Statistics**

To determine whether HLM are appropriate for given achievement data, Raudenbush and Bryk (2002) suggest a series of steps in analysis of data using HLM. These steps include the following: sampling and data collection, univariate frequency distributions for all level 1 variables, model specification, parameter estimation and testing, and observation of residuals and variance testing. Univariate analyses yielded descriptive statistics to provide an overview of student and school characteristics included in this study. Means and standard deviations for each variable were gathered using STATA.

**Centering**

According to Raudenbush and Bryk (2002) intercepts at the student–level of the multilevel model can only be interpreted based on the location of the student-level covariates. Thus if the meaning of a covariate at 0 does not conceptually make sense, the researcher can move the covariate that will make it more meaningful. This is known as centering. Since zero is
a meaningful category for the predictor variables and within the dataset, centering the student
and school level predictors is not necessary in this analysis.

**Inferential Statistics**

Raudenbush and Bryk (2002) and Tabachnik (2009) describes hierarchical linear modeling as a multilevel model that allows the examination of nested cases (students within schools) as well as the examination of the relationship between outcomes (standardized tests scores) and time. It has been called various names by scholars in various disciplines including covariance component models (Goldstein, 1987), random effects and mixed effect models (Singer, 1998), and multilevel regression (Tabachnik, 2009). Each of these authors has applied HLM to education research with nested data. It’s goal according to Boyd and Iverson (1979) is to explain individual (smallest unit of analysis) level phenomena in terms of individual and group level factors. In order to accomplish this, HLM combines methods from ordinary least squares regression and maximum likelihood estimation. It also provides reliable estimates with only a small number of cases.

Hierarchical linear modeling is a version of the hierarchical generalized linear model. Two and three level HLM has been used many times in education research to predict student outcomes on standardized test data (Lee & Bryk, 1989). Longitudinal HLM allows each student to serve as his own control, which then addresses confounding variables (Duckworth, Tsukayama, & May, 2010). The use of longitudinal data also facilitates the identification of variance within individuals over time. We can model student achievement over four years and treat all other student and school level variables as time-varying covariates. The resulting growth curve gives information about a student’s starting level and change from one year to the next.
Advantages of Hierarchical Linear Modeling

HLM can accommodate violations of several assumptions of OLS including sphericity, missing data, large group sample sizes, homogeneity of variances across repeated measures. Hierarchical linear modeling does not ignore variation between groups or within groups, offering a clearer picture of what characteristics and at which level are influencing an individual outcome.

Three-Level Hierarchical Linear Model

This analysis used a three level hierarchical linear model. The first level of analysis is the individual student growth data for repeated measures on the outcome variables. The level 2 analysis examines students within schools, and the level three analysis examines the variation between schools on outcome measures over time, in this case, LEAP/iLEAP scaled score.

Model Assumptions for Hierarchical Linear Model

Many of the same assumptions for ordinary regression equations apply to the hierarchical linear model, but are slightly adjusted to address the nested data. The modified assumptions are as follows:

1. Linearity: This refers to the existence of a linear relationship between the independent variables and student achievement. In other words, the covariates on the right hand side of the equation are linearly related to the outcome variable. Scatterplot graphs were generated of the residuals to ensure the form of the data.

2. Normality: Level-1 and Level-2 errors were assumed to be normally distributed. A violation of this assumption can lead to biased standard errors at both levels.

3. Homoscedasticity: Level-1 residual variance is constant for each level-2 unit. This was examined by assessing the level-1 residuals for each level-2 unit (Raduenbush & Bryk, 2002).
4. Independence: Level-1 residuals and level-2 residuals are uncorrelated.

5. Independence: This assumption refers to the independence of cases at the highest level.

6. Adequate sample size. One of the drawbacks to HLM according to Woltman et. al (2012), is that it needs a large sample size to gain adequate power, which is particularly true for level-1. Likewise, HLM removes missing data from the group-level and can only allow missing data at the level 1. It is important to increase the number of groups, rather than the individuals within the group, for adequate power (Woltman et. al, 2012).

The author followed a multi-step process in order to determine the need for multilevel modeling. First an unconditional model is run for reading and math as shown in table x. The intraclass correlation was determined after these models were run and determined to be significant enough to continue further analysis with the multilevel model.

Next, basic models of the HLM were run. The models include an unconditional model with no predictors at Level 1 (repeated observations), Level 2 (student level), and level 3 (school level). The unconditional model was used to test the assumptions of HLM and will serve as a starting point for the later models (Werblow & Duesbery, 2009). Next, level 2 predictors were added to the level 1 model and are allowed to vary by school. This is known as the conditional model (Raudenbush & Bryk, 2002). The student variables include Free and Reduced Lunch Status, gender, and race. Finally, at the school level, the intercepts from level 2 are used as outcomes across all schools (Werblow & Duesbery, 2009). The school level variables added were mean percentage of the student population that qualify for free and reduced lunch; the mean percentage of black students; the mean percentage of highly qualified teachers; and the school type. Also, deviance tests were conducted to identify any extra explanation of variability in dropout or LEAP/iLEAP scores.
For the second and third outcome variables, ELA achievement score and Mathematics achievement score, a three level HLM was used to examine the relationship between the outcomes and student and school characteristics over time. The first level of the analysis is the within-individual analysis, in which achievement score is predicted as a function of time. At level 2, the level one slopes and intercept become the dependent variables being predicted from student level variables of race, gender, and free/reduced lunch status.

The unconditional level 1 model includes the outcome variable without any predictors. It describes achievement without any predictors.

The unconditional Level 1 model was as follows:

\[ Y_{tij} = \pi_{0ij} + \pi_{1ij}(\text{academic year})_{tij} + e_{tij} \]

Where
\[ Y_{tij} \] is the outcome at time t for child i in school j
\( (\text{academic year})_{tij} = 0 \) at spring of year 1, 1 at spring year 2, 2 at spring of year 3, and 3 at spring of year 4.
\( \pi_{0ij} \) is the initial status of child ij that is the expected outcome for that child in the spring of the first year; academic year = 0
\( \pi_{1ij} \) is the learning rate for child ij during the academic year

The unconditional level 2 model takes the form of
\[ \pi_{0ij} = \beta_{00j} + r_{0ij} \]
\[ \pi_{1ij} = \beta_{01j} + r_{1ij} \]

The unconditional level 3 model takes the form of
\[ \beta_{00j} = \gamma_{000} + u_{000j} \]
\[ \beta_{01j} = \gamma_{100} + u_{100j} \]

The conditional model for achievement uses the unconditional model and adds student level and school level predictors of achievement.

Level 1 of the conditional model is the same as level 1 of the unconditional model.

Level 2 of the conditional model will be as follows:
\[ \pi_{ij} = \beta_{00j} + \beta_{01j}(F&R \text{ Lunch status})_{ij} + \beta_{02j}(gender)_{ij} + \beta_{03j}(minority \text{ status})_{ij} + \beta_{04j}(\text{previous year achievement})_{ij} + \beta_{05j}(\text{repeater})_{ij} + r_{0ij} \]
\[ \pi_{ij} = \beta_{00j} + \beta_{10j}(F&R\ Lunch\ status)_{ij} + \beta_{11j}(gender)_{ij} + \beta_{12j}(minority\ status)_{ij} + r_{ij} \]

Where

\[ \beta_{00j} = \text{mean initial status within school at time } t \]
\[ \beta_{01j} = \text{regression coefficient associated with free and reduced lunch status for the jth school} \]
\[ \beta_{02j} = \text{regression coefficient associated with gender for the jth school} \]
\[ \beta_{03j} = \text{the regression coefficient associated with minority status for the jth school} \]
\[ \beta_{04j} = \text{the regression coefficient associated with previous year achievement for the jth school} \]
\[ \beta_{10j} = \text{the score for the ith student in the jth school on that variable} \]
\[ \beta_{11j} = \text{regression coefficient associated with the poverty gap} \]
\[ \beta_{12j} = \text{regression coefficient associated with the gender gap} \]
\[ \beta_{13j} = \text{regression coefficient associated with the racial gap} \]
\[ (gender)_{ij} = \text{the score for the ith student in the jth school on that variable} \]
\[ (minority\ status)_{ij} = \text{the score for the ith student in the jth school on that variable} \]
\[ R_{ij} = \text{random error associated with student i in classroom j} \]

Level 3 of the conditional model will be as follows:

\[ \beta_{00j} = \gamma_{000} + \gamma_{010}(\text{mean F&R lunch status }\%)_j + \gamma_{020}(\text{mean HQT }\%)_j + \gamma_{030}(\text{mean minority }\%)_j + \gamma_{040}(\text{school type})_j + \gamma_{050}(\text{academic year})_j + u_{00j} \]
\[ \beta_{01j} = \gamma_{010} \]
\[ \beta_{02j} = \gamma_{020} \]
\[ \beta_{03j} = \gamma_{030} \]
\[ \beta_{10j} = \gamma_{100} + \gamma_{101}(F&R\ Lunch\ status)_{ij} + \beta_{12j}(gender)_{ij} + \beta_{13j}(minority\ status)_{ij} + r_{1ij} \]
\[ \beta_{11j} = \gamma_{110} \]
\[ \beta_{12j} = \gamma_{120} \]
\[ \beta_{13j} = \gamma_{130} \]

Where

\[ \gamma_{00} = \text{is the average of the school means on ELA/math achievement} \]
\( \gamma_{010} \) the independent effect of mean free and reduced lunch status on ELA/math achievement
\( \gamma_{020} \) the independent effect of mean percentage of highly qualified teachers on ELA/math achievement
\( \gamma_{030} \) the independent effect of mean percentage of minority students on ELA/math achievement
\( \gamma_{040} \) the independent effect of school type on ELA/math achievement
\( \gamma_{050} \) the independent effect of academic year on ELA/math achievement
\( \gamma_{100} \) the average F&R lunch status-achievement regression slope across schools
\( \gamma_{200} \) the average gender-achievement regression slope across schools
\( \gamma_{300} \) the average race-achievement regression slope across schools

(mean free and reduced lunch status)\( j \) is the percent of students who qualify for free and reduced lunch in school \( j \)
(mean HQT)\( j \) is the percent of teachers who possess a valid teaching certificate in school \( j \)
(mean minority percentage) is the percent of the school population that is minority in school \( j \)
(school type) is the type of school that is represented by school \( j \), either 0=non-RSD or 1=RSD
(academic year)\( j \) is 0 at spring 2008; 1 at spring 2009; 2 at spring 2010; and 3 at spring 2011.

\( U_{00j} \) is the effect of school \( j \) on ELA/math achievement

**Hypotheses**

The test of the overall relationship and the effect of the independent variables will be conducted using the likelihood ratio test. According to Woltman, et al. (2012) for the hypotheses to be supported at each level of the HLM, five conditions must be met. They include the following:

1. There must be systematic between and within group variance in student achievement.
2. The variance of the level-1 intercept and slope must be significant.
3. The independent variables in the level-1 equation predict the variance in the level-1 intercept.
4. The independent variables in the level-1 equation predict the variance in the level-2.
Table 1: Study Variables

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Metric</th>
<th>Definition</th>
<th>Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dropout Status</td>
<td>Dichotomous</td>
<td>Describes whether a student has or has not dropped out of school</td>
<td>0=no drop out</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1=drop out</td>
</tr>
<tr>
<td>ELA score</td>
<td>Continuous</td>
<td>Achievement score on ELA portion of the LEAP/iLEAP</td>
<td>0-500</td>
</tr>
<tr>
<td>Math score</td>
<td>Continuous</td>
<td>Achievement score on Math portion of the LEAP/iLEAP</td>
<td>0-500</td>
</tr>
<tr>
<td>Gender</td>
<td>Dichotomous</td>
<td>Gender of student</td>
<td>0=male, 1=female</td>
</tr>
<tr>
<td>Race</td>
<td>Dichotomous</td>
<td>Whether or not student’s race is Black</td>
<td>0=non-black, 1=black</td>
</tr>
<tr>
<td>F&amp;R Lunch Status</td>
<td>Dichotomous</td>
<td>Whether students qualify for federal free or reduced lunch program</td>
<td>0=paid lunch</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1=free lunch, 2=reduced lunch</td>
</tr>
<tr>
<td>% F&amp;R Lunch</td>
<td>Continuous</td>
<td>Percentage of students attending the school that qualify for free/reduced lunch</td>
<td>Percentage 0-100</td>
</tr>
<tr>
<td>% Black</td>
<td>Continuous</td>
<td>Percentage of black students attending the school</td>
<td>Percentage 0-100</td>
</tr>
<tr>
<td>% HQT</td>
<td>Continuous</td>
<td>Percentage of teachers who possess a valid teacher certification</td>
<td>Percentage 0-100</td>
</tr>
<tr>
<td>Type</td>
<td>Dichotomous</td>
<td>Whether the school is classified as a Recovery School or Traditional Public School</td>
<td>0=traditional public school, 1=RSD school</td>
</tr>
<tr>
<td>Academic year</td>
<td>Continuous</td>
<td>This variable denotes the school year of the data.</td>
<td>0-academic year 2007-2008</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>1-academic year 2008-2009</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2-academic year 2009-2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3-academic year 2010-2011</td>
</tr>
</tbody>
</table>
CHAPTER 4A: RESULTS OF MULTILEVEL SURVIVAL ANALYSIS

This chapter describes the results and findings from the multilevel discrete time survival analysis and includes the following sections:

Characteristics of the Sample

Exploratory Data Analysis

Level One Discrete Time Survival Analysis Results

Level Two Discrete Time Survival Analysis Results

**Characteristics of the Sample**

The sample used in the current study was drawn from the total population of schools and students in the Louisiana public school system. The sample consisted of the entire population of RSD schools as of fall 2007 (N=71) and a matched comparison group of traditional public schools (N=74).

The original data set of all public schools, including both TPS and RSD schools in the state of Louisiana included over 1300 schools between the study years (Fall 2007-Spring 2011). The schools were initially stratified by urbanicity, yielding two parishes from which to perform the one-to-one school match. The two parishes selected were East Baton Rouge Parish and Caddo Parish. The matched comparison sample was then selected using a one-to-one match on mean socioeconomic status and mean percentage of African American students in each school.

The student sample originally included 356,767 students between the study years (Fall 2007-Spring 2011). After the school match was performed, a one-to-one propensity score match was performed at the student level based on race and free/reduced lunch status. Only students who had data for each of the 4 years of interest were kept in the dataset. Even though a student may have dropped out of school, this student would be included in the analysis and have a code
of “1” on the dropout variable. Thus, all students included at the beginning of the study remained in the study for the 4-year period.

The final sample included 145 elementary, middle, and high schools had a total of n=11,501 students enrolled in public schools within the LA-RSD, East Baton Rouge and Caddo parishes. The total number of observations for these students over 4 years was 46,004.

Univariate analyses revealed that there was no extensive missing data for the dependent or independent variables, therefore, none were removed from the study. Individual level variables included Free/Reduced Lunch, Gender, and Race. School level variables are preceded by the word “school” and include School Free/Reduced Lunch; School Highly Qualified Teachers, School Race, and School Type.

Table 2. Missing Data by Independent Variable, Dropout

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percentage Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free/Reduced Lunch</td>
<td>2.2%</td>
</tr>
<tr>
<td>Gender</td>
<td>0%</td>
</tr>
<tr>
<td>Race</td>
<td>10.1%</td>
</tr>
<tr>
<td>School Free/Reduced Lunch</td>
<td>1.1%</td>
</tr>
<tr>
<td>School Highly Qualified Teachers</td>
<td>1.1%</td>
</tr>
<tr>
<td>School Race</td>
<td>2.0%</td>
</tr>
<tr>
<td>School Type</td>
<td>0%</td>
</tr>
</tbody>
</table>

N=46,004

Table 2 summarizes the extent of missing data in the analysis. The highest percentage of missing data, 10.1%, was for the variable, Race, in the year 2010. Missing data was addressed
using listwise deletion of cases with missing data, so that no variables would be excluded from the study. There were no others variables with extensive missing data in the dataset.

Table 3. Descriptive Statistics for Demographic Variables, Dropout

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency</th>
<th>Percent</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free/Reduced Lunch</td>
<td>Free-42,896</td>
<td>93.3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Reduced-2,102</td>
<td>4.6%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>Male-22,668</td>
<td>49.28%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Female-23,334</td>
<td>50.72%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>AA-39,332</td>
<td>85.5%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Non-AA-1,590</td>
<td>3.46%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Free/Reduced Lunch</td>
<td></td>
<td>88.11</td>
<td>50.25</td>
<td></td>
</tr>
<tr>
<td>School Highly Qualified Teachers</td>
<td></td>
<td>50.97</td>
<td>25.52</td>
<td></td>
</tr>
<tr>
<td>School Race</td>
<td></td>
<td>95.36</td>
<td>8.84</td>
<td></td>
</tr>
<tr>
<td>School Type</td>
<td>RSD-71</td>
<td>49%</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>TPS-74</td>
<td>51%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N=46,004
AA=African American
SD=Standard Deviation

Table 3 details the student and school demographic variables used in this analysis. This table demonstrates that females comprised 50.72% of the sample and males made up 49.28%. African American students comprised 85.5% of the sample, while non-African American students made up 3.46% of the sample. Students who qualified for Free lunch made up 93.3% of the sample, and those students who qualified for Reduced lunch composed 4.6% of the sample.
RSD schools comprised 49% percent of the sample and traditional public schools comprised 51% percent of the sample. The mean percentages of the school level variables were as follows: school free and reduced lunch=88.11 (s.d.=50.25); school highly qualified teachers=20.97 (s.d.=25.52); and school race=95.36 (s.d.=8.84).

Table 4 defines the original format of the data used in the study. Originally, the data included one row per student with repeated values on the dropout variable at each time point. To conduct the discrete time survival analysis, the data were reformatted into “long” or “person-period data,” which creates a line entry for each year of data for each student. The first column in table 4 depicts the observation number, the second through fifth columns lists the student score on the outcome variable, dropout. The sixth column lists the type of school the student attended, whether RSD or traditional public school. Other variables in the dataset would be listed on the same row by observation as all other variables.

Table 4. Person-Oriented Data Set

<table>
<thead>
<tr>
<th>Observation</th>
<th>Y1</th>
<th>Y2</th>
<th>Y3</th>
<th>Y4</th>
<th>School Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 5 displays the person-period or “long” data format. As an example, observation number 5 was a part of the study for 4 years while subject 7 was a part of the study for 3 years. The additional variables in this table are the score on the outcome (Y), censoring variable, duration, free and reduced lunch score, and gender. The censoring variable indicates which observations did not experience the outcome (dropout) during the time period. Thus, observation
number 5 scored a “0” on the censoring variable for time periods 1 through 3 which indicates that he was censored. In time period 4, observation number 5 scored a “1” on the censoring variable indicating he was not censored and had experienced the event, or dropped out.

Table 5. Person-Period Data Set

<table>
<thead>
<tr>
<th>Observation</th>
<th>Y</th>
<th>Censor</th>
<th>Duration</th>
<th>FRL</th>
<th>Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>0</td>
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<td>7</td>
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</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>0</td>
<td>1</td>
<td>3</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Exploratory Data Analysis

The Life Tables for student dropout are depicted in Tables 6 and 7 and are grouped by school type: Recovery School District (RSD) and traditional public schools (TPS). They show the dropout patterns of the 46,004 students in the study. Also, the table shows when the student dropped out of school or when the study ended between the years 2007/2008-2010/2011.

Column number one in each table shows how many years a student was enrolled in school. Columns two through four show the number of students enrolled in school at the beginning of each year, the number of students who dropped out before the start of the next year, and the number of students who were censored at the end of the year. Students that were censored at the
end of the year, had not dropped out by the end of the study. At the end of the study, 102 traditional public school students dropped out and 386 RSD students dropped out for a total of 488 dropouts. At the end of the study, 4,950 traditional public school students were still enrolled in public school and 6,463 RSD students were still enrolled in the study.

Table 6. Life Table of Number of Years a TPS Student Stays In School

<table>
<thead>
<tr>
<th>Year</th>
<th>Enrolled at start of the year</th>
<th># who left during the year</th>
<th>Censored at the end of the year</th>
<th>Proportion students still enrolled at end of the year</th>
<th>Proportion students at the start of year and left during year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>21050</td>
<td>1</td>
<td>5561</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>2</td>
<td>15488</td>
<td>0</td>
<td>5446</td>
<td>1.000</td>
<td>0.000</td>
</tr>
<tr>
<td>3</td>
<td>10042</td>
<td>11</td>
<td>5081</td>
<td>0.998</td>
<td>0.001</td>
</tr>
<tr>
<td>4</td>
<td>4950</td>
<td>90</td>
<td>4860</td>
<td>0.981</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Table 7. Life Table of Number of Years an RSD Student Stays In School

<table>
<thead>
<tr>
<th>Year</th>
<th>Enrolled at start of the year</th>
<th># who left during the year</th>
<th>Censored at the end of the year</th>
<th>Proportion students still enrolled at end of the year</th>
<th>Proportion students at the start of year and left during year</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>24655</td>
<td>49</td>
<td>5871</td>
<td>0.998</td>
<td>0.002</td>
</tr>
<tr>
<td>2</td>
<td>18735</td>
<td>42</td>
<td>5927</td>
<td>0.9958</td>
<td>0.002</td>
</tr>
<tr>
<td>3</td>
<td>12766</td>
<td>69</td>
<td>6234</td>
<td>0.990</td>
<td>0.005</td>
</tr>
<tr>
<td>4</td>
<td>6463</td>
<td>226</td>
<td>6237</td>
<td>0.996</td>
<td>0.035</td>
</tr>
</tbody>
</table>
The survival probability is listed in the fifth column of the Life Table. It is the proportion of all students still enrolled in school at the end of each year. The survival function is the proportion of students that did not dropout throughout the study. From the table, the numbers for survival at the end of year one for traditional public school students is 1.00 and for RSD schools is 0.998. The numbers for survival at the end of the study are .981 for traditional public school students and for RSD schools is .956.

The risk is defined as the number of students enrolled at the beginning of each year. The last column of Tables 6 and 7 give the proportion of students that were enrolled at the beginning of the school year but did not return to school at the start of the next year. The hazard probability is defined as the proportion of students who dropped out of school by the end of each year. The table illustrates that 0% of the 21,050 traditional public school students dropped out of school in year 1 and 0.2% of the 24,655 students in RSD schools dropped out in year 1. In years 2, 3, and 4, the percentages of dropout for traditional public schools were as follows: 0%, 0.1%, and 2%. In years 2, 3, and 4, the percentages of dropout for RSD schools were as follows: 0.2%, 0.5%, and 4%.

**Level One Discrete Time Survival Analysis**

The central objective of this analysis was to model time to dropout with a multilevel discrete time survival analysis to determine what predictors are related to student dropout. The first step in this objective was to create a series of discrete time hazard models with the STATA xtmelogit commands. The discrete time hazard models are suited to this analysis due to its ability to incorporate longitudinal and nested data, time-variant and time invariant variables, censored data, and straightforward testing of assumptions.
The first model run was the unconditional model without demographic predictors, the second model was run with level-one student demographic predictors. The first model included a set of dummy variables representing the four time periods in the study. It was run as a logistic regression and gives the shape of the baseline logit-hazard curve.

Table 8 gives the estimates for the unconditional model, the parameter estimates for the time-variables. The inclusion of these variables in the first model gives an estimation of the risk of dropout each year. Results indicate that in year 1, the parameter estimate = -5.43 (s.d. = .142, N=46,004, p<.00). This estimate yielded a hazard of .002 for RSD schools and 0.000 for traditional public schools. In year two, the parameter estimate was -5.601 (s.d. = .155, p<.000), which yielded a hazard of .002 for RSD schools and 0.00 for traditional public schools. The third year parameter estimate was -4.965 (s.d. = .113, p<.000) with a hazard = .005 for RSD schools and 0.001 for traditional public schools. Lastly, in year four the hazard for RSD = .035 and .012 for traditional public schools with an estimate of -3.559 (s.d. = .057, p<0.00). This model demonstrates that the longer a student remained in the public school system the higher the risk of dropping out. Also from the results one can see that the RSD numbers were higher than traditional public schools in each period.
Figures 1 and 2 depict the survival and hazard probability curves for model 1, the unconditional model. From these figures, one can also notice that the RSD survival is lower than the traditional public school curve suggesting lower overall rates of survival for RSD students. The hazard curve increased across time for both types of schools, indicating that the longer a student was enrolled the higher the risk of dropout. Again, the RSD curve shows a difference from the tps curve. In figure 2, the RSD curve is higher than the TPS curve indicating a higher risk of dropout for RSD students. To find the odds of an RSD student dropping out in a given
year, the antilog $\beta_1$ was estimated. For RSD students the odds were 3.25 times greater than traditional public school students.

**Research Question #1**

Do student characteristics influence the risk of student dropping out of school at a given time?

**Hypothesis #1**: Student characteristics of disadvantage (low socioeconomic status, race) increase the risk of students dropping out of school at a given time.

To examine research question one, the addition of several level-one demographic covariates were included in the Model 2. Results are demonstrated in Table 9. These demographic covariates at the student level included gender, race, and free/reduced lunch status. The results indicate that the time indicators, race, and gender were all found to be significant at the $p<.001$ level. Free/reduced lunch status was found to be significant at $p<.10$ level. The estimates for the time variables were as follows: year 1 (-5.875, s.d.=1.712, $p<.001$); year 2 (-5.858, s.d.=1.687, $p<.000$); year 3 (-5.677, 1.659, $p<.001$); and year 4 (-3.558, s.d.= .057, $p<.000$). The student level predictors were all significantly different than zero implying that the hazard functions between genders, race, and lunch statuses were also significantly different.

To further examine gender, the significant difference of .027 demonstrates that the fitted-logit hazard function for females was slightly raised above that of males. To find the odds of a female student dropping out in a given year, the antilog $\beta_1$ was estimated. For females, the odds of dropping out were 1.02 times greater than males.
Table 9. Parameter Estimates for Model 2 Logistic Regression, Dropout

| Parameter | DF | Estimate | SD   | Z     | P>|z| | 95% Conf. Int. |
|-----------|----|----------|------|-------|-----|----------------|
| T1        | 1  | -5.875   | 1.712| -3.42 | 0.001| -9.215 -2.501  |
| T2        | 1  | -5.858   | 1.687| -3.48 | 0.000| -9.182 -2.568  |
| T3        | 1  | -5.677   | 1.659| -3.44 | 0.001| -8.909 -2.445  |
| T4        | 1  | -3.448   | .057 | -3.25 | 0.001| -8.781 -2.378  |
| FRL       | 1  | -1.682   | .451 | -3.73 | 0.080| -2.567 -.798   |
| Race      | 1  | .307     | .779 | 0.39  | 0.000| .223 .423      |
| Gender    | 1  | .027     | .028 | 0.97  | 0.001| .012 .395      |

N=46,004

Figure 3: Hazard Probability Curve for Gender, Dropout

Figure 3 demonstrates the hazard probability curve for female students and male students. The female hazard curve was used as a baseline to determine whether there was a difference between males and females. The curves were both parallel following the proportional odds assumption. By observing the curves, females had a slightly greater risk (.027) of dropout than males over time.
Next, represented in figure 4 is the survival probability for gender. There is very little separation between the two curves. Each year a student remained enrolled the lower the probability of survival for both genders.

To further examine race, the significant parameter estimate of .307 demonstrates that the fitted-logit hazard function for African American students was slightly raised above that of non-African American students. To find the odds of an African American student dropping out in a given year, the antilog $\beta_1$ was estimated. For African American students that odds was 1.35 times greater than non-African American students.

Figure 5 demonstrated the hazard probability curve for African American students and non-African American students. The non-African American hazard curve was used as a baseline to determine whether there was a difference between African American and non-African American students. The curves were both parallel following the proportional odds assumption. The figure also demonstrates that African American students had the greater risk of dropout.
Next, represented in figure 6 is the survival probability for race. There is separation between the two curves at times 3 and 4, but not at times 1 and 2 demonstrating that African American students had a lower survival rate than non-African American students. Each year a student was enrolled the lower the probability of survival for both racial categories.

Figure 5: Hazard Probability Curve for Race, Dropout

<table>
<thead>
<tr>
<th></th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA</td>
<td>0.002</td>
<td>0.003</td>
<td>0.005</td>
<td>0.023</td>
</tr>
<tr>
<td>Non-AA</td>
<td>0.003</td>
<td>0.001</td>
<td>0.003</td>
<td>0.013</td>
</tr>
</tbody>
</table>

Figure 6: Survival Probability Curve for Race, Dropout

<table>
<thead>
<tr>
<th></th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA</td>
<td>0.998</td>
<td>0.996</td>
<td>0.991</td>
<td>0.967</td>
</tr>
<tr>
<td>Non-AA</td>
<td>0.997</td>
<td>0.996</td>
<td>0.993</td>
<td>0.976</td>
</tr>
</tbody>
</table>
Figure 7 demonstrates the hazard probability curve for Reduced Lunch students and Free Lunch students. The Reduced Lunch hazard curve was used as a baseline to determine whether there was a difference between Free and Reduced Lunch Students.

The curves were both parallel following the proportional odds assumption. Students eligible for free lunch had a higher risk of dropout than students who qualified for reduced lunch.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reduced</td>
<td>0.001</td>
<td>0</td>
<td>0</td>
<td>0.014</td>
</tr>
<tr>
<td>Free</td>
<td>0.001</td>
<td>0.001</td>
<td>0.004</td>
<td>0.028</td>
</tr>
</tbody>
</table>

Figure 7: Hazard Probability Curves for Free/Reduced Lunch, Dropout

Next, represented in figure 8 is the survival probability for Free and Reduced Lunch Status. There is separation between the curves indicating a difference in the survival probability for both categories. Reduced lunch students had a higher survival rate than free lunch students. Each year a student enrolled the less probability of survival for both.

Next model 3 resembled model 2 but included the addition of an intercept. There were no school level predictors included in model 3. Only the intercept was significant at the p<.00 level. The covariate Free and Reduced Lunch was significant at the p<.10 level. These results are demonstrated in Table 10.
Figure 8: Survival Probability Curve for Free and Reduced Lunch, Dropout

Table 10. Parameter Estimates for Model 3 Logistic Regression, Dropout

| Parameter | DF | Estimate | SD  | z    | P>|z| | 95% Conf. Int. |
|-----------|----|----------|-----|------|-----|----------------|
| T1        | 1  | -.181    | .243| -.74 | 0.457 | -.657     .296 |
| T2        | 1  | -.198    | .244| 1.000| 0.999 | -.677     .281 |
| T3        | 1  | -.178    | .244| 0.998| 0.998 | -.643     .292 |
| T4        | 1  | -.174    | .241| 0.981| 0.977 | -.632     .281 |
| FRL       | 1  | -1.682   | 1.005| -1.67| 0.094 | -3.652     .288 |
| Race      | 1  | .306     | .510| .60  | .548  | -.694     1.307 |
| Gender    | 1  | .027     | .191| .14  | .886  | -.347     .402 |
| Intercept | 1  | -5.678   | .535| -10.60| 0.000 | -6.727   -4.628 |

N=46,004

Brief Summary of Level 1 Model

All level 1 covariates were significant in the level 1 models including time. This indicated significant differences between the levels of each independent variable and the hazard and survival probability curves for each independent variable. The parameter estimate for free
and reduced lunch estimate was p<.10. When an intercept was added to the model, all other predictors were not significant.

**Level Two Discrete Time Survival Model**

A two level multilevel model was used to determine the influence of several school predictors in the model. At the school level, the covariates included school type, the mean school percentage black students, mean school percentage free/reduced lunch population, and the mean school percentage of highly qualified teachers. There was also a variable denoting school type at the school level model. School type indicated whether the school attended by the student was an RSD or traditional public school.

**Research Question #2**

What is the likelihood that a student will drop out of RSD schools compared to a matched set of traditional public schools?

Hypothesis #2: According to the theory of choice and competition, there should be a smaller likelihood that students in RSD schools will dropout when compared to traditional public schools.

To investigate research question 2, Model 4 was estimated adding the school level covariate, school type, to the student level model. The parameter estimate, $\beta_1=1.79$ (s.d. .267, p<.000), represented the overall effect of school type, This can be interpreted as the odds of student in an RSD dropping out is 3.25 times greater than that of a traditional public school students. Parameter estimates for this model are included in Table 11.
Table 11. Parameter Estimates for Model 4 Logistic Regression, Dropout

| Parameter   | DF | Estimate | SD  | Z    | P>|z| | 95% Conf. Int. |
|-------------|----|----------|-----|------|-----|----------------|
| SchoolType  | 1  | 1.794    | .267| 6.71 | 0.000 | 1.270     2.318 |
| FRL         | 1  | -.744    | 1.014| -.73 | 0.463 | -2.733  1.244  |
| Race        | 1  | -1.739   | .546| -3.19| 0.001 | -2.808  -.669   |
| Gender      | 1  | -.097    | .209| -.47 | 0.642 | -.50788  .313   |
| Intercept   |    | -7.876   | 1.526| -5.16| 0.000 | -10.867  -4.886 |

N=46,004

Research Question #3

Do school characteristics influence the risk of students dropping out of school at a given time?

Hypothesis #3: School characteristics of disadvantage (low socioeconomic status, low percentage of highly qualified teachers, high percentage African American students) increase the risk of students dropping out of school at a given time.

To address research question 3, Model 5 was then estimated adding all remaining school level predictors including school mean percentage African American students, school mean percentage highly qualified teachers, and school mean percentage of students who qualify for free and reduced lunch. The model results, demonstrated in Table 11, show that student race (p<.000) and school level mean percentage African American students (p<.10) were significant. These estimates yielded a first year hazard=.01, a year two hazard=.00, a year three hazard=.01, and a year four hazard=.01. No other predictors were significant in this model.
Table 12. Parameter Estimates for Model 5 Logistic Regression, Dropout

| Parameter       | DF | Estimate | SD  | Z   | P>|z| | 95% Conf. Int. |
|-----------------|----|----------|-----|-----|-----|----------------|
| School%Blk      | 1  | .153     | .082| 1.87| 0.061|-.007           | .314           |
| SchoolHQT       | 1  | -.001    | .008| -0.13| 0.895|-.0174          | .0152          |
| SchoolFRL       | 1  | -.011    | .019| -0.57| 0.572|-.048           | .0260          |
| SchoolType      | 1  | -.586    | .372| -1.58| 0.101|-1.314          | 1.142          |
| FRL             | 1  | -.744    | 1.014| -0.73| 0.463|-2.733          | 1.244          |
| Race            | 1  | -1.739   | .546| -3.19| 0.001|-2.808          | -.669          |
| Gender          | 1  | -.097    | .209| -.47 | 0.642|-0.50788        | .313           |
| Intercept       | 1  | -7.876   | 1.526| -5.16| 0.000|-10.867         | -4.886         |

N=46,004

Assumptions for the Two-Level Discrete Time Survival Analysis

The proportionality odds assumption was tested at both level 1 and level 2. The proportionality odds assumption states that if two individuals have different values on the covariates, the ratio of the hazard functions should not be dependent on time. Both levels were tested using model 6. The level 1 proportionality odds assumption for gender was tested by examining the interactions between gender and the duration covariates. Duration covariates indicate the amount of time a student was in the study before experiencing the event. The duration and duration squared variables are included in the model to define the shape of the baseline hazard curve. Table 12 demonstrates the results of the model, which indicate a non-significant difference from zero for the interaction between gender and duration. The estimate was $\beta_3=.016$ (s.d. = .027, p=0.547). The insignificant difference from zero caused a failure in
rejecting the proportionality odds assumption for the interaction between duration and gender. School type demonstrated a marginal significance in this model.

The level 1 proportionality odds assumption for race was tested by examining the interactions between race and the duration covariates. Table 12 demonstrates the results of the model, which indicate a significant difference from zero for the interaction between race and duration. The estimate was $\beta_{1} = -0.231$ (s.d. = 0.118, p = 0.05). The significant difference from zero allowed the rejection of the proportionality odds assumption for the interaction between duration and race.

The level 1 proportionality odds assumption for FRL was tested by examining the interactions between free and reduced lunch and the duration covariates. Table 12 demonstrates the results of the model, which indicate a significant difference from zero for the interaction between FRL and duration. The estimate was $\beta_{3} = -0.249$ (s.d. = 0.127, p < 0.05). The significant difference from zero allowed the rejection of the proportionality odds assumption for the interaction between duration and FRL.

The parameter estimates for the level 2 proportionality odds assumption are also shown in Table 12. The interactions between school type and duration and duration squared were significantly different than zero. The parameter estimate for duration was $\beta_{7} = -0.164$ (p < 0.10). The parameter estimate for duration squared was $\beta_{8} = -0.153$ (s.d. = 0.088, p < 0.10). This indicates differences in dropout by school type.

The parameter estimates for the level 2 proportionality odds assumption are also shown in Table 16. The interactions between school mean percentage of African American and duration and duration squared were significantly different than zero. The parameter estimate for duration
was $\beta_{11} = .011$ (s.d.=.004, p<.01). The parameter estimate for duration squared was $\beta_{12} = .007$ (s.d.=.001, p<.03). This indicates differences in dropout by race.

Table 13. Parameter Estimates for Models 6-9 Logistic Regression, Dropout

| Parameter          | DF | Estimate | SD  | Z      | P>|z|  | 95% Conf. Int. |
|--------------------|----|----------|-----|--------|------|----------------|
| Race*Dur           | 1  | -.231    | .118| -1.95  | 0.05 | -0.462 .001    |
| Race*DurSq         | 1  | -.211    | .107| -1.93  | 0.041| -.424 .001     |
| Gender*Dur         | 1  | .0161    | .027| .60    | 0.547| -.036 .069     |
| Gender*Dursq       | 1  | .007     | .022| .54    | 0.501| -.028 .056     |
| FRL*Dur            | 1  | -.249    | .127| -1.96  | 0.050| -.498 -.000    |
| FRL*Dursq          | 1  | -.212    | .103| -1.86  | 0.061| -.466 -.001    |
| SchoolType*Dur     | 1  | -.164    | .093| -1.75  | 0.08 | -.348 0.19     |
| SchoolType*Dursq   | 1  | -.153    | .088| -1.69  | 0.07 | -.255 0.10     |
| SchFRL*Dur         | 1  | .000     | .000| .24    | .811 | -.001 .001     |
| SchFRL*Dursq       | 1  | .000     | .010| .178   | .621 | -.05 .05       |
| SchRace*Dur        | 1  | .011     | .004| 2.66   | 0.01 | .003 .019      |
| SchRace*Dursq      | 1  | .007     | .001| 1.99   | 0.025| .001 .0      |
| SchHQT*Dur         | 1  | -.002    | .001| -1.06  | .290 | -.004 .001     |
| SchHQT*Dursq       | 1  | -.001    | .000| -1.01  | .237 | -.002 .007     |
| Intercept          | 1  | -7.828   | 1.545| -5.07  | 0.000| -10.856 -4.799 |

Dur=Duration
Dursq=DurationSquared

The interactions between HQT and duration and duration squared were not significantly different than zero. The interactions between SchFRL and duration and duration squared were
not significantly different than zero. For these covariates there was a failure to reject the proportionality odds assumption.

The level two proportional error assumption is met if all the level 2 parameter estimates with duration and duration squared variables have error terms that are equal to zero. If any of them are not equal to zero then the assumption is not met. In the Model 9, all of the level 2 error terms are not zero except for one term. Thus, the proportional error assumption was not met.

Comparison of the level 1 models was conducted using the -2 log likelihood statistics. For level 1 the comparison demonstrated that the -2 log likelihood for Model 2 was -717.717 with a likelihood ratio test=6.41, (df=7, P<.0001). This was a better fit than Model 1 which had a -2 log likelihood -698.583 with a likelihood ratio test=2408.59 (df=4, P<.0000). Comparison of the level 2 models demonstrated that Model 4 had the best fit of the models with a -2 log likelihood=-1825.371.

**Brief Summary of the Level Two Discrete Time Survival Results**

School type was a significant parameter estimate yielding the odds of an RSD student dropping out being 3.25 times greater than a traditional public school student. When the rest of the predictors were added to the model the significance of school type was reduced to p<.10, marginally significant results. School percentage African American students was also significantly different from zero at p<.10 in the two level model. None of the other school level covariates were significant, suggesting no difference in the hazard indicating no difference in risk of dropout based on the school level covariates. The proportionality odds assumptions for level 1, level 2, and the errors were not met. Student race was the only student covariate in the level 2 model that was significant.
CHAPTER 4B: RESULTS OF THREE-LEVEL HIERARCHICAL LINEAR MODEL

This chapter describes the results and findings from the three-level hierarchical linear model predicting ELA and Math scores and includes the following sections:

Characteristics of the Sample
Exploratory Data Analysis
Research Question #1
Research Question #2
Research Question #3

Characteristics of the Sample

There were two samples used in this study. Results will first be presented for Sample A, then B. Both samples were drawn from the total population of schools and students in the Louisiana public school system. Sample A consisted of the entire population of RSD schools as of fall 2007 and a matched comparison group of traditional public schools (tps). The years of data for Sample A included fall 2007 through spring 2011; 4 years of data. This included data for only the Spring administration of LEAP/iLEAP/GEE.

The original data set of all Louisiana schools included over 1300 schools between the study years (Fall 2007-Spring 2011). The schools were initially stratified by urbanicity, yielding two parishes from which to perform the one-to-one school match. The two parishes selected were East Baton Rouge Parish and Caddo Parish. The matched comparison sample was then selected using a one-to-one match on mean socioeconomic status and mean percentage of African American students in each school.

After performing the school match, the student sample was selected. The student sample for both samples A and B originally included 356,767 students between the study years (Fall
2007-Spring 2011). After the school match was performed, a one-to-one propensity score match was performed at the student level based on Race and Free/Reduced Lunch status. For Sample A, only students who had data for each of the 4 years of interest on achievement were kept in the dataset.

The LEAP is only administered to 4th and 8th graders, and the ELA and Math portion of the GEE was administered to 10th graders until 2011-2012. The iLEAP is administered to 3rd, 5th, 6th, 7th, and 9th graders. Thus, for the achievement analysis the only grades included were 3rd through 10th. Only relevant variables were kept for the study.

Students in Sample A were followed for 4 years of the study. The final sample of schools for Sample A was 145, with a total of n=5,925 for 4 years. The total student observations for all years in the study for Sample A were 23,707. The breakdown by school type and year is as follows:

<table>
<thead>
<tr>
<th>Beginning School Year</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSD</td>
<td>2,511</td>
<td>2,511</td>
<td>2,511</td>
<td>2,511</td>
<td>10,047</td>
</tr>
<tr>
<td>TPS</td>
<td>3,414</td>
<td>3,414</td>
<td>3,414</td>
<td>3,414</td>
<td>13,659</td>
</tr>
<tr>
<td>Total</td>
<td>5,925</td>
<td>5,925</td>
<td>5,925</td>
<td>5,925</td>
<td>23,707</td>
</tr>
</tbody>
</table>

Univariate analyses revealed that there was no extensive missing data for the dependent or independent variables, therefore, none were removed from the study. Each variable was inspected for summary statistics, including minimum and maximum values, frequency distribution, mean, and standard deviation. A summary of these statistics can be found in Table 15. There was also an inspection for outliers, of which there were no unusual values or outliers. Table 15 summarizes the extent of missing data in the analysis. The highest percentage of
missing data was 2.0% was for the variable, SchoolRace, in the year 2010. There were no other variables with extensive missing data in the dataset.

Table 15. Missing Data by Independent Variable, Sample A

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percentage Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free/Reduced Lunch</td>
<td>1.5%</td>
</tr>
<tr>
<td>Gender</td>
<td>0%</td>
</tr>
<tr>
<td>Race</td>
<td>0.1%</td>
</tr>
<tr>
<td>School Free/Reduced Lunch</td>
<td>1.1%</td>
</tr>
<tr>
<td>School Highly Qualified Teachers(HQT)</td>
<td>1.1%</td>
</tr>
<tr>
<td>School Race</td>
<td>2.0%</td>
</tr>
<tr>
<td>School Type</td>
<td>0%</td>
</tr>
</tbody>
</table>

Table 16 details the student and school demographic variables used in the analysis of Sample A. This table demonstrates that females composed 52.20% of the sample and males made up 47.80%. African American students comprised 90.59% of the sample, while non-

Table 16. Descriptive Statistics for Demographic Variables, Sample A

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency</th>
<th>Percent</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free/Reduced Lunch</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Free</td>
<td>21,089</td>
<td>91.51%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reduced</td>
<td>1,618</td>
<td>7.02%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>11,015</td>
<td>47.80%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>12,031</td>
<td>52.20%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AA</td>
<td>20,878</td>
<td>90.59%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-AA</td>
<td>2,168</td>
<td>9.41%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Free/Reduced Lunch</td>
<td></td>
<td>89.84</td>
<td>8.36</td>
<td></td>
</tr>
<tr>
<td>School HQT</td>
<td></td>
<td>48.22</td>
<td>24.37</td>
<td></td>
</tr>
<tr>
<td>School Race</td>
<td></td>
<td>97.7</td>
<td>3.05</td>
<td></td>
</tr>
<tr>
<td>School Type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RSD</td>
<td>71</td>
<td>42.38%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TPS</td>
<td>74</td>
<td>57.62%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N=23,707 AA=African American
SD=Standard Deviation

African American students made up 9.41% of the sample. Students who qualified for Free lunch made up 91.5% of the sample, and those students who qualified for Reduced lunch composed 7.02% of the sample. RSD schools comprised 42.38% percent of the sample and traditional public schools comprised 57.62% percent of the sample. The mean percentages of the school level variables were as follows: school percent free and reduced lunch=89.84 (s.d.=8.36); school
percent highly qualified teachers=48.22 (s.d.=24.37); and school percentage African American students=97.7 (s.d.=3.05). The mean percentages on the scaled score outcomes were as follows: ELA scaled score=292.73 (s.d.=50.22) and math scaled score=296.13 (s.d.=55.69).

**Exploratory Data Analysis**

Preliminary data analysis included merging school and student level data files, generating correlations between variables; and conversion of scaled outcomes to z-scores. First, school level data was merged to the student level file by school site code. Then, correlations were run to determine the strength of the relationship between the achievement scores and the predictors of interest. Correlations demonstrate that the outcome variables have a weak relationship to predictors. Also, the correlation table demonstrates that scores on achievement outcomes correlate with one. All correlations in the table are significant the p<.05 level unless otherwise indicated. Negative correlations ranged from -.661 to -.001. Positive correlations ranged from .013 to .694 and all were significant.

<table>
<thead>
<tr>
<th></th>
<th>ELA scaled</th>
<th>Math scaled</th>
<th>FRL</th>
<th>Gender</th>
<th>Race</th>
<th>SFRL</th>
<th>SHQT</th>
<th>SRace</th>
<th>SType</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELA scaled</td>
<td>1.000</td>
<td>.694**</td>
<td>.054</td>
<td>-.133</td>
<td>-.038</td>
<td>.105</td>
<td>-.010</td>
<td>-.001</td>
<td>-.015</td>
</tr>
<tr>
<td>Math scaled</td>
<td>1.000</td>
<td>.048</td>
<td>.020</td>
<td>-.061</td>
<td>.083</td>
<td>-.045</td>
<td>-.007</td>
<td>.692</td>
<td></td>
</tr>
<tr>
<td>FRL</td>
<td>1.000</td>
<td>-.004**</td>
<td>-.067</td>
<td>.016</td>
<td>-.027</td>
<td>-.080*</td>
<td>-.115</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender</td>
<td>1.000</td>
<td>-.003</td>
<td>-.003</td>
<td>.006</td>
<td>-.018</td>
<td>-.021</td>
<td>.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race</td>
<td>1.000</td>
<td>.001</td>
<td>.015**</td>
<td>.197</td>
<td>.205**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SFRL</td>
<td>1.000</td>
<td>.089</td>
<td>.062</td>
<td>-.107</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SHQT</td>
<td>1.000</td>
<td>.130</td>
<td>.661**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SRace</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.523**</td>
<td></td>
</tr>
</tbody>
</table>

N=23,707
Significance level *p<.01, ** p<.001

Next in the preliminary analysis, both ELA and math outcomes were converted to Z-scores to address the vertical alignment of tests from year to year. Students do not take the same
test each year, however, general content knowledge is tested each year. Z-scores allow comparisons of tests from year to year with the determination of where the students fall within the distribution over time. The z-scores yielded the same correlation coefficients as the scaled scores when Pearson correlations were run.

**Assumptions**

To begin the analysis of the three level hierarchical linear model, the assumptions of the model were first tested.

1. To examine the linearity function, a scatterplot was used and inspected for the linear trend. The plot demonstrated a general linear trend.

2. Normality: According to (Raudenbush & Byrk, 2002) non-normality of the level 2 residuals has a small effect on the parameters. Fixed effects errors are accurate but random effects errors are inaccurate, thus robust standard errors perform better than maximum likelihood errors. Robust standard errors need at least 100 groups. There are 145 schools or level-3 groups. There are 5,924 level 2 groups or students followed over time and 23,000 total observations. Thus, a sufficient number of groups were available.

3. Homoscedasticity: This assumption was tested using scatterplots and box and whisker to ensure that residuals fall along the best fit line and the plots demonstrated that the residuals fall within the same standard deviation along the curve.

4. Independence. Pearson correlations were used to examine the correlation of the level 1 and level 2 residuals. The correlation was .204 suggesting that the residuals were not strongly correlated.

5. Independence. Absence of collinearity for level 1 and level 2 residuals: OLS regression was run, residuals were saved. This was followed by an ANOVA to test whether the residuals are
independent by level. The significant F in the ANOVA analysis suggests that the data are correlated by level and not independent. This makes the use of the multilevel model with nested data an appropriate analysis.

6. Adequate Sample Size: The student level analysis for Sample A had a total of 23,707 observations derived from 5,925 students followed for 4 years. The school level sample included 145 schools of which 74 were traditional public schools and 71 were RSD schools. Hox (1995) suggested that the level 2 or 3 sample have at least 20 groups. Thus with 145 level 3 groups, this sample is an adequate size.

**Multilevel Model**

To determine the need for further analysis, the unconditional models (Models 1a and 1b) were run for ELA and math and the intraclass correlation (ICC) was computed from the model estimates. Table 18 demonstrates the ICC for the unconditional model. A very small ICC indicates that a multilevel model is unnecessary, but this model demonstrates that approximately 13% of the variance in ELA is due to school differences and 11% of the variance in math is due to school differences. The parameter estimate of the ELA mean score for sample A is -0.112 and the standard deviations are 0.370, 0.715 and .637 at the school (level 3), student (level 2), and repeated observations of student scores for all years of the study (level 1). The estimate of the math mean score is -0.078 with standard deviations of .332, .701, and .651.

<table>
<thead>
<tr>
<th></th>
<th>Unconditional Model 1a</th>
<th>SD</th>
<th>Unconditional Model 1b</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjusted mean</td>
<td>-.112</td>
<td>.033</td>
<td>-.078</td>
<td>.029</td>
</tr>
<tr>
<td>Residual</td>
<td>.637</td>
<td>.004</td>
<td>.651</td>
<td>.004</td>
</tr>
<tr>
<td>ICC</td>
<td>.13</td>
<td>.113</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N=23,707
Models 2a and 2b were then estimated by adding time as a level-1 covariate. From Table 19 the average growth rate for students was .115 (p<.000) standard deviations above the mean over time in ELA and .084 (p<.000) standard deviations above the mean in math. The level 2 and level 3 standard deviation estimates for ELA and math were .116 and .084. The estimate of the ELA mean score in Model 2a is -231.52 and the standard deviations are 0.372, 0.712 and .627 at the school, student, and observation levels. The estimate of the math mean score in Model 2b is -166.75 and the standard deviations are .333, .701, and .646 at the school, student, and observation levels. The intraclass correlation coefficient, was .13 and .12 for ELA and math, suggesting that schools explained 13% and 12% of the variance in ELA and math growth.

Table 19: Level 1 Models with Time as Predictor of Educational Achievement, Sample A

<table>
<thead>
<tr>
<th></th>
<th>Model 2a</th>
<th>SD</th>
<th>Model 2b</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>.115***</td>
<td>.005</td>
<td>.084***</td>
<td>.005</td>
</tr>
<tr>
<td>Adjusted Mean</td>
<td>-231.52</td>
<td>10.39</td>
<td>-166.75</td>
<td>10.642</td>
</tr>
<tr>
<td>Residual</td>
<td>.627</td>
<td>.004</td>
<td>.646</td>
<td>.004</td>
</tr>
<tr>
<td>ICC</td>
<td>.13</td>
<td>.116</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

N=23,707  ~P<.10, *P<.05, **P<.01, ***P<.001

Research Question #1

Do standardized test scores vary by school type (RSD versus TPS) in Louisiana?

Hypothesis #1: According to the state takeover model, RSD schools should have higher test scores than traditional public schools.

Models 3a and 3b were run to examine research question 1 and results are shown in Table 20. The school level covariate, school type, was included in the model as a fixed effect covariate. Time, in years, was also in the model as a covariate. This accounts for any variation in the effect of school type regardless of the time period. From Table 20, the average growth rate for RSD children was -.308 (p<.000) standard deviations below TPS in ELA. In Math, RSD students scored .207 (p<.000) standard deviations below TPS students over time. The school type variable
is coded “0”-TPS, “1” for RSD, thus the parameter estimates in these models refer to RSD schools. The estimate of the ELA mean score is -233.27 and the standard deviations are 0.341, 0.712 and .627 at the school, student, and observation levels. The estimate of the math mean score is -168.29 and the standard deviations are .320, .701, and .646 at the school, student, and observation levels. The intraclass correlation coefficient was .11 and .10 for ELA and math, revealing that the school level explained 11% and 10% of the variance in ELA and math growth, respectively.

Table 20: Estimates for Effect of School Type on Educational Achievement, Sample A

<table>
<thead>
<tr>
<th></th>
<th>ELA</th>
<th>MATH</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fixed Effect</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-233.27*** (10.387)</td>
<td>-168.29*** (10.645)</td>
</tr>
<tr>
<td>SType</td>
<td>-.308*** (.062)</td>
<td>-.207*** (.059)</td>
</tr>
<tr>
<td>Time</td>
<td>.117*** (.005)</td>
<td>.084*** (.005)</td>
</tr>
<tr>
<td></td>
<td>Random Effect</td>
<td></td>
</tr>
<tr>
<td>Within School SD</td>
<td>.712</td>
<td>.701</td>
</tr>
<tr>
<td>Between School SD</td>
<td>.341</td>
<td>.320</td>
</tr>
<tr>
<td>ICC</td>
<td>.11</td>
<td>.10</td>
</tr>
</tbody>
</table>

N=23,707 P<.10, *P<.05, **P<.01, ***P<.001 Parameter estimates (Standard deviation)

Research Question #2

Do student characteristics account for the variation in standardized test scores between RSD and TPS?

Hypothesis #2: Student characteristics of disadvantage (low SES, African American) will decrease standardized tests score performance in schools.
Models 4a and 4b added the student demographic covariates, gender, race, and ses. Table 21 describes the significant differences between students of different races, ses, and gender. The race covariate is coded “0” for non-African American students and “1” for African American students. Thus, the significant race covariate, -0.147 (s.d.=.031, p<.000) suggests that African American students score lower over time than non-African Americans: 0.148 standard deviation units lower. For math, the parameter estimate was -0.373 (s.d.=.031, p<.000) suggesting that African American students fall 0.373 standard deviations below non-African American students in the standardized distribution of test scores. The scores of males in the sample were 0.273 (s.d.=.016, p<.001) standard deviations below females. The gender variable was coded “0” for females and “1” for males. Males performed worse over time than females in ELA. However, in math males scored 0.034 (p<.05) standard deviation units higher than females. The other significant covariate was free and reduced lunch status in these models. The estimate for this predictor was 0.109 (s.d.=.024, p<.001) for ELA, indicating that students who qualified for reduced lunch outperformed students who qualified for free lunch at a rate of 0.109 standard deviations. In Model 4b, the covariate reduced lunch was significant, indicating that reduced lunch students scored 0.113 standard deviations above free lunch students. These student level differences explained 48.98% of the variance in ELA. For math, the differences explained 48.6% of the variance in math.

In this model, the school level covariate, school type, was significantly different from zero in ELA (P<.000) and in Math (P<.01), when controlling for student level covariates. The parameters signify that students in RSD schools performed 0.297 standard deviation units below TPS students in ELA and 0.189 standard deviation units below TPS in math. For Model 4a, the random effects indicate that the average ELA score varies by school with a standard deviation of
0.110, while the change over time has a standard deviation of 0.005. Variation at the student level was also noticeable; expected student scores varied with a

Table 21. Estimates for Level 2 and 3 Models Educational Achievement, Sample A

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>ELA</th>
<th>Math</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 4a</td>
<td>Model 5a</td>
</tr>
<tr>
<td>Intercept</td>
<td>-235.04*** (10.46)</td>
<td>-222.94*** (10.84)</td>
</tr>
<tr>
<td>AA</td>
<td>-.147*** (.031)</td>
<td>-.133*** (.033)</td>
</tr>
<tr>
<td>Gender</td>
<td>-.273*** (.016)</td>
<td>-.261*** (.017)</td>
</tr>
<tr>
<td>FRL</td>
<td>.109*** (.024)</td>
<td>.096*** (.025)</td>
</tr>
<tr>
<td>SType</td>
<td>-.297*** (.061)</td>
<td>-.317*** (.086)</td>
</tr>
<tr>
<td>SFRL</td>
<td>-.000 (.000)</td>
<td>-.000 (.000)</td>
</tr>
<tr>
<td>SHQT</td>
<td>.001 (.002)</td>
<td>.001 (.002)</td>
</tr>
<tr>
<td>SRace</td>
<td>.000 (.002)</td>
<td>.000 (.002)</td>
</tr>
<tr>
<td>Time</td>
<td>.117*** (.005)</td>
<td>.112*** (.005)</td>
</tr>
</tbody>
</table>

Random Effect

| Within School SD |  .483 | .693 | .692 | .683 |
| Between School SD| .110 | .252 | .301 | .254 |
| ICC              | .11  | .06  | .092 | .068 |

N=23,707
AA=African American
~P<.10, *P<.05, **P<.01, ***P<.001

standard deviation of .483. For Model 4b, the random effects indicate that the average math score varies by school with a standard deviation of 0.302, while the change over time has a standard deviation of 0.005. Variation at the student level was also noteworthy. For Model 4b, the expected student scores varied with a standard deviation of 0.692.

Research Question# 3

Do school characteristics account for the variation in standardized test scores between RSD and TPS?
Hypothesis #3: School characteristics of disadvantage (low socioeconomic status, high percentage African American population, low percentage of highly qualified teachers) will decrease standardized tests score performance in schools.

Models 5a and 5b added the school level covariates of mean percentage free and reduced lunch, mean percentage highly qualified teachers, and mean percentage African American students. Results, as shown in table 21 describe significant differences on the school level variables for the outcomes. For ELA, Model 5a, there were no significant differences on the school level predictors. The significant race covariate, -0.133 (s.d.=.033, p<.000) suggests that African American students score lower regardless of the time period. Their scores fall .133 standard deviations below the comparison group, which included all other racial categories besides African American. For Model 5b, the race parameter estimate was -0.364 (s.d.=.033, p<.001) suggesting that African American students score .364 standard deviations below non-African American students. Gender was another significant covariate in Models 5a and 5b. For Model 5a, the estimate was -0.261 (s.d.=.017, p<.001) indicating that males scored .261 points below female in the distribution over time. For Model 5b, gender was also significant, but had an opposite effect from ELA. Males scored an average of .044 standard deviations above females. Lastly, these models also had free/reduced lunch status as a significant student level predictor. The estimate for Model 5a, .096 (s.d.=.025, p<.001) indicates that students who were eligible for reduced lunch scored .096 standard deviations above free lunch students. These students scored significantly higher than students who were eligible for free lunch. In Model 5b, the estimate was .113 (s.d.=.024, p<.001), implying that students eligible for reduced lunch outperformed free lunch students by .113 standard deviations. These student level differences explained 48.98% of the variance in ELA. For math, the differences explained 48.6% of the variance in math.
For ELA the random effects in these models indicate that the average score varies by school with a standard deviation of 0.252, while the change over time has a standard deviation of 0.005. Variation at the student level is noticeable; expected student scores vary with a standard deviation of 0.693. For math, the random effects indicate that the average score varies by school with a standard deviation of 0.254, while the change over time has a standard deviation of 0.005. Variation at the student level is also noticeable, like ELA. The expected student scores vary with a standard deviation of 0.683. Variation at the student level in math was .683 standard deviation units.

All of the student level variables were significant in Models 5a and 5b. School type was also significant in both models 5a and 5b. For ELA, the parameter estimate -.317 (s.d.=.086, p<.000) indicates that RSD students perform .317 standard deviations below TPS students. In math, the parameter estimate -.256 (s.d.=.086, p<.01) indicates that RSD students performed .256 standard deviation units below TPS students over time. There were no other significant school level covariates in the model. The ICC for the school level factors was .068 and the student level ICC was .511. This indicates that the school level factors accounted for about 7% of the variance in student ELA scores, while the student level factors accounted for about 51% of the variance in student ELA scores. Student factors reduced the significance level of the school level, suggesting that student level factors have a stronger relationship to ELA and math scores on LEAP/GEE/iLEAP.

**Brief Summary of Hierarchical Model Results for Sample A**

Models 2-5 yielded a significant result at the p<.001 level for time as a covariate, indicating an increase in student scores over time. For models 4 and 5 all the student level covariates were significant at the P<.000 level in ELA. In math, gender was less significant in
Models 4b and 5b (P<.05, P<.01). In ELA males scored lower than females, but in math males scored higher than females. For all models, school type was significant. In ELA, school type was significant at the P<.000 level and in math it was significant at the P<.01 level indicating significant differences between RSD and TPS students when controlling for student characteristics. In models 3a and 3b, school type was significant (P<.000) for ELA and Math indicating a significant variation in ELA and math scores by school type. In these models RSD schools performed below TPS schools on both outcomes.

**Sample B**

The second section will present similar results as the first section, however, results will be for Sample B. Sample B consisted of the 6 additional RSD schools opened in the year 2008-2009 and 6 matched comparison traditional public schools (n=12). The years of data for these

Table 22. Students by School Type and Year, Sample B

<table>
<thead>
<tr>
<th></th>
<th>Beginning School Year</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2008</td>
<td>2009</td>
</tr>
<tr>
<td>RSD</td>
<td>201</td>
<td>201</td>
</tr>
<tr>
<td>TPS</td>
<td>905</td>
<td>905</td>
</tr>
<tr>
<td>Total</td>
<td>1,106</td>
<td>1,106</td>
</tr>
</tbody>
</table>

N=3,318

schools included Fall 2008 through Spring 2011 (3 years). The additional schools included 1,106 students in RSD and tps students who were followed for 3 years of data. The final sample for Sample B was 12 schools with n= 1,106 students for 3 years. For Sample B, only students who had data for each of the 3 years of interest were kept in the dataset. There were a total of 3,318 observations for Sample B. The breakdown by school type and year are listed in Table 22. There was also an inspection for outliers, of which there were no unusual values or outliers. Table 23 summarizes the extent of missing data in the analysis. The highest percentage of
missing data was 1.1% was for the variable, SchoolRace, in the year 2009. There were no others variables with extensive missing data in the dataset.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percentage Missing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Free/Reduced Lunch</td>
<td>0%</td>
</tr>
<tr>
<td>Gender</td>
<td>0%</td>
</tr>
<tr>
<td>Race</td>
<td>0%</td>
</tr>
<tr>
<td>School Free/Reduced Lunch</td>
<td>.08%</td>
</tr>
<tr>
<td>School Highly Qualified Teachers</td>
<td>.02%</td>
</tr>
<tr>
<td>School Race</td>
<td>1.1%</td>
</tr>
<tr>
<td>School Type</td>
<td>0.3%</td>
</tr>
</tbody>
</table>

N=3,318

Summary statistics for each variable were inspected, including minimum and maximum values, frequency distribution, mean and standard deviation. A summary of these statistics can be found in Table 24. Table 24 details the student and school demographic variables used in the analysis of Sample A. This table demonstrates that females composed 51.87% of the sample and males made up 48.13%. African American students comprised 98.67% of the sample, while non-African American students made up 1.33% of the sample. Students who qualified for Free lunch made up 93.73% of the sample, and those students who qualified for Reduced lunch composed 6.27% of the sample. RSD schools comprised 50% percent of the sample and traditional public schools comprised 50% percent of the sample. The mean percentages of the school level variables were as follows: school percent free and reduced lunch=83.96 (s.d.=8.22); school percent highly qualified teachers=66.02 (s.d.=12.40); and school percentage African American students=98.20 (s.d.=1.65). The mean percentages on the scaled score outcomes were as follows: ELA scaled score=294.31 (s.d.=89.95) and math scaled score=300.96 (s.d.=87.25).
Exploratory Data Analysis

Preliminary data analysis included merging school and student level data files, generating correlations between variables; and conversion of scaled outcomes to z-scores. First, correlations were run to determine the strength of the relationship between the achievement scores and the predictors of interest. Correlations demonstrate that the variables have a weak relationship to one another. Also, the correlation table demonstrates that scores on achievement outcomes correlate with one another across years. Negative correlations ranged from -.595 to -.005. Positive correlations ranged from .030 to .907. All correlations were significant at the p<.05 level unless otherwise indicated in Table 25.

Next in the preliminary analyses both ELA and math outcomes were converted to Z-scores to address the vertical alignment of tests from year to year. These allow comparisons of tests from year to year and determination of where the students fall within the distribution based on standard deviations. The z-scores were all correlated to predictors at the same level as the scaled scores.
Assumptions

To begin the analysis of the three level hierarchical linear model, the assumptions of the model were first tested. Assumptions for this model were tested using the same strategies as used with Sample A. The assumptions were met for this sample as well.

Multilevel Model

To determine the need for further analysis, the unconditional models (Models 6a and 6b) were run for ELA and math. The intraclass correlation was computed. Table 26 demonstrates the ICC for the null model. A very small ICC indicates that a multilevel model is unnecessary, but Model 6a demonstrates that approximately 7% of the variance in ELA outcomes is due to school differences. The estimate of the Model 6a mean score is -0.079 and the standard deviations are 0.56, 0.76 and 1.23 at the school, student and observation levels. For Model 1b, the ICC was .046 suggesting that approximately 5% of the variability in the model can be explained by the school level. The estimate of the mean score in Model 6b was -.099 with standard deviations of .405, at the school, student, and observation levels.
Table 26: Unconditional Model Educational Achievement, Sample B

<table>
<thead>
<tr>
<th></th>
<th>Unconditional Model 6a</th>
<th>SD</th>
<th>Unconditional Model 6b</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>ELA</td>
<td>-0.079</td>
<td>0.031</td>
<td>-0.099</td>
<td>0.050</td>
</tr>
<tr>
<td>Math</td>
<td>1.231</td>
<td>0.215</td>
<td>0.405</td>
<td>0.022</td>
</tr>
<tr>
<td>ICC</td>
<td>0.070</td>
<td></td>
<td>0.046</td>
<td></td>
</tr>
</tbody>
</table>

N=3,318

Models 7a and 7b were run using time as a covariate. From Table 27 the average growth rate for children was .245 (p<.000) over time in ELA and .195(p<.000) in math. The level 2 and level 3 standard deviation estimates for ELA and math were .023 and .029. The intraclass correlation coefficient, was .070 and .047 and math, revealing that the school explained 7% of the variance in ELA and 5% of the variance for math scores.

Table 27: Unconditional Model with Time as Covariate Educational Achievement, Sample B

<table>
<thead>
<tr>
<th></th>
<th>Model 7a</th>
<th>SD</th>
<th>Model 7b</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>.245***</td>
<td>.023</td>
<td>.195***</td>
<td>.029</td>
</tr>
<tr>
<td>Adjusted Mean</td>
<td>-493.11</td>
<td>46.98</td>
<td>-391.86***</td>
<td>.024</td>
</tr>
<tr>
<td>Residual</td>
<td>.435</td>
<td>.204</td>
<td>.601</td>
<td>.106</td>
</tr>
<tr>
<td>ICC</td>
<td>0.070</td>
<td></td>
<td>0.047</td>
<td></td>
</tr>
</tbody>
</table>

N=3,318
Significance Level *P<.05, **P<.01, ***P<.001

Research Question #1

Do standardized test scores vary by school type (RSD versus TPS) in Louisiana?

Hypothesis #1: According to the state takeover model, RSD schools should have higher test scores than traditional public schools.

Models 8a and 8b were run to examine research question 1. The school level covariate school type was included in the model as a fixed effect covariate and added to the time covariate.
### Table 28: Estimates for Effect of School Type on Educational Achievement, Sample B

<table>
<thead>
<tr>
<th></th>
<th>ELA</th>
<th>MATH</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Model 8a</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Fixed Effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-495.10*** (57.65)</td>
<td>-495.75*** (64.19)</td>
</tr>
<tr>
<td>SType</td>
<td>-.412** (.144)</td>
<td>-.362** (.147)</td>
</tr>
<tr>
<td>Time</td>
<td>.246*** (.023)</td>
<td>.247*** (.032)</td>
</tr>
<tr>
<td><strong>Model 8b</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Random Effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within School SD</td>
<td>1.016</td>
<td>.999</td>
</tr>
<tr>
<td>Between School SD</td>
<td>.125</td>
<td>.135</td>
</tr>
<tr>
<td>ICC</td>
<td>.014</td>
<td>.052</td>
</tr>
</tbody>
</table>

N=3,318
~P<.10, *P<.05, **P<.01, ***P<.001

From Table 28 the average growth rate for RSD children was .412 (p<.01) standard deviations lower than TPS schools in ELA and .362 (p<.01) lower than TPS schools in math. The estimate of the ELA mean score is -495.10 and the standard deviations are .125, 1.016, and .310 at the school, student, and observation levels. The estimate of the math mean score is -495.75 and the standard deviations are .135, .999, and .355 at the school, student, and observation levels. The intraclass correlation coefficient was .014 for ELA and .052 for ELA and math, revealing that the school explained 1% and 5.2% of the variance in ELA and math growth.

**Research Question #2**

Do student characteristics account for the variation in standardized test scores between RSD and TPS?
Hypothesis #2: Student characteristics of disadvantage (low socioeconomic status, African American) will decrease standardized tests score performance in schools.

Models 9a and 9b added the student demographic covariates, gender, race, and ses. Table 29 describes the significant differences between students of different races, ses, and gender. For ELA and math, the race covariate was significant. The parameters were as follows: for ELA, -1.021 (s.d.=.437, P<.05) and for math, -0.870 (s.d.=.431, P<.05). These parameters indicate that African American students score lower than non-African American students in both subject areas over time. In Models 9a and 9b gender was significantly different from zero. The estimate for ELA, -0.159 (s.d.=.071, p<.05) suggests that male students score lower over time than female students. For math, the gender parameter estimate, .291 (s.d.=.070, P<.010) indicating that males score higher than females in math. Lastly, the parameter estimate for Reduced Lunch students was not significantly different from zero in models 9a or 9b. These student level estimates explained 66.94% of the variance in ELA. For math, the student differences explained 64.6% of the variance in math.

School type was still significant both in ELA (P<.01) and in math (P<.01) for these models, indicating that RSD students perform below their TPS counterparts even when controlling for student level factors. For ELA, RSD students performed .443 standard deviations below TPS counterparts and for math, RSD students performed .392 standard deviation units below TPS counterparts.

For ELA, the random effects indicate that the average score varies by school with a standard deviation of .017, while the change over time has a standard deviation of 0.029. Variation at the student level is noticeable; expected student scores vary with a standard deviation of 0.105. For math, the random effects indicate that the average score varies by school
with a standard deviation of .132, while the change over time has a standard deviation of 0.032.

Variation at the student level in math is also noteworthy. The expected student scores vary with a standard deviation of 0.998.

**Table 29. Estimates for Levels 2 and 3 Educational Achievement, Sample B**

<table>
<thead>
<tr>
<th></th>
<th>ELA</th>
<th>Math</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed Effect</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-490.54*** (58.06)</td>
<td>-463.58*** (50.40)</td>
</tr>
<tr>
<td>AA</td>
<td>-1.021* (.437)</td>
<td>-263.235 (-.431)</td>
</tr>
<tr>
<td>Gender</td>
<td>-.159* (.071)</td>
<td>104** (.035)</td>
</tr>
<tr>
<td>FRL</td>
<td>.100 (.086)</td>
<td>.151** (.060)</td>
</tr>
<tr>
<td>SType</td>
<td>-.443** (.147)</td>
<td>-.066 (.169)</td>
</tr>
<tr>
<td>SFRL</td>
<td></td>
<td>-.012** (.005)</td>
</tr>
<tr>
<td>SHQT</td>
<td>.004 (.005)</td>
<td>.016~ (.009)</td>
</tr>
<tr>
<td>SRace</td>
<td>.026 (.028)</td>
<td>.043* (.023)</td>
</tr>
<tr>
<td>Time</td>
<td>.245*** (.029)</td>
<td>.233*** (.025)</td>
</tr>
</tbody>
</table>

**Random Effect**

<table>
<thead>
<tr>
<th></th>
<th>Within School SD</th>
<th>Between School SD</th>
<th>ICC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.05</td>
<td>.017</td>
<td>.014</td>
</tr>
<tr>
<td>Within School SD</td>
<td>.448</td>
<td>.065</td>
<td>.01</td>
</tr>
<tr>
<td>Between School SD</td>
<td>.998</td>
<td>.132</td>
<td>.044</td>
</tr>
<tr>
<td>ICC</td>
<td>.427</td>
<td>.081</td>
<td>.01</td>
</tr>
</tbody>
</table>

Parameter Estimates (standard deviation)

AA = African American
Significance Level, ~P<.10, *P<.05, **P<.01, ***P<.001

**Research Question #3**

Do school characteristics account for the variation in standardized test scores between RSD and TPS?

Hypothesis #3: School characteristics of disadvantage (low ses, high percentage African American population, low percentage of highly qualified teachers) will decrease standardized tests score performance in schools.

Models 10a and 10b added school level covariates of mean percentage free and reduced lunch, mean percentage highly qualified teachers, and mean percentage black students. Results,
as shown in table 29 describe significant differences on the school level variables for the outcomes. The percentage of students eligible for free/reduced lunch was significant for Model 10a with an estimate of -.012 (s.d.=.005, p<.01). This can be interpreted as a .012 standard deviation decrease in ELA score for schools with a 1 unit increase in percentage of free and reduced lunch student population. Mean percentage of African American student population was also significant for math, with an estimate of .043 (s.d.=.023, p<.05) indicating that for every 1 unit increase in mean percentage of African American students, the standardized math score increases by .043 standard deviation units. No other school level variables were significant.

For student level covariates in Model 10a, race was not significant in ELA indicating no difference for African American versus non-African American students in ELA. For math, however, the significant race parameter estimate was -.873 (.431, P<.05) indicating that African American students performed .873 standard deviation units below TPS students in math when controlling for all other predictors. Also, gender was significantly different from zero in ELA and math. The significant gender covariate, .104 (s.d.=.035, p<.01) suggests that male students outperformed female students over time in ELA. Their scores are .104 standard deviations above females. For Model 10b, males scored .291 standard deviation units above females over time. Lastly, these models also had free/reduced lunch status as a significant student level predictor. The estimate for Model 10a, .151 (s.d.=.000, p<.01) indicates that students who were eligible for reduced lunch scored .151 standard deviations above free lunch students. In Model 10b, the estimate was .121 (s.d.=.064, p<.05), implying that students eligible for reduced lunch outperformed free lunch students by .121 standard deviations above free lunch students. These student level differences explained 50.7% of the variance in ELA. For math, the differences
explained 48.9% of the variance in math. Schools explained only 1% of the variance in these models.

For ELA the random effects indicate that the average score varies by school with a standard deviation of 0.065, while the change over time has a standard deviation of 0.005. Variation at the student level is at a noticeable level; expected student scores vary with a standard deviation of 0.448. For math, the random effects indicate that the average score varies by school with a standard deviation of 0.081 while the change over time has a standard deviation of 0.028. Variation at the student level in math was at a noticeable level also. The expected student scores vary with a standard deviation of 0.427.

The ICC for the school level factors in Model 10a was 0.01 and the student level ICC was 0.91. This indicates that the school level factors accounted for about 1% of the variance in student ELA scores, while the student level factors accounted for about 91% of the variance in student ELA scores. Student factors reduced the significance level of the school level factors, suggesting that student level factors had a stronger relationship to ELA scores on LEAP/GEE/iLEAP. For Model 10b the school level ICC was 0.01 indicating that school level accounted for about 1% of the variance in student Math scores. The student level ICC was 0.088 indicating that student level accounted for 88% of the variance in student Math scores.

**Brief Summary of Hierarchical Model Results for Sample B**

Models 6-8 yielded a significant result at the p<0.001 level for time as a covariate, indicating an increase over time for student scores. For models 9 and 10 all the student level covariates were significant at the p<.01 level. In ELA, males scored lower than females, but in math males scored higher than females. For both ELA and math the school level variable, school type, was significant (p<.05), suggesting that RSD students scored lower than TPS students over
the 3 years of the study. When added to the full model with student and school factors, the effect of school type disappeared.
CHAPTER 5A: DROPOUT CONCLUSIONS AND RECOMMENDATIONS

This chapter describes the conclusions drawn from the results of the multilevel discrete time survival analysis. The chapter includes the following sections: 1) overview 2) summary of the major findings 3) implications for future research and 4) limitations and next steps.

Overview

As countries’ graduation rates are compared globally, the United States ranks among the bottom of the list of developed nations (Cardoza, 2012). The consequences of dropout from high school are extensive for the student who drops out and for the larger society (McKinsey & Company, 2009). Not only is dropout linked to an increased crime rate, but also to lower earnings for individuals and society (McKinsey & Company, 2009). At a time when the American economy is in a delicate state, the billions of dollars lost from the economy due to high school dropouts is even more costly. Education reforms aimed at reducing the dropout rate stand to improve all of these outcomes.

The current study employed a multilevel discrete time survival analysis to determine the relationship between one such reform and student outcomes. More specifically, this project examined the relationship between student and school level characteristics and dropout and the extent to which the risk of dropout varied by school type between RSD and traditional public schools.

The study sample included students within all RSD schools that opened in 2007-2008 (n=71) and a matched set of traditional public schools (n=74) in East Baton Rouge Parish and Caddo Parish. The student level sample included all students in these schools that had 4 years of data with relevant variables. The students were matched using propensity score matching on race and free and reduced lunch status. The final student sample was 46,004 observations nested
within 11,501 students, nested within 145 schools and followed across 4 years. The study components included the level one model and level 2 model as well as the testing of assumptions and addressed the following questions:

1. What is the likelihood that a student will drop out of RSD schools compared to a matched set of traditional public schools?

2. Do student characteristics influence the risk of students dropping out of school at a given time?

3. Do school characteristics influence the risk of students dropping out of school at a given time?

The main objective in this study was to examine the nature of the relationship between dropout and school and student level characteristics. For level one or the student level, race was found to be statistically significant in Model 4. This indicates a difference in the hazard functions of African Americans and non-African Americans. Free and reduced lunch status and gender were not found to be significant indicating no difference in the influence of socioeconomic status or gender or the risk of dropout in this sample. These findings are consistent with numerous studies of the racial correlates of dropout. African American students have been demonstrated to have an increased risk of dropout (McKinsey & Company, 2009). These results deviate from other studies that also demonstrate that students from low socioeconomic backgrounds and males have been more likely to dropout in education literature (Cataldi et al., 2009; McKinsey & Company, 2009; Planty et al., 2009).

The secondary objective was to determine whether school type (RSD versus TPS) was related to risk of dropout. School type was significantly different than zero in Model 4 indicating that students in RSD schools had a 3.25 times higher risk of dropout than their TPS counterparts.
Time enrolled in school was also significant in all models. This indicates that the risk of dropout increased with each year. When the additional school level variables were added to the model, the significance level of school type decreased to p<.10 indicating that the difference between dropout risk in RSD and TPS schools is marginal when controlling for several key student and school predictors along with it. The risk of dropout is rather small across years for RSD students, echoing reports and sources that indicate the RSD decreases student dropout. This effect is minimized, however, when compared to traditional public school students. The results of this study suggest that the RSD students have a higher risk of dropout than their TPS counterparts.

**Summary of Major Findings**

- The level 1 model revealed differences in dropout risk according to year and race. Each year that a student was enrolled, he/she had an increased hazard function of dropout. African American students had increased risk of dropout.
- To test the individual effect of school type, the level 2 covariate, school type was added and demonstrated significance at the p<.000 level in Model 4 when added to the student level covariates. This indicates a significant difference in the hazard of dropout between types of schools, with an RSD student being 3.25 times more likely to dropout than a student in a traditional public school.
- When the remainder of the school level variables were added to the model, the significance of school type decreased to p<.10 and school mean percentage of African American students was also significant at the p<.10 level indicating that schools with higher mean percentage of African American students had increased risk of dropout.
- The level 1 proportional odds assumptions, the level 2 proportional odds assumption, the level 2 proportional error assumptions were not met.
Implications for Future Research

This study demonstrates that research utilizing sophisticated analyses is useful in studying dropout. Because the nature of dropout is correlated to many factors, multilevel modeling offers many advantages as an analysis. Not only can dropout be modeled as a function of time and individual factors, but with multilevel modeling it can also be modeled as a function of school factors. In Louisiana, as well as other states, many interventions are employed to improve student retention. Methods such as those used in this study assist in explaining the complicated nature of dropout. Multilevel models assist researchers in avoiding the ecological fallacy, in which school level effects are extrapolated to the student level. As seen in this study, student level factors account for more of the dropout risk when controlling for school level factors. Aggregated data has been used in all published sources regarding the RSD’s relationship to dropout (Cowen, 2010; Smith 2011). Future research that centers on the Recovery School District should incorporate student level analysis since student differences account for more variation in student dropout.

The analysis of student level dropout data in this study also demonstrates the usefulness of the Louisiana student information system (SIS) in modeling dropout patterns over time. Currently, cohort dropout rates are created for calculation of school performance scores, but this study offers another method of utilizing dropout data from the SIS.

Limitations and Next Steps

One major limitation of this study was the sample size. Considering the large population of students in the RSD from years 2007-2008 through 2010-2011 (N>30,000), the current study was able to select a small percentage of those students due to data limitations and availability of data across a 4-year period. The sample, however, was representative of the
larger population of recovery school district students and can thus be generalized to this population. In future research, models should incorporate those students who leave schools after a certain amount of time and transfer to other non-RSD schools. In addition, a next step would be to include more years of study. There will be an additional 2 years of data available since this study has been written. Another step would be to change the time measurements to determine whether risk varies as a function of a certain month or time of the year. This could lead to interventions tailored to addressing the risk factors by time of year. Lastly, the current study utilized a 2 level analysis, next steps would be to use a 3 level model to determine the risk of dropout. An additional level could include classrooms or neighborhoods. What about more concise measures of SES, teacher characteristics, etc.?
CHAPTER 5B: ACHIEVEMENT CONCLUSIONS AND RECOMMENDATIONS

This chapter describes the conclusions drawn from the results of the three-level hierarchical linear model. The chapter includes the following sections: 1) overview 2) summary of the major findings 3) implications for future research, and 4) limitations and next steps.

Overview

The central objective of this study was to compare the relationship between the RSD and student outcomes on the LEAP/iLEAP/GEE over time to the performance of a set of matched traditional public schools and students. In addition, identification of the nature of the relationship between student and school predictors to achievement was a second objective. The following research questions were addressed in this study:

1. Do standardized test scores vary by school type (RSD schools versus traditional public schools) in Louisiana?
2. Do student characteristics account for the variation in standardized test scores in state takeover and traditional public schools?
3. Do school characteristics account for the variation in standardized test scores between recovery schools and traditional public schools?

This study examined the research questions by utilizing a student sample comprised of 3rd-10th graders in both RSD and a matched sample of traditional public schools from the years 2007-2010 (Sample A) and 2008-2010 (Sample B). The first conclusions will be described for Sample A. The total student population after selecting those that remained in the sample schools for the entire study and were consistently promoted each year was reduced to 5,925 student over 4 years of data for a total number of observations, n=23,707 (Sample A).
Preliminary analyses yielded correlations that were statistically significant on all predictors to outcomes. This result is consistent with countless other studies that demonstrate student and school characteristics that are related to student testing performance (Alliance for Excellence in Education, 2007; Cataldi et al., 2009). Both ELA and math have been consistently correlated to school level factors including percentage of highly qualified teachers and percentage of minority students (McKinsey & Company, 2009). Test score outcomes have also been linked to student level factors including race, gender, and socioeconomic status (NCES, 2004; Planty et al., 2009). To summarize, student predictors and school predictors correlate to student scores and z-scores on math and ELA portions of the LEAP/iLEAP/GEE.

Next, the multilevel model was fit to address the research questions. Objective #1 was to determine the extent to which outcomes on the ELA and math sections of the LEAP/iLEAP/GEE varied as a function of school type. A statistically significant estimate for school type was found when added to the unconditional model. When controlling for student characteristics, school type was still significant. When controlling for both student and school level factors, school type remained significant, suggesting that RSD students performance is significantly lower than TPS students over time in both ELA and math when controlling for all other predictors in the models.

Since this has been an understudied topic, there were very few comparison studies with which to examine the consistency of the current. This research breaks from those sources that highlight the ways in which the RSD outpaces traditional public schools in achievement (Smith, 2011; Hill & Murphy, 2012). Results of this study counter the hypothesis stating that RSD schools should be outperforming comparable traditional public schools.

A second objective was to determine if student characteristics were related to ELA and math score performance on LEAP/iLEAP/GEE in this sample. This was examined by modeling
the student score as a function of student level characteristics. Models 4a and 4b demonstrate that predictors were all significantly different from zero, suggesting that holding all other variables constant, females outperformed males, non-African American students outperformed African American students, and students eligible for reduced lunch outperformed students who qualify for free lunch. In Model 4b, all student level predictors were also significant suggesting that for math, males outperformed females, non-African American students outperformed African American students, and students eligible for free and reduced lunch outperformed students who qualify for free lunch.

Objective #3 was to examine other school level factors in addition to school type that may be related to ELA/Math performance. Models 5a and 5b include school level predictors and the only significant predictor was free/reduced lunch status in ELA. This suggests that there was a significant difference in student scores based on the school population mean for reduced versus free lunch students.

**Summary of Major findings**

- Time was a significant covariate across all models suggesting that student scores varied over time. The unconditional model demonstrated that the student covariates accounted for more of the variation in ELA and math scores than the school level.
- Level-two or student level covariates were significant in all models indicating that students with characteristics of disadvantage, including low socioeconomic status and minority status, perform lower than those students who are not. Males outperformed females in math, whereas females outperformed males in ELA.
- The school level covariate, school type, was statistically significant in ELA and math in all models, revealing that RSD students perform lower than their tps counterparts when
school type included in the model alone and when controlling for other student and school level factors.

- When other school level covariates, including mean percentage of African American students, mean percentage of free and reduced lunch students, and mean percentage of highly qualified teachers, were added to the model, school type remained significant. No other school level covariates were significant, except for mean percentage of free and reduced lunch population in ELA. This indicates that student characteristics and school type, rather than the remaining school characteristics accounted for the variation in test scores over time.

**Implications for Future Research**

As the first nested, longitudinal assessment of the RSD’s impact on student achievement this study serves as a foundation for future research. This study demonstrates the use of a hierarchical linear model suited to study the multifaceted problem of student achievement and the effects of the RSD. The hierarchical linear model is suited to study nested data, which is characteristic of all school data. Students are nested within classrooms, within schools, within districts across Louisiana. While achievement trends have been reported for the RSD, sophisticated statistical analysis has been lacking. The majority of sources utilize school performance scores to make conclusions about RSD performance. School performance scores are aggregated to the school level and exclude student level comparisons.

The RSD now includes over 70 schools with more on the brink of takeover and over 60,000 Louisiana students already enrolled in the RSD. Since achievement scores are the largest metric used to identify failing schools that subsequently are taken over by the RSD, it is crucial to see how this very outcome is then improved by the RSD. School reform models are ever
changing and evolving across the nation. These results do not demonstrate that RSD’s outpacing of traditional public schools. It demonstrates the opposite effect, that TPS schools have outpaced RSD schools during the study period on both outcomes. These findings are a promising contribution to the field of education research as a first look into the relationship between the RSD and achievement over time at both the student and school levels.

**Limitations and Next Steps**

Limitations of the study include the sample composition and size. This study only included students who were consistently promoted over time within the sample of schools. Thus, the current study does not account for those students who repeat grades or who left the schools in the sample during the study years. Next steps to address this limitation would be to study patterns of achievement for repeaters and highly mobile populations of students who transition between schools. These students may be the most at risk of poor performance that influences school takeover. Another limitation is the sample size. Considering the amount of students within the school sample for the given years (N>20,000), only following 5,984 students over time is a small percentage of that sample. These results can therefore only be generalized to students who were consistently promoted and remained in the school sample over time.

Further study should also add additional years of data to deal with the changes in testing formats like End of Course Tests, which were introduced in the Spring 2010 for incoming high school freshman. Likewise, other school and student demographic variables can be added to the model to further explain the variance in student scores, such as parental education level or previous year achievement score.
Sample B

Overview

The central objective of this study was the same as that for Sample A: to compare the relationship between the RSD and student performance on the LEAP/iLEAP/GEE to the performance of a set of matched traditional public schools and students. Likewise, identification of the nature of the relationship between student and school predictors to these outcomes was a second objective.

The total student population after selecting those that remained in the sample schools for the entire study and were consistently promoted each year was reduced to 1,106 student over 3 years of data for a total number of observations, n=3,318. Preliminary analyses yielded correlations that were statistically significant on all predictors to outcomes.

Objective #1 was to determine the extent to which outcomes on the ELA and math sections of the LEAP/iLEAP/GEE varied as a function of school type. When school type was added to the unconditional model, it was significant (p<.01) for both ELA and Math. The parameter estimates suggest that RSD students perform lower than TPS students over time. A statistically significant estimate for school type was found even when controlling for student level predictors. When additional school level factors were entered into the model, however, school type was not significant, indicating no effect when controlling for school factors.

Since this has been an understudied topic, there were very few comparison findings to highlight consistency of other findings. Of those limited number, this study breaks from those sources that highlight positive trends in achievement for RSD schools (Cowen, 2010; Hill & Murphy, 2012; Smith, 2011). Indeed, the significant estimates demonstrate that RSD students perform below average over time and below tps students.
A second objective was to determine if student characteristics relate to ELA and math score performance on LEAP/iLEAP/GEE. This was examined by modeling the student level HLM in models 9a and 9b. Predictors were all significantly different from zero except for free and reduced lunch status. This suggests that holding all other variables constant, females outperformed males in ELA, males outperformed females in math, and non-African American students outperformed African American students in ELA and math.

Objective #3 was to examine other school level factors in addition to school type that may be related to ELA/Math performance. Models 10a and 10b included school level predictors. The only significant predictor for ELA was mean percentage of students who qualify for free and reduced lunch. This suggests that for every 1 unit increase in mean percentage of students who qualify for free and reduced lunch there is an associated .012 standard deviation decrease in ELA scores. For math the only predictor that was significant was mean percentage of African American students, indicating that for every 1 unit increase in mean percentage of African American students in a school, the math score of students increased by .043 standard deviation units.

**Summary of Major Findings**

- Time was a significant covariate across all models suggesting that student scores varied over time. The unconditional model demonstrated that the student covariates accounted for more of the variation in ELA and math scores than the school level.
- Level-two or student level covariates were significant in all models indicating that students with characteristics of disadvantage, including low socioeconomic status and being African American, perform lower than those students who are not. Males outperformed females in math, whereas females outperformed males in ELA.
• The school level covariate, school type, was significant for both Math and ELA, revealing that RSD students in Sample B performed lower than their tps counterparts over time. Even when student level predictors were added to the model, school type remained significant indicating that controlling for student level factors, school type is a significant predictor of the variance in student scores in ELA and math.

• When other school level covariates were added to the model, school type was not significant. School covariates that were significant are mean percentage of students who qualify for free and reduced lunch in ELA and mean percentage of African American students in math. Other school level covariates, including mean percentage of African American students (in ELA) and mean percentage of highly qualified teachers, were not significant. In the full model, student race was not significantly different from zero. Gender and free/reduced lunch status were significant predictors at the student level in ELA for the full model. Only free and reduced lunch status was significant for math scores. This indicates that student characteristics rather than school characteristics account for more of the variation in test scores over time.

Implications for Future Research

As the first longitudinal, nested assessment of the RSD’s impact on student achievement this study serves as a foundation for future research. This study provides a hierarchical analysis suited to study the multifaceted problem of student achievement and its relationship to the RSD. The hierarchical linear model is suited to study nested data, which is characteristic of all school data. Students are nested within classrooms, within schools, within districts across Louisiana. While achievement trends have been reported for the RSD (Cowen, 2010; Smith, 2011), sophisticated statistical analysis has been lacking. Most reporting utilizes school performance
scores, which are tallied by the state department of education and aggregated at the school level. Student level analysis of the RSD has not yet been done.

The RSD now includes over 70 schools with more on the brink of takeover and over 60,000 Louisiana students already enrolled in them. Since achievement is a true metric used to identify failing schools that subsequently are taken over by the RSD, it is crucial to see how this very outcome is then improved by the RSD. School reform models are ever changing. The results demonstrate that when controlling for student factors, school type is significant and RSD schools perform below their TPS counterparts. This is an opposite effect than has been suggested and published regarding RSD school and student performance. School type was not significant when controlling for student and school factors. This also suggests no difference between RSD and TPS schools, which is also a different outcome than sources have claimed. This particular sample included the RSD’s schools located outside of New Orleans, mainly in the city of Baton Rouge. Conclusions can be generalized to these schools and students and the matched comparison group.

**Limitations and Next Steps**

Limitations of the study include the sample composition and size. This study only included students who were consistently promoted over time within the sample of schools. This does not account for those students who repeat grades or who left the schools in the sample during the study years. Next steps to address this limitation would be to study patterns of achievement for repeaters and highly mobile populations of students who transition between schools. Another limitation is the sample size. Considering that the amount of students within the school sample for the given years, only following 1,106 over time is a small percentage of that
population. These results can therefore only be generalized to students who were consistently promoted and remained in the school sample over time.

Further study should also add additional years of data to deal with the changes in testing formats like End of Course Tests, which were introduced in the Spring 2010 for incoming freshmen.
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VITA

Jandel Crutchfield, a native of Baton Rouge, Louisiana received her Bachelor’s degree at Washington University in St. Louis in 2004. Thereafter, she pursued and earned her Master’s of Social Work Degree in 2006. After beginning her career as a school social worker in Louisiana schools, she decided to engage in doctoral education at the LSU School of Social Work. She will receive her Doctor of Philosophy in Social Work in August 2013 and plans to continue to her research.

Her main research focus is evidence-based practices for practitioners working with children and families influenced by education reforms aimed at reducing the achievement gap. Her specialization within school social work is the effectiveness of achievement gap education reforms; factors contributing to differences in performance between traditional and schools implementing new education reforms; and school social work’s role as a profession within the context of achievement gap education reform. Within her specialization, she expands on the current knowledge base of effectiveness studies of charter schools, magnet schools, and non-traditional public schools, with a more specific focus on newer, more highly politicized and stigmatized reforms. These reforms include forced conversion charter schools, school vouchers, restructured schools, and state takeover or recovery school district schools.